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Participants matter: Effectiveness of VR-based training on the knowledge, trust in the robot, and self-efficacy of construction workers and university students

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ABSTRACT

Virtual Reality (VR)-based training has gained attention from the scientific community in the Architecture, Engineering, and Construction (AEC) industry as a cost-effective and safe method that eliminates the safety risks that may impose on workers during the training compared to traditional training methods (e.g., in-person hands-on training, apprenticeship). Although researchers have developed VR-based training for construction workers, some have recruited students rather than workers to understand the effect of their VR-based training. However, students are different from construction workers in many ways, which can threaten the validity of such studies. Hence, research is needed to investigate the extent to which the findings of a VR-based training study are contingent on whether students or construction workers were used as the study sample. This paper strives to compare the effectiveness of VR-based training on university students' and construction workers' knowledge acquisition, trust in the robot, and robot operation self-efficacy in remote operation of a construction robot. Twenty-five construction workers and twenty-five graduate construction engineering students were recruited to complete a VR-based training for remote operating a demolition robot. We used quantitative analyses to answer our research questions. Our study shows that the results are dependent on the target sample in that students gained more knowledge, whereas construction workers gained more trust in the robot and more self-efficacy in robot operation. These findings suggest that the effectiveness of VR-based training on students may not necessarily associate with its effectiveness on construction workers.

1. Introduction

Since the 1990s, many researchers have recognized the potential of Virtual Reality (VR) in the education realm and have advocated for its increased usage in training applications[1,2]. Over time, VR has gained increased attention and has been implemented to support learning programs in a variety of domains including healthcare (robotic surgery) [3,4], aerospace and aviation [5], manufacturing [6–8], and mining [9]. Similarly, VR-based training has received considerable recognition from construction industry researchers in applications that involve educating construction workers. Several VR-based training programs have been developed and empirically compared to traditional training methods such as lecture-based, video-based, and hands-on training. While most of the studies have concentrated on safety training (specifically, hazard identification) [10–14], there are also many studies on VR-based training for task execution [15–18], equipment operation [19–23], and ergonomic behavior [24,25].

Empirical results have shown a series of advantages of VR-based training over traditional training methods. First, VR-based training can provide a safe environment for workers to fail without being exposed to dangers [26,27]. VR-based training can also prepare the trainees to respond to more complex and/or dangerous situations by creating simulations that would be too dangerous, or expensive, or even unfeasible to simulate in real-world conditions [28]. Next, VR-based training provides an interactive training experience for the workers in contrast to the traditional passive methods based on audio, text, or

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images [11]. Another advantage of VR-based training over current in-person training methods is that it is a one-time development effort and is cost-effective while increasing workforce training consistency, applicability, and efficiency. In contrast, lecture-based training sessions require a trainer and the necessary equipment to provide the trainees with hands-on experience [29]. Nevertheless, VR-based training has some limitations, such as the potentially time-consuming, expensive, and challenging process of developing realistic virtual environments and its needs for computational power and equipment to run the training.

While researchers have studied the effect of VR-based training on construction workers, some researchers have used undergraduate and graduate students as the subject population in evaluating the effectiveness of VR-based training. Generally, these studies have explored the effectiveness of VR-based training on various measures such as knowledge acquisition, task performance, self-efficacy, hazard identification, and safety behavior [18,30,31]. Although all these studies have mentioned the student sample population type as a limitation of their study or have considered their research a pilot study to gather initial data/feedback, the generalizability of these findings to the professional population (e.g., construction workers) has not been explored among the research community. VR-based training may have a different impact on construction workers compared to students, thus, it is essential to identify how the effectiveness of VR-based training differs between these two populations.

Furthermore, researchers and engineers in the AEC industry have been developing an increased interest in new automation and robotic systems over the past decades. These new technologies may address the industry's established challenges, including low productivity rate, skilled labor shortages, and safety hazards [32]. Nevertheless, interacting with these new technologies can create new hazardous issues on construction sites given their unstructured working environment [33]. Additionally, construction workers might not trust automation or robots because of their fear that these technologies will replace them [34]. They might perceive traditional solutions as a better fit than robots to the dynamic and uncertain working conditions on construction sites [34,35]. Thus, Human-Robot Interaction (HRI) is a crucial area to be investigated for the successful adoption of construction robots.

