Impacts of Collaborative Robots on Construction Work Performance and Worker Perception: Experimental Analysis of Human-Robot Collaborative Wood Assembly

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Abstract

Collaborative robots are increasingly recognized as potential assistants to relieve workers from repetitive and physically demanding tasks on construction jobsites. Despite the great potential, most efforts have focused on developing various artificial intelligence (AI) and robotic technologies to achieve specific human-robot collaboration (HRC) functions. However, there is a significant lack of research regarding the impacts of such collaboration on construction work performance and workers' perception and acceptance of collaborative robots, which could be a critical influence factor on the feasibility and effectiveness of HRC on construction jobsites. To this end, this study aims to evaluate the multi-dimensional impacts of collaborative robots on work efficiency, quality, workers' workload, as well as workers' perception and acceptance. HRC experiments on sample construction tasks (i.e., wood assembly) were conducted in conjunction with quantitative measurements and subject surveys. Through comparison between HRC experiments and human-human collaboration (HHC) experiments based on this case study, it was found that HRC could improve up to 29.3% and 88.6% in work efficiency and assembly accuracy, respectively, and reduce worker's workload by up to 20.3%. Furthermore, workers' perception of HRC is found to be positive overall with higher acceptance after HRC experience, characterized by questionnaires designed based on the technology acceptance model. Through physical experiments, this research is expected to produce more reliable results compared to conventional approaches where participants are simply provided with imaginary scenarios. The findings will also guide the development of robotic technologies to enhance the practical application of HRC in construction.

1. Introduction

Automation and robotic technology have been increasingly recognized as promising solutions to longstanding challenges in construction, such as low productivity and safety, and workforce aging and shortage (de Soto et al., 2018; Saidi et al., 2016). For instance, as indicated by a worldwide survey (ASEA Brown Boveri Group, 2021), 91% of construction companies face a skills crisis over the next decades, and 81% of them are willing to introduce or increase the use of construction robots to alleviate such issues. The global construction robot market size is expected to reach 242.4

million U.S. dollars in 2030, a 238% increase from the size in 2020 (Statista, 2022). Robotic technology has been introduced in various applications in construction, ranging from single-task construction robots, including robotic excavators (ASI, 2019), brick-laying robots (Madsen, 2019), rebar-tying robots (Cardno, 2018), painting robots (Asadi et al., 2018), to recent general-purpose robotic platforms (e.g., collaborative robots) for more flexible human-robot collaboration (HRC) (Kim et al., 2021). Specifically, collaborative robots are considered potential assistants to relieve workers from repetitive and physically demanding construction tasks, such as material handling (Liu et al., 2021b), assembly (Kramberger et al., 2022), and wall installation (Wang et al., 2021), etc.

Despite the research achievements, most efforts have been focused on developing various AI and robotic technologies to achieve specific capabilities for certain tasks. Significantly less research focused on studying the impacts of HRC on construction work performance, as well as workers' perception and acceptance, which could be a critical influence factor on the feasibility and effectiveness of HRC in field construction. Some studies conducted interviews and surveys with industry experts to identify the challenges of adopting automation and robotic technologies in practice (Bademosi & Issa, 2021; Delgado et al., 2019). Another study developed a modeling framework through the simulation of HRC processes to evaluate the impacts of HRC on construction productivity (Wu et al., 2022). The main limitation is that imaginary or simulated scenarios were used to elicit insights from domain stakeholders and estimate potential impacts, which could be biased and do not reflect reality. Physical HRC experiments are needed to quantify the multi-dimensional implications for construction work, such as quality, productivity, etc., and to obtain workers' feedback after experiencing real collaboration.

Therefore, using HRC experiments on sample construction tasks (i.e., wood assembly), combined with quantitative measurements and subject surveys, this study aims to evaluate the multi-dimensional impacts of a collaborative robot on construction work and workers in terms of work efficiency, quality, workers' workload, as well as worker's perception and acceptance of collaborative robots. This study contributes to the body of knowledge in two aspects. First, through comparison between HRC experiments and human-human collaboration (HHC) experiments on tasks with different complexity levels, the improvement of HRC over traditional HHC was quantified, including the increase in efficiency and quality, and the reduction in worker's workload, proving the validity and benefits of introducing HRC in construction operations. Second, through surveys that are designed based on the technology acceptance model (TAM), the change of attitudes before and after HRC experiments was identified, and the perception of workers on HRC in various aspects, such as perceived usefulness, perceived ease of use, and safety anxiety, was characterized. Our findings also suggest the need for enhancing acceptance of HRC among construction workers to facilitate its implementation in the construction industry.

2. **Related Studies**

2.1. Robotic Applications and Human-Robot Collaboration in Construction

With advances in AI, sensing technology, and robotics systems, a wide range of assistive robots has emerged in different construction tasks such as bricklaying (Bruckmann et al., 2018), additive manufacturing (Tankova & da Silva, 2020), demolition (Adami et al., 2021), etc. The idea of using fully autonomous construction robots to improve safety and productivity, and mitigate challenges of labor shortage has been explored by different researchers (Groll et al., 2019; Ha et al., 2002; Jud et al., 2021; Ma et al., 2022; Petereit et al., 2019; Yang et al., 2019). For instance, La et al. (2019) presented a steel climbing robot for monitoring and inspection of steel structures and bridges. Multiple sensors were attached to the robot to aid in both navigation and steel surface inspection. The suggested system can gather pictures and 3D point cloud data and transmit those data to the ground station for additional monitoring. Groll et al. (2019) presented an autonomous trenching system that uses a hierarchical organization of primitives to excavate trenches in complex environments. The system combines high-level task planning and low-level motion control to increase efficiency. A human-robot teaming approach was explored for the construction inspection and monitoring process using quadruped robots through an on-site experiment to investigate inspector assistant robot for future construction inspection tasks (Halder et al., 2023). Despite the great potential, the nature of construction tasks still requires human judgment, adaptability, and precision, which are missing in available autonomous construction robots (Pan et al., 2020). The presence of various entities (e.g., workers, machines, other resources) on the worksite, combined with frequently changing operations, generates a dynamic and unorganized work environment that usually impedes the safe operation of autonomous robots, posing significant challenges to automating construction processes (Carra et al., 2018).

Liang et al. (2021) investigated the evolution of construction robots over the last two decades. They concluded that HRC is more effective than autonomous robots for complicated construction tasks that involve a combination of construction methods or materials and knowledge transfer from human workers. Through HRC, workers can be relieved from tiresome and repetitive work and concentrate on operations that involve flexibility and dexterity, thus improving the safety, productivity, and quality of work (Okpala et al., 2020). To enable effective HRC, many studies have been dedicated to developing various human-robot interfaces (Berg et al., 2019; Gustavsson et al., 2018; Kim et al., 2019). For instance, Liu et al. (2021a) proposed a brain-computer interface to teleoperate a robot by continuously capturing workers' brainwaves received from a wearable electroencephalogram device. The electroencephalogram data was then processed by a computer, which analyzes the worker's brainwaves and translates them into specific commands for the robot with 90% accuracy. Liu et al. (2021b) also made it possible for robots to assess worker workload by monitoring their brainwaves and modifying their performance accordingly to relieve the workload of human workers. Czarnowski et al. (2018) suggested that virtual reality (VR) and audible sound systems are viable options to bridge the remote contactless interaction gaps between construction workers and robots because the generated explicit information such as visual cues, and sound alarms could teach workers about the robot's behavior during HRC tasks. Dimitropoulos et al. (2021) proposed a system for parts assembly in a human-robot collaborative assembly cell using AI and wearable devices. They used AI algorithms to enable the robot to anticipate and adapt to the movements of the human worker, and wearable devices to facilitate communication between the human worker and the robot. The experimental evaluation of the proposed system proved to improve the efficiency and safety of the assembly process, and the system was able to adapt to the movements of the human worker. They also report positive feedback from the participants who used the system, indicating that the system provides a satisfactory user experience.

2.2. Work Performance in Human-Robot Collaboration

The inclusion of robotics in the construction industry is promising to improve the productivity of construction workers in performing challenging tasks and maintaining a safe workspace (Kim et al., 2018). Extensive research focuses on investigating different approaches of HRC and developing advanced collaborative robots to improve work productivity by increasing efficiency, quality, and safety. A high-performance collaborative robot has been introduced for proactively assisting workers in maintenance jobs (e.g., handover tasks, and tool-fetch tasks) to enhance efficiency in real-world scenarios (Asfour et al., 2019). HRC has also been applied on construction sites. The mobile robot can provide construction workers with exact design information of pipelines by projecting it onto the walls using projective augmented reality to improve work quality (Xiang et al., 2021). To examine work performance in HRC, Wu et al. (2022) evaluated work productivity based on modeling HRC scenarios with different worker-to-robot ratios in the bricklaying task, where the robot continuously brings in bricks.

In addition, as the mental workload of workers is critically connected to their performance in construction, studies have been conducted to explore whether the HRC is associated with workload reduction (Dybvik et al., 2021; Memar & Esfahani, 2018; Tao et al., 2019). A theoretical data-driven analysis states that the human workload for some jobs, among 16 selected occupations, decreased by introducing collaborative robots (Liu et al., 2022). Sadrfaridpour and Wang (2017) examined human workload in a manufacturing assembly task. They found that the interaction approaches of HRC (i.e., physical and social factors in controllers) could affect human workload. HRC was proven to increase productivity by reducing the cognitive load of the worker during task performance (Landi et al., 2018). These studies examined work performance from theoretical perspectives (e.g., effectiveness of methods) and lack of proof in validating the practical effects of HRC in construction tasks.

2.3. Worker Perception of Human-Robot Collaboration

Despite considerable attention and investment in HRC, there has been limited success in translating HRC from research to real-world practice (Bröhl et al., 2016; Delgado et al., 2019). One factor that impedes the successful realization of HRC is the workers' acceptance of the robots (Bröhl et al., 2019). Workers are the ones who experience the most changes after introducing HRC into construction jobsites. However, unlike researchers dedicated to advancing collaborative robots, construction workers have limited knowledge of HRC and may feel unwilling to collaborate with robots, which could lead to non-usage and ineffective HRC. The existing worker perception could lower workers' acceptance of HRC, which could limit its successful implementation (Kopp et al., 2021).

TAM is the most influential model that predicts and explains the acceptance and rejection of advanced technology (e.g., information systems). Initially proposed by Davis (1989), TAM has been confirmed by numerous studies for its applicability in various fields (Marangunić & Granić, 2015). Bertrand and Bouchard (2008) applied TAM to the use of virtual reality, where they revealed the parameters determining the final intention of use. Also, there are several studies that adapted TAM to analyze the acceptance of HRC. Lotz et al. (2019) explored and validated three key factors of anxiety that employees have in the manufacturing industry to address workers' intentions for facilitating HRC implementation. Bröhl et al. (2016) extended the TAM-based acceptance model with ethical, legal, and social implications for HRC in the production industry to give a more precise prediction on the acceptance of HRC in a real-world application. In the construction sector, Park et al. (2023) applied TAM to investigate comprehensive factors that could affect the worker's acceptance of assistant robots. Thus, to advance the HRC implementation in the construction industry, this study adapted TAM-based constructs to HRC usage in construction tasks for understanding the attitudes of workers toward HRC.

2.4. Performance Evaluation of Human-Robot Collaboration

The concept of assessing construction performance has been well-explored in existing research (Bassioni et al., 2004). The evaluation holds significant value in traditional construction, where HHC is prevalent. Likewise, the evaluation is crucial for determining whether the implementation of HRC in construction projects is successful. However, an assessment that focuses solely on work quality is not adequate for HRC scenarios, as humans may be reluctant to collaborate with robots, potentially hindering the implementation of an effective HRC.

Steinfeld et al. (2006) identified key metrics for evaluating human-robot interaction, focusing on work performance, encompassing efficiency and quality, and human performance including workload and situation awareness. This is consistent with Freedy et al. (2007) conclusion, which suggests two categories for assessing the performance of HRC teams: measures of team performance and measures of effectiveness. These include both individual and collaborative performance, as well as the quality of the tasks completed by the team. Typically, for work performance, time efficiency and task quality are the primary indicators used in HRC assessments. For instance, Mitterberger et al. (2022) measured the completion time and the angles of each timber strut in a wooden structure assembly task to gauge HRC work performance. In the pursuit of more precise quality metrics, Qin and colleagues evaluated error frequency, framing accuracy, and time to completion in the assembly of wood frame walls with Augmented Reality (Qin et al., 2021). Therefore, in our study, which also involves wooden structures, task completion time, frame layout accuracy, and nailing quality are employed as the key metrics to assess work performance.

The significance of the human component in evaluating HRC is paramount. The success of HRC implementation hinges on the willingness of human workers to engage with it (Meissner et al., 2020). Understanding the degree to which individuals adopt or resist collaborative robots involves examining their attitudes and acceptance levels. Coronado et al. (2022) emphasized the importance of these aspects in assessing HRC. Additionally, Shah and colleagues expanded their analysis beyond the realm of work performance in scenarios where a robot assists humans in material retrieval, incorporating qualitative data derived from participant questionnaires and feedback to gain insights into human perceptions of collaborative robots (Shah et al., 2011). Accordingly, for worker assessment, our study focuses on measuring both the workload experienced by humans and their acceptance levels towards collaborative robots.

2.5. Motivation and Objective

It has been shown that HRC could be a promising solution for the challenges (i.e., poor productivity, aging force, labor shortage) that construction is struggling with. Previous studies have validated and evaluated the influence of HRC either in simulated scenarios (e.g., virtual reality) (Faccio et al., 2020; Freedy et al., 2007; Wu et al., 2022; Zhu et al., 2020) or in experimental assessments. However, such assessments focused on a particular perspective (i.e., the influence of product characteristics) or the performance of their proposed methods (e.g., projective augmented reality) (Faccio et al., 2020; Xiang et al., 2021). Limited studies have explored the practical impact (i.e., work performance) of HRC on construction tasks (i.e., assembly tasks) compared with traditional HHC on the same tasks, where users can give feedback and insights into the collaboration process. Considering that an effective HRC is joint work between workers and robots in real-world construction tasks, workers' willingness and attitude towards the robot are critical. Although previous studies have investigated acceptance models and factors for HRC implementation via online surveys collected from workers and managers (Bröhl et al., 2016; Meissner et al., 2020; Park et al., 2023), the majority of the participants have no physical experience in completing a construction task with the assistance of collaborative robots, which could limit their actual experience and perceptions with HRC.