As construction tasks become automated [36], VR-based training plays a pivotal role in preparing construction workers for the future of work. This training method has the capability to allow workers to build trust in the robot and their ability (self-efficacy) so that they are prepared to remote operate the robot safely and effectively on construction sites. Researchers have strived to understand the impact of VR-based training for construction workers to interact with these new technologies [22,37]. They have also used virtual environments to understand how to effectively measure and enhance human-related factors in HRI such as trust in automation/robot, robot operation self-efficacy, situational awareness, and mental workload [38–40]. However, even though the research is intended to draw conclusions about training *for construction workers* (e.g., how much training could help construction worker population), researchers usually do not recruit their samples from this population. Instead, most researchers recruited students for their studies [12,15,18]. Accordingly, it is unclear if their results would generalize to the actual target population: construction workers.

The use of students as a convenience sample would, in theory, be acceptable *if* students do not differ from construction workers in their response to VR-based training. However, to the extent of our knowledge, no research has directly compared the effect of VR-based training on learning in construction workers versus students. This comparison is important for several reasons. If students show a larger effect of VR-based training on learning than construction workers, for example, then the previous work using students could be systematically overestimating the effect of VR-based training. In contrast, if students show a smaller effect of VR-based training on trust in the robot than workers, for example, research concluding that there is little or no effect, would underestimate results obtained if construction workers were used in the study.

Accordingly, we conducted a study to directly compare the effect of VR-based training in construction workers vs graduate construction engineering students on several relevant outcome variables. Specifically, we answer three research questions, one for each outcome of interest:

1. How does VR-based training affect *knowledge acquisition* for construction engineering students, compared to construction workers?
2. How does VR-based training affect construction engineering students' *robot operation self-efficacy*, compared to construction workers?
3. How does VR-based training affect construction engineering students' *trust in the robot*, compared to construction workers?

Section 2 of this paper provides a literature review of existing studies of VR-based training from a range of knowledge acquisition and trust in automation literature. Section 3 presents study's methodology, including the VR-based training, the experimental procedure, and analysis methods, followed by the study's results. After a discussion, the conclusions and future directions section is presented.

2. Literature review

2.1. Knowledge acquisition

In the past two decades, VR-based training has been promoted in the construction industry due to its interactive and realistic simulations and has gained popularity as an alternative training method to safely educate construction workers, especially in hazard identification and construction safety [10,13,41]. Even though the existing research field in VR-based vocational education in the AEC industry essentially positions VR as a valuable tool [42], only a few studies have explicitly focused on training for machine operation [18,42]. Across the existing studies, VR-based training methods have been increasingly recommended over existing common training methods (i.e., lecture-based training, or 2D visual slides) as VR-based training is cost-effective and allows workers to practice skills at their own time and pace [29,43,44]. Additionally, it offers researchers a powerful alternative that can make the training more accessible and eliminate the need to transition the training from on-site to off-site locations. Studies [11,28,45] have discussed that VR-based training has caused higher knowledge retention and a higher skills to identify hazards that appear in real-world job sites.

Existing studies suggest that the improved outcomes of VR-based construction safety training are mainly due to two reasons, both of which are aligned with Pantelidis' [46] guidelines for using VR as an educational method. First, the immersive nature of VR hardware, i.e., simulations, creates an illusion of a construction site in a non-physical risk-free environment that allows trainees to acquire "hands-on experience" with construction equipment that can be dangerous in case of failures at construction sites [47–49]. Multidisciplinary teams can now generate simulations that conform the research findings on cognitive development and adult learning theories to ensure construction workers' higher degrees of knowledge acquisition [50,51]. VR-based training can also reduce error rates by making normally invisible hazards visible (such as electricity). Second, VR-based training also enhances construction workers' attentiveness and involvement as it requires them to interact in real-time with the content and does demand active involvement, unlike the conventional methods of learning through audio, text, or images [11].

While some researchers have evaluated the influence of VR-based training on construction workers as the core population of their experiments, others have recruited students as participants [10,12,18,52,53]. The findings of some of these studies (e.g., [12,18,53]) have shown that knowledge gain for students in VR-based training was higher compared to video-based or lecture-based training, but the differences between the two training methods were not significant (Table 1). In contrast, Dzeng and colleagues [52] found that students participated in VR-based hazard identification training scored significantly higher than the students participating in traditional lecture-based training with a large effect size ($d = 2.2$) (Table 1). Similarly, results from Jeelani and colleagues [10] reveal that students who participated in personalized VR-based safety training can identify significantly more hazards after the training with a very large effect size ($t(52) = 20.02$, $p < 0.01$, $d = 2.76$) (Table 1).

As some researchers have noted as limitations of their studies, these findings with students may not be applicable and generalizable to the professional labor population. VR-based training may have a different impact on construction workers' knowledge acquisition rather than the level of knowledge gained by university students. In this regard, it is essential to investigate and understand the difference in knowledge acquisition between students and construction workers with VR-based training methods.