To this end, the present study aims to examine the impact of HRC on work performance and the perception of workers via experimental analysis using sample construction tasks. To achieve the goal, this research (1) quantifies the efficiency, quality, and workload of HRC in a sample task (i.e., wood structure assembly) across two difficulty levels and compares them to the performance in traditional HHC settings, and (2) identifies workers' perception and attitude toward HRC by analyzing the survey data based on TAM. By focusing on both work performance and workers' perception in a human-robot collaborative task, this research provides valuable insights into HRC in construction tasks from the implementation side and the worker's side. Additionally, this study generates stimulating ideas from workers' post-interview to inspire future HRC research in the construction field.

3. Methodology

This study used experimental analysis to investigate the impact of HRC on construction work performance and worker perception, where two wood assembly tasks with different levels of complexity were conducted in a controlled environment as a simplified setup. Besides the HRC experiments, HHC experiments were performed as comparison groups. A total of 13 participants were recruited to form nine groups, and the assignment of groups was based on participants' demographic information and their work experience. Each group was tasked to conduct both HRC and HHC experiments for comparison. The work performance was examined in terms of time efficiency, product quality, and task workload. Additionally, worker perception was investigated through the constructs of TAM such as perceived usefulness, perceived ease of use, and intention to use etc., where data was collected before and after HRC, to study the acceptance of collaborative robots in construction tasks. Fig. 1 illustrates the overall framework.

3.1.Experiment Design

3.1.1. Task Design

On-site jobs involving assembly tasks require reasonable productivity and reduced human errors due to a limited project budget and completion time commitment to the subject (Liang et al., 2021). Wood framing is a prevalent method employed in the construction of residential, commercial, and industrial structures (Belousov et al., 2022; Dietz, 2015). Roof trusses are a fundamental element of wood-based construction. The complexity of roof trusses assembly requires the team effort of multiple workers, often positioned at elevated heights. This scenario is marked by a high occurrence of falls and fatalities among roofers, highlighting an urgent need for innovative approaches. By incorporating HRC into wood assembly tasks, especially in roof construction, the construction sector could potentially enhance both productivity and safety.

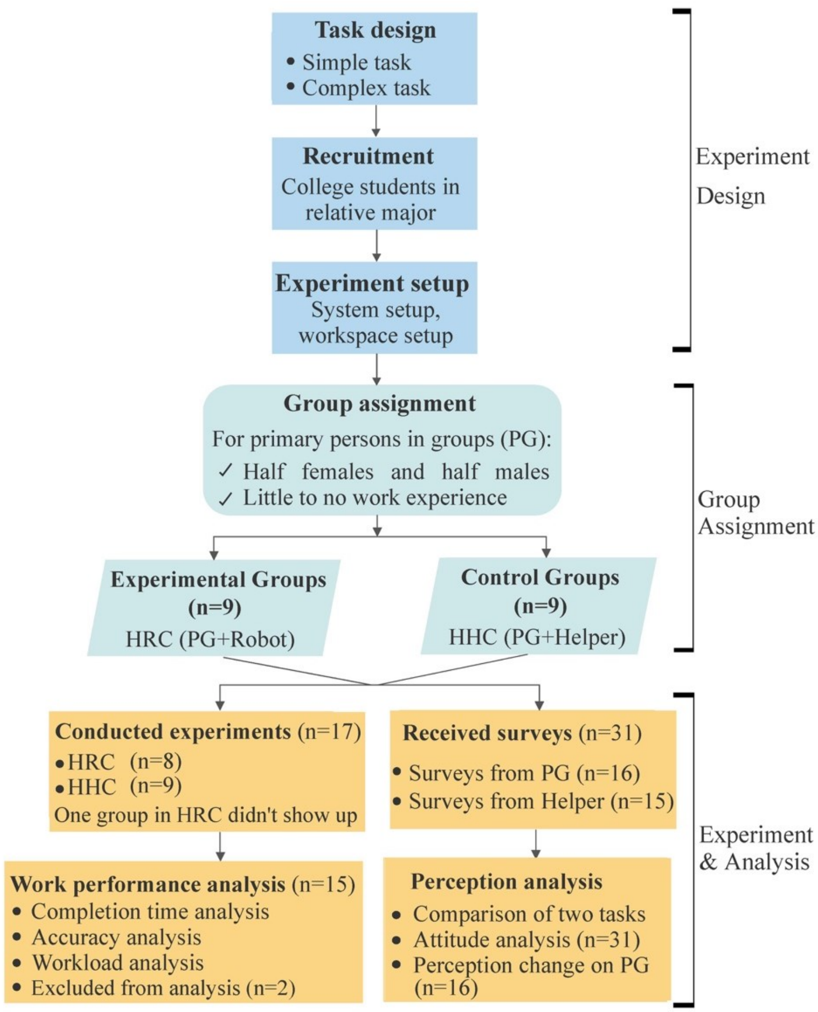
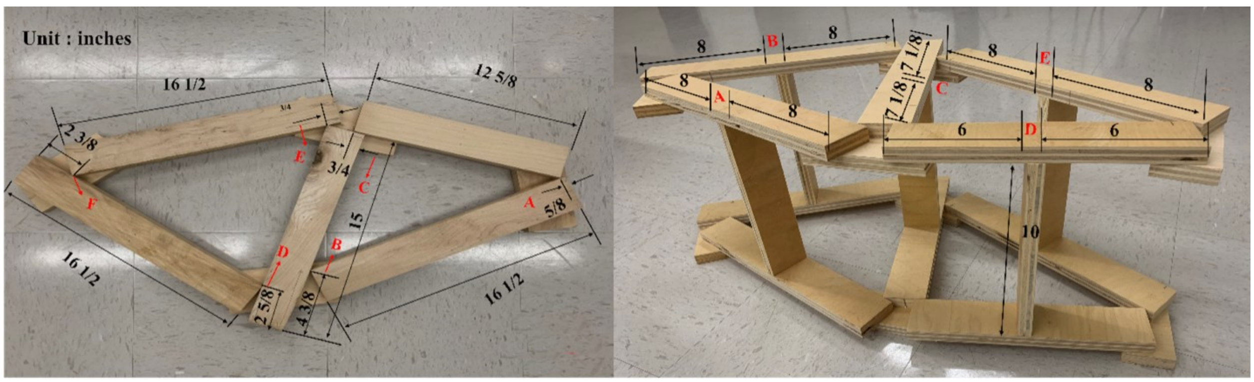


Fig. 1. Overall Research Method

The design of the task was formulated after consulting with industrial professionals who work for a wood manufacturing company. They shared real-world experiences and challenges encountered in wood assembly tasks. It was noted that one worker holds the heavy part, and another concentrates on nailing. However, it's always challenging for the worker to hold the piece for an extended period, especially when the workpieces are positioned at non-vertical or non-horizontal angles and must be maintained at specific orientations (Nath et al., 2017). Therefore, the design of the task was inspired by the issues faced in actual timber assembly operations, mirroring the complexity found in real-world construction scenarios. For both simple and complex tasks, robots could serve as assistants to take over dangerous and tedious tasks, like handling heavy trusses, while human workers could focus on connecting different components. Considering the capability of collaborative robots used in research, laboratory assembly tasks are simplified and scaled based on roof trusses (a typical wooden structure to assemble) in actual construction tasks for practical implication. Despite the scaled experiments in this study, the task settings could be potentially extended to real-world settings.

Two wood assembly tasks were designed in two difficulty levels, i.e., a simple-structured task and a complex-structured task, to better understand the impact of HRC on different complexity. The design criteria were reflected by practical insight. In consultation with industrial professionals from a wood manufacturing company, the experts highlighted that the assembly on a stable surface, such as a table, enables easier connection of two parts. Conversely, the challenge amplifies when pieces, particularly heavy trusses, require positioning and holding in mid-air for connection, extending the duration of the physical effort of workers. Therefore, a 2D wood structure was adopted as a simple-structured task, and a 3D wood structure as a more complex task within this study.

Fig. 2 shows the layouts of both tasks, where labeled joints as A, B, C, D, E, and F indicate the placement and connection point of each lumber. The simple-structured task is a 2D structure task with only one layer structure, requiring participants to work stably on the flat tabletop. The complex-structured task is a 3D structure task with two layers, which requires participants to assemble two simple structures spatially. This 3D structure makes it difficult to hold both layers and connecting pieces still while nailing. Regarding task allocation in HRC assembly, the robot is tasked to pick and place the main lumber pieces while the joints are placed manually in the simple-structured task (Liau & Ryu, 2020). In the complex-structured task, the robot is assigned to hold the vertical connection pieces in place for the human worker.



(a) (b)

Fig. 2. Design of wood assemblies: (a) simple structure, (b) complex structure

3.1.2. Experiment Design

To evaluate the work performance of HRC in construction assembly tasks, HRC and HHC experiments were performed for each task, where HHC is considered as the baseline. For the same task, HRC and HHC experiments were performed on different days to avoid bias due to repeated practice. There are two participants in the HHC experiment, one primary person and one helper. In HHC, the helper fetches all wood pieces and places them on the workbench. The primary person collaborates with the helper to assemble the wood structure according to the design drawing. In the procedures, the helper works with the primary person in measuring and placing the lumbers, and then only the primary person uses a nail gun to connect wood pieces. On the other hand, the robot plays the helper's role in HRC, where it is programmed to pick and place the wood pieces following the design drawing. That means the primary person can focus on connecting workpieces while the robot continuously places lumbers for the participant based on the drawing.

In this study, Clearpath Husky A200 equipped with Universal Robot 5 e-Series (UR5e) and a 2-finger Robotiq gripper was used as the collaborative robot in this wood assembly task. The Husky is an Unmanned Ground Vehicle with four wheels, suitable for various ground conditions. The UR5e is a robot arm with six degrees of freedom, which has the ability to perform pick-up and placement tasks. In real-world manufacturing settings, this robot arm has demonstrated its capability to assist human workers with different frame structures by manually changing how and when to hold a piece in place. It has more flexibility than task-specific robot systems like framing machines. Although the capacity for material transportation is critical in the construction environment, due to the scope of the study, the aspect of mobility was not encompassed within the experimental framework. Emphasis has been placed on the collaborative assembly with a robot arm. A workbench was placed as the assembly space for this experiment. The wood pieces used for the tasks were distributed in a pile on the ground near the bench for each group. Besides, for recording purposes, two cameras were set up from both the front view and back view of the working space. Fig. 3 shows the experimental setup and procedures for a simple task. The upper row in Fig. 3 shows the experiment procedures for HHC, where the helper fetches the lumbers, works with the primary person to place them according to the design drawing, and then the primary person nails them. The lower row in Fig. 3 shows the experiment procedures for HRC, where the primary person makes the connection while the robot brings and places more lumber simultaneously. The experiment protocol was approved by the Institutional Review Board at the university.

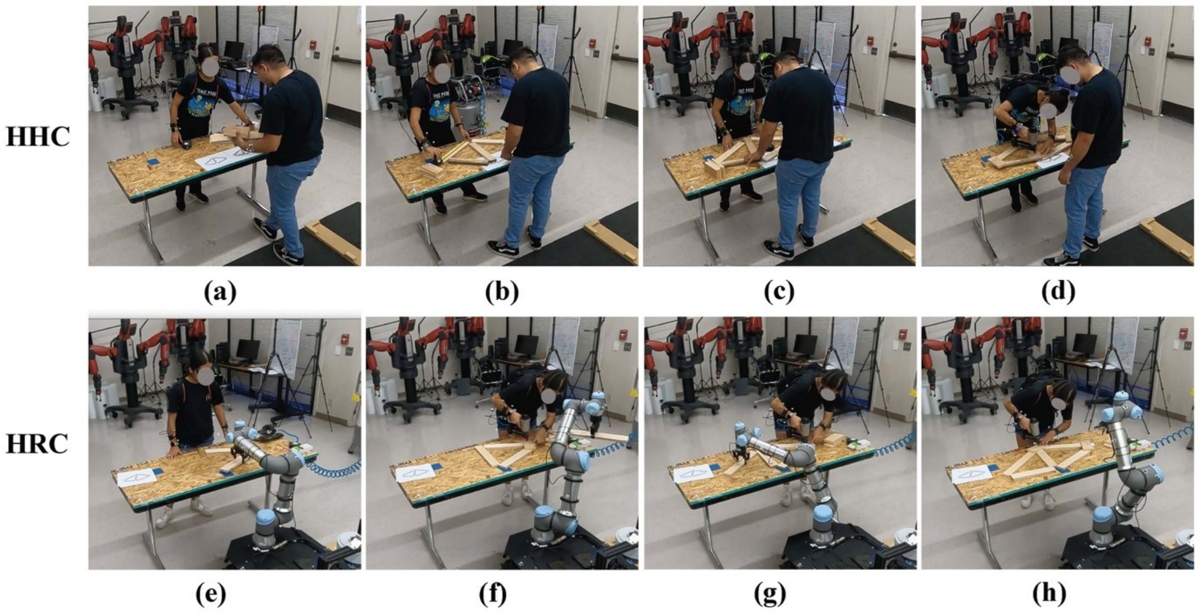


Fig. 3. Experiment procedures for HHC and HRC. (a) the human helper picks and places lumber on the table; (b) the primary person and the helper measure the lumber; (c) the primary person and the helper place the lumber; (d) the primary person connects wood pieces. In the second row, € the robot picks and places lumber; (f) the primary person focuses on the connection while the robot brings more lumber; (g) the robot continuously places more lumber according to the design; (h) the primary person finishes the connection.

3.1.3. Robot Setup

The PolyScope interface was used to pre-program robots for construction tasks. This software enables the manual positioning of the robot to establish and record specific movement trajectories. Key operational actions, including 'Grip' and 'Release', were incorporated into these programmed sequences to ensure the effective execution of tasks. Following the programming and saving of these movements and actions, a research assistant performed detailed testing to confirm that the robot's functioning was in precise accordance with the planned tasks.