2.2. *Trust in the robot & robot operation self-efficacy*

The construction industry has recently experienced a growth in the number of robots and autonomous systems being used on-sites [54]. Reports have predicted the possibility of automation for half of the current construction tasks, and>7,000 new construction robots will be deployed on construction sites worldwide by 2025 [55]. Despite the enthusiasm that automation and robotics would reduce human risk and increase speed, efficiency, and profits, there are also concerns that interaction with new technologies may create new safety challenges. To avert this, the inclusion of robots on construction sites to execute dangerous tasks requires a high level of collaboration between humans and robots. As the interaction between humans and robots becomes more common, trust in robots and self-efficacy becomes essential factors in making human and robot collaborations successful, especially in high-risk construction sites such as working at heights and demolition sites [56]. Therefore, construction workers will need to develop trust in the automation or robotic system.

A well-recognized definition of trust in human-robot interaction is: "the attitude that an agent [e.g., automation, a robot, or a human] will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability" [57]. The use of VR-based training to enhance trust in different fields of automation has been well studied, e.g., drivers' and pedestrians' trust in autonomous vehicles [58–61]. However, trust in Human-Robot Interaction (HRI) in construction applications is understudied and limited to the study of perceived safety in HRI teams (related to the physical partition between humans and robots and its influences on fostering team identification and trust) [62]. Researchers have employed virtual environments and recruited university students to validate their frameworks and examine the results [62]. However, it is not clear how the results of these studies can be extrapolated to construction workers who interact with automation and robotic systems on actual construction sites.

Table 1
Studies on Effectiveness of VR-based training on students' knowledge acquisition.

Study	Number of participants (groups)	Education Level	Objective	Effect Size (VR Group)
[12]	32 (16 VR vs 16 video-based)	Undergraduate & Graduate	Effectiveness of a VR-based safety training compared to the video-based training in precast/ prestressed industry	$d = 0.72$
[53]	32 (16 VR vs 16 video and lecture-based)	Graduate	Effectiveness of a value stream mapping-based VR training compared to the traditional personalized training	–
[10]	52 (all VR)	Undergraduate	Personalized hazard recognition and management VR-based training	$d = 2.76$
[52]	98 (40 VR vs 58 traditional course)	Undergraduate	Effectiveness of VR-based hazard identification training compared to the traditional lecture-based training	$d = 2.2$

Self-efficacy is defined as a human-related characteristic and refers to an individuals' confidence about their performance skills in a task [63]. In this sense, robot use self-efficacy is related to the workers' confidence about their ability to use a robot [64]. Although studies investigating the connection between self-efficacy and learning effectiveness in VR-based training are scarce in the field of HRI (human-robot interaction), existing studies [65,66] have found that self-efficacy and trust in automation or robots are correlated. Song et al. [22] studied the effectiveness of VR-based crane operator training (i.e., overhead, container, and tower cranes) using 108 technical high school students (who were preparing for the national crane operation certification test) as the sample. They have found a significant difference (improvement) in participants' self-efficacy between pre-training ($M = 4.36$, $SD = 1.95$) and post-training ($M = 5.5$, $SD = 1.33$), $t(107) = -5.98$, $p < 0.001$) for all three types of crane operation training. They showed that VR-based training effectively enhances competence in crane operation skills and may be generalizable for young apprentices. However, this may not be applicable to workers who have significant crane operation experience [22].

While the research community is diving deeper into understanding human trust and self-efficacy in collaborative interaction with construction robots, VR-based training, and virtual environments are used as a simulation platform, and students are recruited as the sample population. Investigating the difference in the effect of VR-based training on students' and workers' trust in the robot and robot operation self-efficacy might shed light on the generalizability of the findings to the professional population in future studies. As of this date, to the extent of our knowledge, the research community in the AEC industry has not strived to identify if the results of VR-based training, studied on the student sample population, are transferrable to the construction worker population. Hence, we investigate the effectiveness of the same VR-based training on construction workers' and university students' trust in the robot and robot operation self-efficacy.

3. Methods

3.1. *VR-based training*

We have selected a remote-operated demolition robot named Brokk. as the test case in our study. Remote-operated demolition robots have been employed on construction sites to enhance safety and productivity for dangerous, complex tasks. Indeed, workers are routinely exposed to hazardous work conditions during demolition tasks such as collapses, extreme weather conditions, dust, and radioactivity contamination [67]. We have used the model Brokk110, which is equipped with a 360-degree working radius in our empirical study [68]. The worker role in this interaction is "operator" since the worker controls the robot directly. The team composition is one human to one robot since only one worker operates this robot. Participants in our study can operate the robot through a manual controller consisting of buttons, joysticks, and a small monitor to show the robot's settings and status. The physical proximity in this interaction is collocated, and the temporal proximity is synchronous since the worker and the robot work simultaneously.