PolyScope's functionality as a programming tool lies in its ability to direct robots along defined trajectories and maneuvers. Thus, precision in executing construction tasks is attainable irrespective of their complexity, provided that the trajectories and maneuvers are distinctly outlined and programmed.

3.2. Group Assignment

3.2.1. Participants Recruitment

The participants of the experiments are college students, who have basic carpentry skills (i.e., cutting, drawing reading) and have passed safety training in the woodshop. Most of these participants will enter the construction and architecture industry after graduation, and some of them have already worked in the industry. Therefore, the individuals included in this pilot study have been determined to be appropriate candidates. A demographic survey was administered before the group assignment. A total of 13 persons participated in the experiment, including 9 primary persons and 4 helpers. Helpers played the same role in different groups. Among participants, around 42% are female, and 58% are male. The groups were assigned based on gender and work experience, where the primary persons had never experienced any kind of collaborative robots and had little to no work experience. The participants playing helper roles have two to three years of work experience. All participants were trained to use the nail gun safely before the experiment.

3.2.2. Group Assignment

A total of 13 participants were assigned to 9 groups as two persons in one group (some participants played the helper role more than once but in different tasks). To analyze the impact of HRC on construction work performance, a within-subjects design was used (de Winter et al., 2017). In each group, one person performed as the primary person who worked in HHC and interacted with a robot in HRC. Another person played as a helper who assisted the primary person in HHC. Additionally, a between-subjects design was applied to compare work performance in different difficulty-level tasks. As shown in Table 1, there are four groups in the simple task and five groups in the complex task. Each group had two participants in HHC, but only one person was in HRC because the robot served as the helper.

Table 1: Group assignment for HHC and HRC

	Human-Human Collaboration	Human-Robot Collaboration
Simple Task	PG1+H1; PG2+H2; PG3+H3; PG4+H4;	PG1+R; PG2+R; PG3+R; PG4+R
Complex Task	PG5+H1; PG6+H2; PG7+H3; PG8+H4; PG9+H1;	PG5+R; PG6+R; PG7+R; PG8+R

Note: PG represents the primary person in a group and H represents the helper. R represents the robot. Group 9 did not perform the HRC experiment.

3.3. TAM-based Pre- and Post-surveys

Pre-survey was distributed and collected from participants before the HRC experiment to establish a base understanding of workers' perception of HRC. Post-survey was distributed and collected after the HRC experiment to identify the change in workers' perception after actually working with the robot. The surveys were adapted based on the TAM's constructs (Venkatesh & Bala, 2008; Venkatesh & Davis, 2000). TAM proposed that perceived usefulness (PU) and perceived ease of use (PEU) are two key factors determining whether users will accept a specific technology. PU refers to the user's expectation of the extent to which the technology will improve the user's performance. For example, in the context of HRC in construction, a worker may be concerned about how the robot will improve his/her construction task performance. On the other hand, PEU is defined as the expected amount of effort required to use the technology effectively and addresses questions on whether the worker believes that the robot will be easy to collaborate with (Davis, 1989). The person's PU and PEU jointly determine the intention of use (IU) (Davis, 1989; Venkatesh & Davis, 2000). Both PU and PEU could be affected by external variables, including self-efficacy (SE), intrinsic motivation of use (IMU), safety anxiety (SA), job relevance (JR), output quality (OQ), and result demonstrability (RD), etc. Table 2. lists the definition and a sample question of each construct asked in the surveys. The scores of each factor collected before and after HRC were analyzed and compared to obtain the attitude change of workers towards HRC.

Table 2. Definitions of variables in pre- and post-surveys

Item	Definitions	Sample Questions (7-likert-scale)
PU	The degree of usefulness that a person feels about a collaborative robot.	Using a collaborative robot improves my task performance.
PEU	The level of easiness that a person believes when working with a collaborative robot.	I find it easy to get collaborative robot to do what I want it to do.
IU	The willingness to use a collaborative robot in future construction tasks.	In the future, I plan to work with a collaborative robot.
SE	The degree of ability to work with a collaborative robot that a person holds.	I can complete the task with a collaborative robot if someone showed me how to do it first.
IMU	The motivation to use a collaborative robot that a person has intrinsically.	I feel playful when I work with a collaborative robot.
SA	The degree of anxiety that a person feels when working with a collaborative robot	Robots do not scare me at all.
PE	The degree of enjoyment that a person perceived when working with a collaborative robot	The actual process of using a collaborative robot is pleasant.
JR	The degree of relevance to his/her task that a person believes when using collaborative robot	In the task, the usage of the collaborative robot is important.
OQ	The quality of the end product that a person feels by the performance of HRC	The quality of the output I get from working with a collaborative robot is high.
RD	The degree of observability and tangibility that a person holds on the results of HRC	The results of using collaborative robot are apparent to me.

3.4.Data Analysis

The work performance was evaluated in terms of work efficiency, quality, and workload of participants. The time of completion for each trial was recorded and used as an indicator of work efficiency. To capture the work quality, we quantified the accuracy of the end product (i.e., wood assembly), and nailing quality. The accuracy was calculated by measuring the connection of each lumber and comparing it to the design. For nailing quality, a visual inspection was conducted and nails that went through the lumber but not connecting the lumber and connector were counted as "bad nailing quality". For the workload quantification, the Heart Rate Reserve (HRR), the average of beats per minute used to measure the intensity of physical activity level was employed and calculated based on one standardized equation to represent the workload of workers (Jae et al., 2016).

3.4.1. Work Performance Analysis

To quantify work efficiency, the time of completion for each trial was recorded and compared between HHC and HRC. Different error types were examined to evaluate the work quality of the end product (i.e., wood structure). For accurate measurement of the structure, the accuracy of assembling individual joints was calculated first based on Equations (1) and (2), and the product of accuracies of all joints was used to calculate the accuracy of the final product, shown in Equation (3) (Devore et al., 2012; Guang et al., 1995; Khair et al., 2017).

$$err = \frac{M_e - M_t}{M_t} \times 100\% \tag{1}$$

$$acc = 1 - err \tag{2}$$

$$acc_{total} = \prod_{k=jointA}^{jointF} acc_k \tag{3}$$

where err is percentage error; M_e is experimental values measured from end product; M_t is theoretical values from design drawing; acc is percentage accuracy; acc_{total} is the total accuracy of a structure (from jointA to jointF); acc_k means percentage accuracy of each joint.

To evaluate the nailing quality of the structure, both the total number of nails used in the structure and the number of nails poorly nailed were counted, such as nails coming out through the wood piece but not connecting the connector, as shown in Fig. 4. By calculating the number of nails poorly nailed out of the total nail counts, the good nailing quality was quantified as a percentage.

To estimate workload, the heart rate was measured by a wearable device, Fitbit, from the primary persons (Gorny et al., 2017). We started to collect the heart rates of the participants around 20 minutes before the experiment time and continuously measured them till 20 minutes after the experiment was completed. With the heart rate data, HRR was calculated based on the Karvonen Formula to measure the intensity of activity (Goldberg et al., 1988) (see Equations (4) & (5)).

$$HR_{max} = 220 - age \tag{4}$$

$$HRR = \frac{HR_{work} - HR_{rest}}{HR_{max} - HR_{rest}} \times 100\% \tag{5}$$

where HR_{max} is maximum heart rate; HR_{work} is the heart rate while the participant is working; HR_{rest} is resting heart rate; age is the number of participant's age.

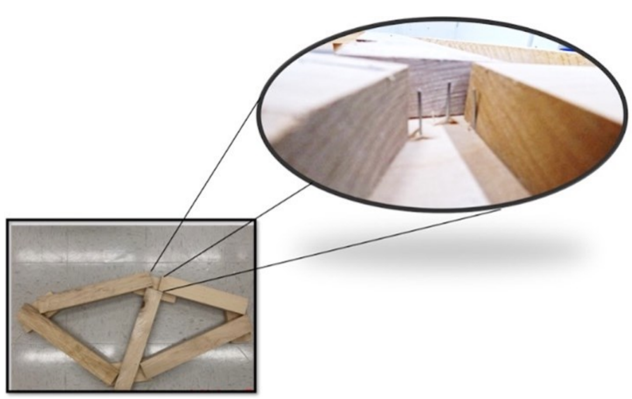


Fig. 4. An example of poor nailing.

3.4.2. Worker Perception Analysis

The 7-likert-scale questionnaires of HRC perception, ranging from "strongly disagree" (1) to "strongly agree" (7), were distributed and collected before and after the HRC experiment. A TAM-based approach was applied to examine the participants' perception of HRC in this study. The mean scores of several questions in one factor were calculated and represented the final scores of the factor. Survey data was collected from all participants, as the helpers observed HRC experiments. The overall attitude of participants was analyzed by comparing the final scores of each factor to the neutral scores (4). To analyze the impact of HRC on worker perception in this construction assembly task, the scores of each variable collected from the primary persons in each group were used and compared before and after the experiment, including PU, PEU, SE, IMU, SA, and JR.

4. Results

A total of 9 groups were included in this study. Four groups' data were collected from HHC and HRC in simple tasks. Five groups' data were collected from HHC in complex tasks, while only four groups' data from HRC in complex tasks because one group did not complete the HRC experiment. Among the groups in complex tasks, the data of group#7 in HHC was excluded from the analysis, because group #7 assembled the structure incorrectly in HHC. The data of group#8 in HRC was also excluded because there was a misunderstanding of the design drawing, so the experimental condition was changed and different from other groups. Thus, for complex tasks, the data of four groups in HHC and three groups in HRC was analyzed.

4.1. Results of Work Performance

Fig. 5 illustrates the results of four aspects regarding work performance, including the time of completion, the workload of participants, the accuracy of structures, and the nailing quality. For the comparison between HHC and HRC within the same difficulty-level task, HRC has a relatively lower completion time for both simple tasks and complex tasks. The participants have a lower workload in HRC, which means that participants in HRC are less stressed in completing those tasks with the assistance of robots. For the accuracy of structures, HRC has a higher mean accuracy than HHC in the same tasks. However, there is no significant difference in the nailing quality, when comparing the results of HHC and HRC. Besides, in all aspects, HRC has a relatively small standard deviation compared to HHC in simple and complex tasks. This indicates that the work performance of HRC is more consistent than that of HHC.

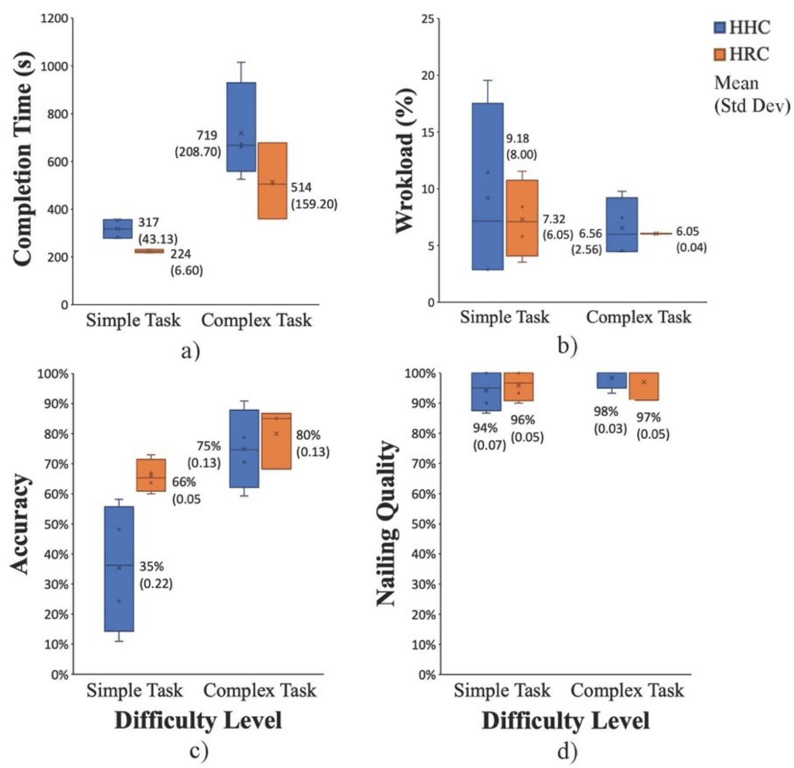


Fig. 5. Results of work performance. a) completion time, b) workload, c) accuracy, d) nailing quality

Comparing two difficulty-level tasks, the difficulty level of tasks has an impact on the time of completion – the complex structure requires more time for assembly. Additionally, HRC has a significantly higher mean accuracy than HHC in simple tasks, showing an 88.6% improvement compared to HHC. In complex tasks, the mean accuracy in HRC consistently outperforms that of HHC. For workload comparison, HRC in complex tasks holds a very small standard deviation, because only two groups of data are included under this condition. The heart rate data of one group in the complex task of HRC is omitted due to its lack of reliability because the wearable device was not tightly attached to the participant. On the other hand, the nailing quality was relatively high around 96% in all conditions.

The accuracy of assembling individual joints for simple and complex experiments in HHC and HRC is shown in Table 3. It shows that the mean accuracy of assembling individual joints of the structure in simple tasks increases in HRC except for joint C which decreases from 90.98% in HHC to 83% in HRC. It could be because the robot sometimes may make collisions with other pieces when placing the lumber which includes joint C, as the pieces could be slightly moved when nailing. In complex tasks, there is no big difference between HHC and HRC in the mean accuracy of all joints, respectively. However, HRC has a smaller standard deviation in each joint compared to the results of HHC. This tells that the accuracy of the wood structure in HRC is more consistent.

Table 3 Accuracy of assembling individual joints of the structure in two tasks (% in unit).