We have taken multiple phases to design our VR-based training so that the structure and content of the program target the crucial human-related factors that workers need to remote-operate the robot safely and effectively. First, we conducted a focus group interview with six expert trainers to confirm that the learning content was generalizable across trainers. A professional trainer also trained our research group via the in-person hands-on training to record subjects covered in a standard training section. Next, using the demolition robot's manuals and information collected during the training session and during the focus groups, we developed the training modules. We developed these modules based on adult learning theories in general and andragogy principles in particular, given that the median age of construction workers in North American is 42.9 years [69]. We have also reviewed the design of previous VR-based training programs and integrated useful features of those training in our design. The in-depth discussion on utilizing adult learning theory and useful components of previous VR-based training programs in our VR-based training can be found in [29,37,51].

The VR-based training has been developed utilizing the Unity3D game engine equipped with an NVIDIA GeForce GTX 1080 graphics card. Trainees experience a simulated construction site, including construction equipment and virtual workers. Importantly, trainees can experience working in different working conditions such as various weather conditions or terrain types to gain a realistic experience of the real-world construction site. We have developed this simulation based on C# coding scripts attached to each virtual object. Trainees experience our VR-based training using HTC Vive Head Mounted Display (HMD) controllers. HMD provides trainees with a full-immersive sense of presence in the environment; trainees can use controllers to interact with objects in the virtual environment to complete the learning modules. For a realistic encounter, we programmed the actual controller of the robot (using Arduino Pro micro serial connection) to operate the simulated robot in the virtual environment. Trainees also use the Virtuix Omni VR treadmill, which provides a controller-free navigation tool to walk/run in the virtual environment. Expert trainers/operators gave us iterative feedback to ensure that we were not missing any critical content, including approval of the final version of our learning modules. We also ran a pilot study with construction workers to verify the simulation of the demolition robot, identify any user experience issues with this population, and forestall any technological issues regarding the hardware and software.

The resulting VR-based training is composed of seven learning modules, each of which is followed by a diagnostic assessment that evaluates whether the worker understood the contents of the learning module before the worker is allowed to move on to the next one. Trainees could choose the language they are comfortable with, as learning contents were developed in English and Spanish. It takes about 120 min to complete all seven learning modules. The VR-based training strived to introduce the robot's objective and applications (module 1), operational safety points by interacting with the robot in the simulated construction sites (module 2) (Fig. 1a), how to utilize the robot's controller to remote-operate the robot (module 3), how to start the robot (Module 4), and how to position the robot's arm system to remote operate safely (Module 5) (Fig. 1b), how to move the robot, and use the outriggers (Module 6) (Fig. 1c), and how to demolish concrete blocks using the hammer (Module 7) (Fig. 1d). Trainees obtained the essential learning material to remote operate the robot by completing the exercises. We developed this training to understand the impact of VR-based training on construction workers' knowledge acquisition, safety behavior, operational skill sets, trust in the robot, robot operation self-efficacy, mental workload, and situational awareness in interacting with robots compared to the traditional in-person training. An in-depth description of how each learning module is designed to enhance the factors mentioned above in workers can be found in [29,37,51].

Our VR-based training provides a realistic simulation of the construction site and the robot where moving objects and workers are around the robot, which represents the perils of remote operating the robot on construction sites. Physics and the robot simulations result in realistic movement of the robot so the trainees can experience robot failures and consequences of poor strategies. Our previous studies have revealed that the same VR-based training builds significantly higher trust in the robot, robot operation self-efficacy, safety behavior, operational skills, and situational awareness in construction workers compared to those who experienced the in-person training [29,37].