Mean accuracy (standard deviation)	**Joint A**	**Joint B**	**Joint C**	**Joint D**	**Joint E**	**Joint F**
Simple task HHC	68.84 (22.20)	89.44 (12.86)	90.98 (5.93)	85.57 (12.21)	80.67 (22.07)	83.57 (19.80)
Simple task HRC	91.25 (5.44)	99.30 (0.69)	83.23 (7.34)	97.97 (1.27)	94.47 (3.43)	96.84 (2.06)
Complex task HHC	95.255 (5.65)	90.575 (4.83)	97.345 (0.81)	98.63 (0.37)	89.72 (7.05)	N/A
Complex task HRC	96.72 (0.80)	88.30 (9.94)	97.04 (1.14)	98.6 (0.40)	97.76 (0.89)	N/A

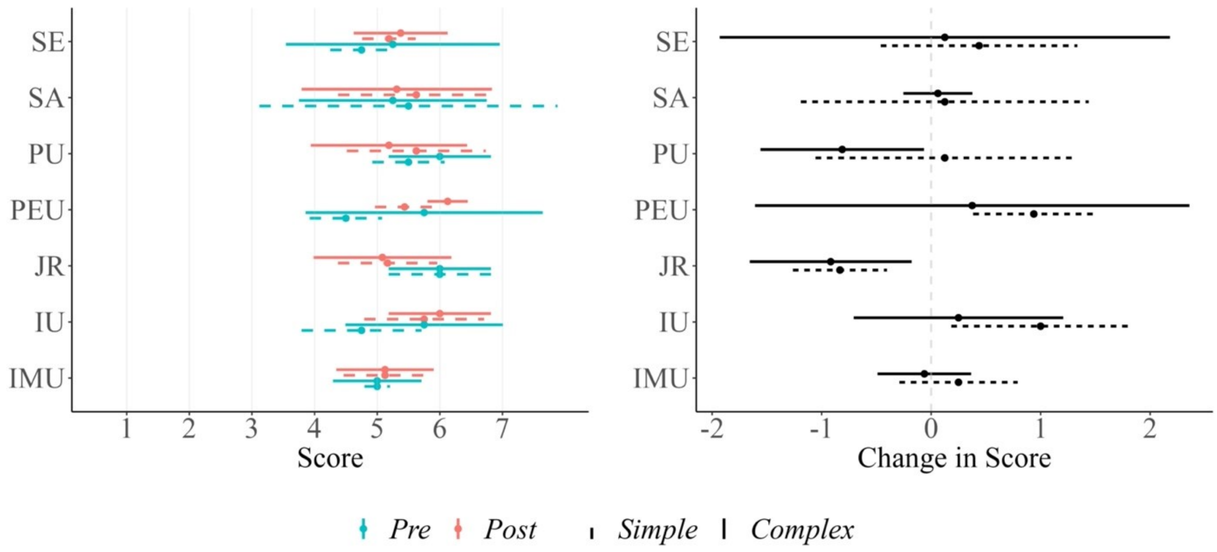
4.2. Results of Worker Perception

Participants, including main persons and helpers, were asked to complete the pre-survey after the HHC experiment. This pre-survey data provides a baseline of participants' perceptions of HRC. Accordingly, participants also completed the post-survey after the HRC experiment. Although the helpers did not interact with the robot physically, their feedback was also included because they sat nearby and observed the HRC experiment. Therefore, survey feedback from both the main persons and helpers was collected. In total, 31 responses were obtained, including 16 on the pre-survey and 15 on the post-survey. One helper's survey response after HRC was missing. The constructs included in the pre-survey are PU, PEU, IU, SE, SA, JR, and IMU. The post-survey constructs are PU, PEU, IU, SE, SA, PE, JR, OQ, RD, and IMU. OQ, RD, and PE are not included in the pre-survey because those questions are detailed in describing HRC experience, which is better to have participants answer afterward.

The mean of each factor over 31 responses is compared to the neutral value of the score. It is found that the means of all the constructs are higher than the neutral value before and after the HRC experiment. This shows that participants held an overall positive attitude toward HRC before and after the practical experiment. The mean scores of each construct collected before the HRC experiment are compared to the values obtained after the experiment. The results show that the means of most constructs increased after the experiment. The scores of PEU, IU, and SA increased by 0.69, 0.38, and 0.31. SE slightly increased by 0.06. It indicates that participants feel safe and easy to use HRC and are more willing to use it than their initial thoughts. Among those constructs, the scores of JR decreased by 0.49; PU and IMU slightly decreased by 0.04 and 0.01. This may arise from the experiment task not mirroring a real-world scale task, rendering it somewhat challenging for participants to draw parallels between the on-site job and this task. The results of

OQ and RD covered in the post-survey show that participants hold a somewhat positive attitude toward the end-product quality and feel the HRC is somewhat tangible and communicable. In conclusion, participants hold a positive attitude toward HRC and have increased their intentions to use HRC after the experiment.

To investigate the impact of difficulty level on worker perception, a comparison between the simple task results and the complex task results is conducted. For this purpose, the primary persons' data is used. Fig. 6 (a) shows the score ranges of each construct, suggesting that the scores of IMU and SE in both tasks are consistent and have no significant difference before and after HRC. While other constructs' scores vary in simple and complex tasks. To investigate how participants' perceptions change after the experimental HRC, the difference of mean values between post- and pre-survey are calculated for each construct, following different tasks (see Fig. 6 (b)). The results show that on both tasks, the scores of IU, PEU, SA, and SE have increased after the HRC experiment, and the simple task has relatively higher scores. It reflects that the participants increased their willingness to use HRC in both tasks after practice. However, PU and IMU have increased after the HRC experiment in simple tasks, while a decrease is observed in complex tasks. It implies that participants feel HRC is useful in simple tasks to improve their performance and have a higher intrinsic motivation to use HRC but not much in complex tasks. A possible reason could be that the complex tasks experienced more uncertainties (e.g., more constraints for the robot). The preprogrammed robot makes it hard to accommodate those uncertainties in complex tasks. In both tasks, the results show a decrease in JR after the HRC experiment. It may suggest that the participants perceive the HRC used in the experiment task as less applicable to on-site scenarios.



(a) (b)

Fig. 6. Impact of task complexity level on worker perception: (a) range of scores for each construct; (b) change in scores between post- and pre-surveys.

The reasons can be found in the interviews with open-ended questions conducted at the end of experiments. Almost all the participants believe that HRC is interesting and innovative, and it improves their work performance, but some drawbacks of the collaborative robot have disappointed them, including the low operating pace of the robot, and lack of communication on the robot's intentions. Besides, despite the increased intention to use HRC, participants are more likely to use HRC in a simple task. It could be because the collaborative robot used in this experiment is a preprogrammed robot, which is not able to adjust its movement accordingly during the collaboration. This aligns with suggestions provided by participants in the interview, including "better navigation" and "dynamic coordination" for future robot systems. This feedback from participants also sheds light on the technical development of intelligent robots.

5. Discussion

5.1. Research Findings and Comparison with Related Studies

This study empirically investigated the impact of collaborative robots on work performance and worker perception in wood assembly tasks. The HRC experiment is designed to mimic typical collaborative processes in such tasks, where the collaborative robot acts in a capacity similar to a human assistant. In the complex task, the robot positions and holds the connecting piece, enabling the human worker to make the connection, similar to how one person might hold a heavy timber while another nails it. In the simple task, human workers concentrate on joining components, while the robot persistently brings, and places additional lumber based on the provided design.

The findings of this study align well with other related studies and further validate the potential benefits of HRC in construction. For instance, it is found that HRC can enhance work quality and efficiency while reducing workers' workload in the given case study. This shows the beneficial impact of HRC on work performance. This concurs with the conclusions drawn by the referenced study, which highlights the promising potential of HRC in a teaching cell for assembling complex timber trusses (Kramberger et al. 2022). In a separate study focused on construction productivity, the beneficial effects of HRC are similarly noted within an agent-based simulation (Wu et al., 2022). The outcomes underscore the potential of collaborative robots to enhance work productivity in the simulated setting. Our results further validate the applicability and benefits of HRC in standard construction assembly tasks.