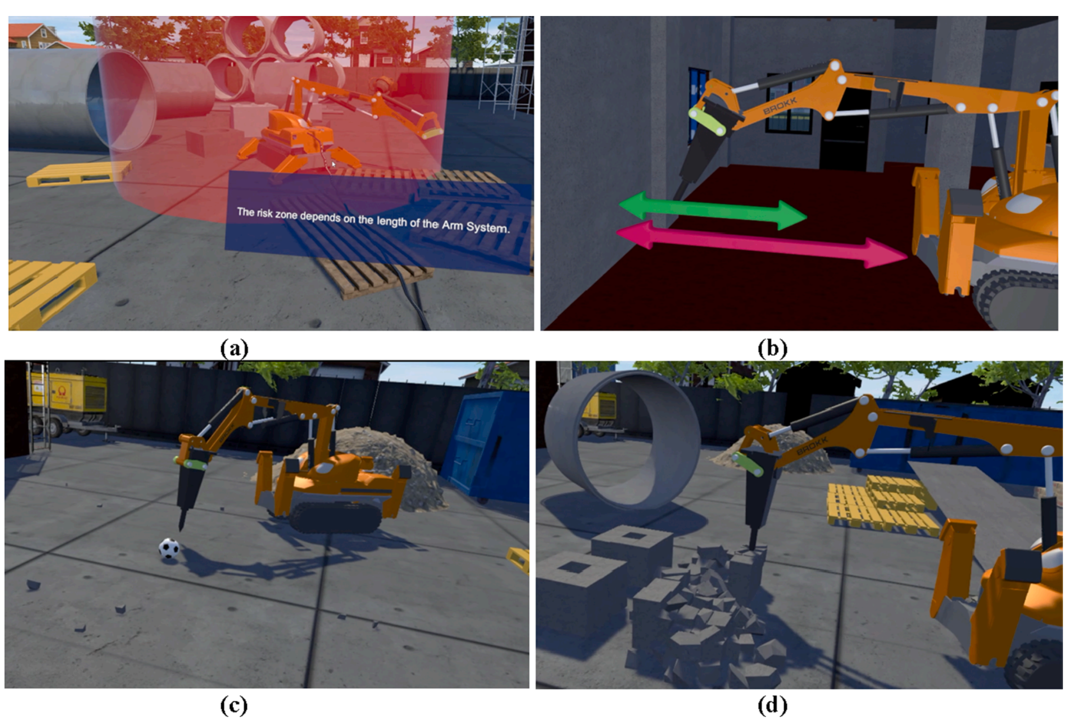

Fig. 1. **(a)** Illustration of risk zone boundary **(b)** Illustration of the safe position of robot **(c)** Practicing moving and utilizing robot's arm system **(d)** Demolition of concrete blocks.

Therefore, our VR-based training program can be an appropriate platform for experiencing the realistic remote-operation of the robot.

3.2. Participants

A total of 50 individuals participated in this study. We recruited twenty-five construction workers (24 males, 1 female) for the experiment from on-campus construction projects at the University of Southern California. Regarding the objective of the training to prepare construction workers to remote operate a demolition robot, the inclusion criteria were being an experienced construction worker over 18 years old. In addition, twenty-five graduate construction engineering students (21 males, 4 females) at the University of Southern California (studying either Master of Civil Engineering with focus on Construction Engineering or Advanced Design & Construction Technologies) have participated in the experiment. These students have participated voluntarily responding to our invitation email sent to the construction engineering graduate students' community. This recruitment strategy aligns with the strategies used by empirical studies that have recruited students as their sample population. Table 2 indicates the participants' demographic details based on their age, language, educational attainment, and experience level in the construction industry. It is vital to mention that recruited participants did not have any experience with the selected demolition robot.

3.3. Experimental procedure

Prior to receiving the training, the participants were first requested to complete a demographics survey that contained questions about age, gender, preferred language, education level, and work experience in the construction industry. This survey also contained questions related to previous experiences with video games and VR-based training. The demographic survey is provided in Appendix A.

After filling out the demographic survey, the participants answered a knowledge assessment survey containing 32 questions related to the robot and the required safety checks that are needed prior and during the operation of the robot. These questions were validated by an expert trainer and covered critical aspects of the safe and effective operation of the robot. Specifically, the questions focused on aspects such as the components of the robot, controller functions and start-up, workplace inspection, safety checks, risk zones, power cable management, robot and arm positioning, and demolition practices. A professional trainer validated the knowledge assessment to confirm the inclusion of the essential content for operating the robot safely and effectively. The knowledge assessment survey is included in Appendix B.

Table 2
Demographics across samples.

Demographics	Construction workers	Construction students
Language		
English	12 (24 %)	25 (50 %)
Spanish	13 (26 %)	0 (0 %)
Age groups		
18–29	9 (18 %)	25 (50 %)
30–39	7 (14 %)	0 (0 %)
40–49	2 (4 %)	0 (0 %)
50–69	7 (14 %)	0 (0 %)
Education levels		
Less than a high school diploma degree	9 (18 %)	0 (0 %)
High school diploma degree	12 (24 %)	0 (0 %)
College degree	4 (8 %)	25 (50 %)
Construction Experience		
<5 years	12 (24 %)	25 (50 %)
5–10 years	6 (12 %)	0 (0 %)
>10 years	7 (14 %)	0 (0 %)
Video games experience	3 (6 %)	24 (48 %)
VR-based training experience	0 (0 %)	5 (10 %)

After finishing the knowledge assessment survey, the participants were asked to complete two surveys that assess trust in the robot and robot operation self-efficacy. Trust was measured with a modified version of the automated trust scale [70], which was used to assess the participant's attitudes towards the robot. The survey contained 21 statements related to the participant's opinions on the reliability, integrity, and safety of the robot, and their opinion on the robot's impact on their careers. The survey was based on a 5-point Likert scale ranging from completely disagree to completely agree. Examples of the sentences in the survey include "I can trust the robot," "The robot is reliable," and "The robot provides safety/security". We developed the robot operation self-efficacy survey based on the modification of the validated robot use self-efficacy scale [64]. It consisted of two sentences ("I am confident in the robot," and "I feel confident around the robot") evaluating participants' self-efficacy and confidence in their ability to remote operate the robot. Similar to the trust in the robot survey, participants were requested to rate using a 5-point Likert scale ranging from completely disagree to completely agree. The trust in the robot and robot operation self-efficacy surveys are provided in Appendix C.

Finally, after the surveys mentioned above were complete, participants experienced the VR-based training. After completing the training, they answered the knowledge assessment, and trust in the robot and robot operation self-efficacy surveys, again.

3.4. Analysis

The collected data from pre- and post-training assessments were utilized to identify the effect of VR-based training on construction engineering students compared to construction workers on three dependent variables: knowledge acquisition, trust in the robot, and robot operation self-efficacy. For each of the outcomes, we conducted 2×2 mixed factorial ANOVAs with time (pre- vs post-training) as the within-subject factor and population type (students vs workers) as the between-subject factor. A mixed factorial ANOVA test compares the mean differences of a dependent variable (e.g., knowledge level, trust in the robot, robot operation self-efficacy) between groups that have been split into two factors (i.e., independent variables), each with two levels (population type: students vs workers, time: pre- vs post-training). This test aims to understand the effect of the two independent variables by calculating the probability (p-value) of incorrectly rejecting the null hypothesis. The null hypothesis in this test is that there is no statistically significant difference in terms of the change in the dependent variable (e.g., knowledge, trust, self-efficacy) from pre-to-post training between students and workers. It is vital to mention that normalized gain has been selected in comparing the change in dependent variables from pre-to-post training. Since the scores have upper limits, using raw changes does not account that the group with lower pre-test ratings have more to gain than the group with higher pre-test rating. Therefore, the normalized gain, independent of population type and pre-test ratings, provides a less biased comparison between students' and workers' rating changes. We also conducted separate paired sample t-tests to test whether the pre-to-post training change was significant in each sample. A paired sample *t*-test compares the means of two measurements (e.g., knowledge, trust, self-efficacy) taken from the same group (e.g., students or workers). The null hypothesis in this test represents that there is no statistically significant difference in mean measurements from pre-to-post training in each population group. The p-value reveals the probability of incorrectly rejecting this null hypothesis. Additionally, we ran independent sample t-tests to test whether there is a significant difference between students' and workers' ratings (e.g., knowledge, trust, self-efficacy) in each pre- and post-training condition. This statistical test provides the probability of incorrectly rejecting the null hypothesis (no statistically significant differences in measures between students and workers). In quantitative studies, it has been recommended to report both substantive significance (effect size) and statistical significance (p value). Therefore, this study reported both the p value and effect size. It is critical to provide effect sizes, i.e., the magnitude of the differences between groups, because merely providing p values can only inform whether an effect exists or not but will not reveal the size and strength of the effect. Additionally, it has been argued that statistically significant result can be achieved using a large sample size whereas effect size is independent of sample size thereby its useful to show the size of a difference between two measures. We used Cohen's (1988) guidelines in this study, which suggest ($d = 0.2$) as small, ($d = 0.5$) as medium, and ($d \geq 0.8$) as large effect size. Cohen's d is an appropriate effect size for the comparison between two means which considers both the deviations and variations.

4. Results

Table 3 presents the means and standard deviations of participants' ratings in knowledge level, trust in the robot, and robot operation self-efficacy assessments. First, an ANOVA revealed a significant interaction, such that the knowledge acquisition gain from VR-based training was significantly greater for construction students than for construction workers ($F(1,47) = 5.582$, $p = 0.022$, Cohen's $d > 1.0$): the average gain for students was 70.32 (out of 100), whereas, for construction workers, it was only 60.21 (Fig. 2). Students had higher scores on the knowledge test than workers in at both pre- ($t(47) = 2.718$, $p = 0.009$, Cohen's $d > 1.0$) and post-test ($t(47) = 5.222$, $p < 0.001$, Cohen's $d > 1.0$). However, paired sample t-tests revealed significant improvement in knowledge from pre- to post-test for both students and workers: from pre- ($M = 16.9$, $SD = 9.5$) to post-test ($M = 87.3$, $SD = 9.7$) for students ($t(24) = 32.9$, $p < 0.001$, $d = 6.58$) and from pre- ($M = 9.7$, $SD = 9.1$) to post-test ($M = 69.9$, $SD = 13.3$) for workers ($t(23) = 16.04$, $p < 0.001$, $d = 3.3$).