The assessment of worker perception measures the acceptance level of HRC and the change occurring before and after the HRC experiment. Results indicate that participants tend to be more receptive to HRC after undergoing the HRC experiment, denoting a rise in acceptance compared to their initial views. Moreover, the derived insights from the study's constructs strengthen the conclusion of another study that both object-related (robot functionality) and subject-related (individual background) factors play a significant role in influencing the thoughts and feelings of workers (Meissner et al. 2020). This finding serves as a complementary extension to another study, which inclusively examined participants regardless of their prior experience with robots, affirming the observation that PU and PEU are intimately associated with IU in HRC (Bröhl et al., 2016). This is particularly noteworthy in the context of individuals surveyed in that study who had no previous hands-on experience with actual HRC scenarios.

5.2. Practical Implications and Future Directions

Simplified versions of wood roof trusses are adopted in this study to represent those typically used in construction work. This small-scale structure facilitates timely and cost-effective usability testing, allowing for the observation of end-user interaction with the new concept (Camburn et al., 2017). Previous research has used small-scale designs for various purposes, such as testing new robot designs in assembly tasks (Jenett et al., 2019; Leder et al., 2019), demonstrating robot arm trajectories in HRC setups with simple timber models (Kramberger et al., 2022), and enhancing HRC intuitiveness through simplified wooden car structures (Gustavsson et al., 2018). Building upon these studies, currently only a small-scale structure was fabricated to investigate the effect of HRC on work performance and worker perception in construction assembly tasks. Future research is needed to focus on large-scale structures to include a broader range of real-world construction scenarios. As the scale increases, more robust programming is needed to meet the demands of these tasks.

The complexity of real-world construction scenarios with sophisticated programming triggers the demand for collaborative robots with enhanced intelligence to engage in the teamwork. Recent literature provides evidence of such innovations. One investigation delved into the potential of equipping robots with gaze-based cues to control a robotic arm, thereby enhancing the intuitiveness of HRC (Wöhle & Gebhard, 2021). In the context of construction, Cai et al. (2023) introduced a novel path-planning approach that incorporates anticipated construction worker movements, ensuring the HRC process is both safe and effective. In addition, participants showed positive feedback on working with the pre-programmed robot in this study and expressed their willingness to work with the robot more intuitively. Eventually, the paradigm would shift from a scenario where operators tediously script every robot function towards a more effortless interaction where collaborative robots are able to independently adjust their movements in response to the evolving environment and the subtle cues of human movement. This level of adaptability could ensure that robots can work alongside human partners safely and intuitively, thus achieving common objectives with greater efficiency.

Furthermore, the generalizability of the effect of HRC needs further investigation. By recruiting college students with minimal or no prior construction experience, our study indicates that HRC increased work efficiency and productivity and was well-accepted. However, we acknowledge that our sample was limited to novice workers only. Future research should replicate and extend these findings to more experienced workers, thereby offering a more comprehensive view of HRC's impact across workers with varying levels of work experience.

Regarding the robots, in the future, we will focus on enhancing the intelligence of collaborative robots. This involves empowering them with autonomous physical interactions and the capacity to proactively and safely plan their actions. Upcoming advancements should merge automatic execution with seamless communication with human worker. It is vital for robots to interpret human intentions and convey their own. These capabilities would greatly facilitate intuitive and smooth HRC in assembly tasks.

6. Conclusions

This research evaluated the multi-dimensional impacts of collaborative robots on construction work and workers in terms of work efficiency, quality, workers' workload, as well as worker's perception and acceptance of collaborative robots, via HRC experiments on sample construction tasks (i.e., wood assembly), combined with quantitative measurements and TAM-based surveys. Two wood assembly tasks were designed in two difficulty levels, and both HRC and HHC experiments for performed as a comparison. In HHC experiments, a primary person was tasked to nail wood pieces and complete the assembly, and a helper was asked to assist the primary person in measuring, placing, and picking up lumbers. In HRC experiments, the robot played the helper's role in HRC, where it was programmed to grasp and place the wood pieces following the design drawings for the primary person.

To examine the impact of HRC on work performance in construction, this pilot study quantified the efficiency, quality, and workload in construction tasks and compared it to HHC. Based on our case study, it is found that HRC can increase the accuracy of construction assembly tasks by 88.6% in simple tasks and 6.7% in complex tasks, and reduce the time of completion by 29.3% in simple tasks and 28.5% in complex tasks. Furthermore, the workload of participants decreased by 20.3% in simple tasks and 7.8% in complex tasks, comparing HRC to HHC.

From the workers' side, surveys adapted from TAM were collected to learn workers' acceptance and perceptions toward HRC, alongside a post-interview. The survey results indicate a generally positive reception towards HRC among workers, with an increased willingness to engage with collaborative robots compared to pre-experiment perspectives. The survey analysis in both simple and complex tasks suggests that HRC holds greater potential in complex tasks, where workers face higher physical and mental demands. Through interviews, it emerges that the primary barriers to workers' acceptance of HRC in their tasks are the lack of flexibility and communication with the collaborative robot. Accordingly, to fully leverage the advantages offered by collaborative robots, it is imperative to engineer intelligent robots that can interact safely and adaptively with human workers, by operating based on the evolving context and human partner's actions.

This research enriches our understanding of HRC in construction in two key areas. First, through case studies of scaled wood assembly experiments, we quantified the advantages of HRC over traditional HHC by comparing experiments with both settings across tasks of varying complexities. The benefits of HRC include enhancements in efficiency and quality and a decrease in worker workload. These findings underscore the potential and merits of integrating HRC into construction processes. Second, leveraging surveys adapted from TAM, shifts in attitudes were identified before and after the HRC experiments. This provided insights into workers' perceptions of HRC, including perceived value, ease of use, and concerns about safety. Future technological advancement can be pivotal to meet the need for enhanced acceptance among construction workers, thereby further encouraging the adoption of HRC in the construction industry.

There remain some limitations that deserve future study. First, as a pilot study, this research leveraged scaled experiments in controlled lab environments. The main purpose and benefit of such settings is the ability to control experiment conditions and environment variables to better examine the impacts of HRC. However, the simplified operational setting of a small-scale experiment might not capture the complexity of real-world construction environments, thus affecting the generalizability of the findings. To accurately examine the impact of HRC on specific construction tasks, more experiments and pilot implementation are needed in real-world settings. Second, the sample size of the experiments is relatively small and the participants in the experiments have limited experience in the field. In future research, more diverse populations from different experience levels and different trades of workers will be recruited to further explore how the impacts of HRC and worker perception will vary based on worker characteristics.

Data Availability Statement

Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

Acknowledgments

This research was funded by the U.S. National Science Foundation (NSF) via Grants 2138514 and 2222670. The authors gratefully acknowledge NSF's support. Any opinions, findings, recommendations, and conclusions in this paper are those of the authors and do not necessarily reflect the views of NSF and The University of Texas at San Antonio.

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