An ANOVA also revealed a significant interaction for trust in the robot, which actually increased significantly more pre- to post-test for workers (1.38 out of 5) than for students (1.06; $F(1,47) = 4.23$, $p = 0.045$, Cohen's $d > 1.0$) (Fig. 3). Additionally, independent sample t-tests showed that, while students had significantly higher trust in the robot (3.30 out of 5) than construction workers (2.81 out of 5) at pre-test ($t(1,47) = 3.604$, $p < 0.001$, Cohen's $d > 1.0$), the difference between samples was reduced to non-significant after the training ($t(1,47) = 1.079$, $p < 0.286$, Cohen's $d > 1.0$). However, paired sample t-tests revealed significant increases in trust from pre- to post-test for both students and workers: from pre ($M = 3.30$, $SD = 0.55$) to post-test ($M = 4.36$, $SD = 0.56$) for students ($t(24) = 11.55$, $p < 0.001$, $d = 2.31$), and from pre- ($M = 2.81$, $SD = 0.37$) to post-test ($M = 4.20$, $SD = 0.50$) for workers ($t(23) = 10.69$, $p < 0.001$, $d = 2.19$).

A parallel ANOVA revealed a significant interaction for robot operation self-efficacy, which -even more so than trust- increased significantly more from pre- to post-test for workers (1.62 out of 5) than for students (0.98; $F(1,47) = 7.634$, $p = 0.008$, Cohen's $d > 1.0$) (Fig. 4). Also like with trust in the robot, independent sample t-tests showed that, while students had significantly higher self-efficacy (3.32) than construction workers (2.79) at pre-test $t(1,47) = 2.678$, $p = 0.010$, Cohen's $d > 1.0$), the difference between samples was reduced to non-significant after the training ($t(1,47) = -0.613$, $p = 0.542$, Cohen's $d = 0.613$). However, again, paired sample t-tests revealed significant increases in self-efficacy from pre- to post-test for both students and workers: from pre- ($M = 3.32$, $SD = 0.69$) to post-test ($M = 4.30$, $SD = 0.68$) for students ($t(24) = 7.00$, $p < 0.001$, $d = 1.40$), and from pre- ($M = 2.79$, $SD = 0.69$) to post-test ($M = 4.42$, $SD = 0.65$) for workers ($t(23) = 8.618$, $p < 0.001$, $d = 1.76$).

Table 3
Means and standard deviations of measures based on population groups.

Measures	Students		Workers	
	Pre-training	*Post-training*	*Pre-training*	*Post-training*
Knowledge level	16.9 (9.5)	87.3 (9.7)	9.7 (9.1)	69.9 (13.3)
Trust in the robot	3.30 (0.55)	4.36 (0.56)	2.81 (0.37)	4.20 (0.50)
self-efficacy	3.32 (0.69)	4.30 (0.68)	2.79 (0.69)	4.42 (0.65)

5. Discussion

5.1. Knowledge acquisition

The results of our study indicate that after experiencing VR-based training, both students and construction workers gained significant knowledge, which might suggest a similarity between these two population types. However, the statistical result from the ANOVA reveals that students gained significantly more knowledge than construction workers. Additionally, looking at the normalized knowledge acquisition reveals that construction workers gained only 66.7 % of the knowledge they could have learned, while students gained the higher 84.7 % of what they could have learned considering their base knowledge. Thus, our findings show that the effectiveness of VR-based training on construction workers' knowledge acquisition is not the same as students. Since it is common in research to use students instead of construction workers as the sample population to study the effectiveness of VR-based training in knowledge acquisition, our findings show that while student samples may be more convenient, accessible, and cost less than recruiting actual construction workers, generalizing about construction workers from studies using students can lead to conclusions that either under- or over-estimate the impact of VR-based training on knowledge acquisition. Therefore, researchers need to be cautious in generalizing results from one population to another. The findings of our study suggest that, compared to students, training construction workers might not improve their knowledge as much. Thus, the results from these studies [10,12,52,53] might not be generalizable to the construction worker population. Additionally, the independent-samples t-test indicates that students had a significantly higher base knowledge both before and after experiencing the training than construction workers. These differences in the knowledge levels between students and workers in pre- and post-training might emanate from demographic variables such as students having a higher degree of education and being more experienced in using technologies (more technology-savvy); however, our sample size was not powered enough to investigate how demographic variables moderate the effect. Nevertheless, if the difference in knowledge acquisition is derived from demographic differences, it further reinforces that the researchers should not use students as the sample population to draw conclusions about construction workers, and they need to be cautious in generalizing their results. Also, our findings are in alignment with previous research, which has indicated that VR-based training might be beneficial for less experienced trainees, such as students (young generations), compared to the more experienced construction workers [28].

The impact of the VR-based training program based on the data collected from a student population had a larger effect size than in prior studies also conducted with students (see Table 1). Such differences could be explained by several factors, such as the characteristics of the student sample across these studies, the choice of data collection tools, or the differences in the programs studied. Yet, our results showed that even when the VR-based program, measures, and the data collection procedures were identical across the two different populations (i.e., students and construction workers), the results were contingent on the population. Indeed, the effect sizes obtained from paired sample t-tests indicate that the size of knowledge gain relative to variation among the students was twice as large as the size of knowledge gain relative to variation in the construction workers experiencing the same program. This result suggests that although both students and workers experience significant knowledge gains by taking the training program, the magnitude of VR-based training's impact on students' knowledge acquisition is more significant than its impact on construction workers. Hence, using students rather than workers in a program aiming to target workers can lead to overestimating the impact of such a program. Taken

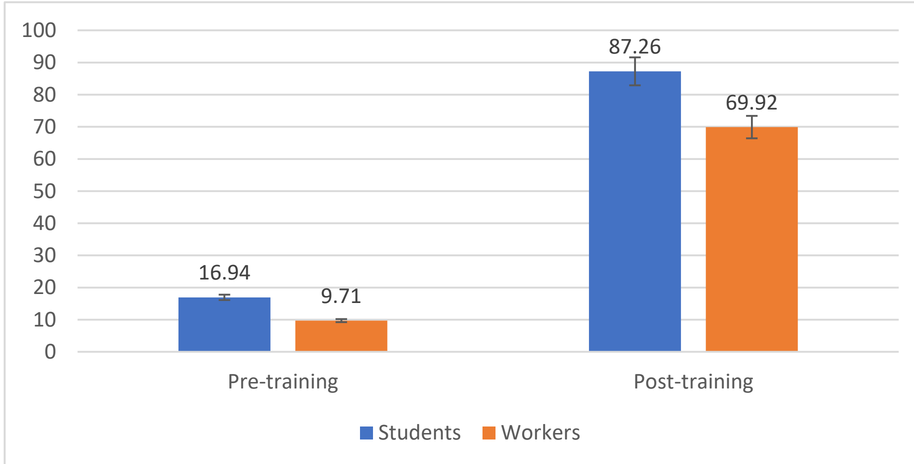

Fig. 2. Participants' average score on the knowledge assessment.

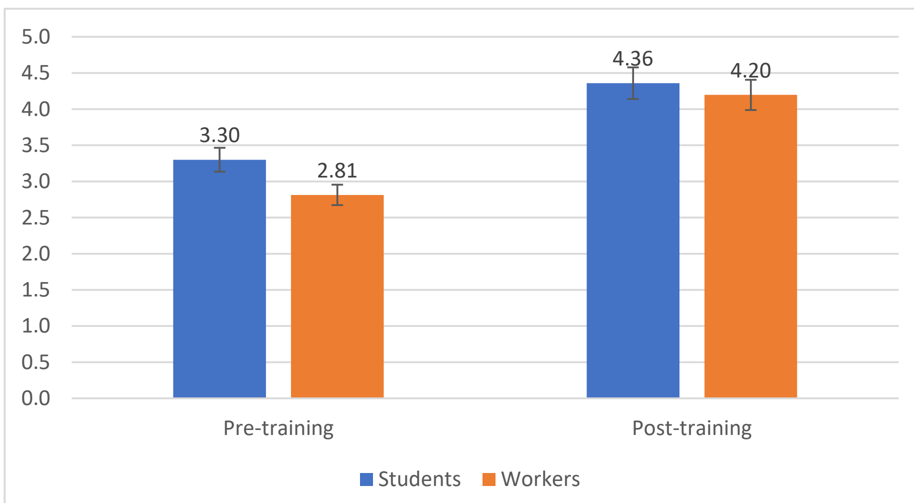

Fig. 3. Participants' average score on the trust in the robot survey.

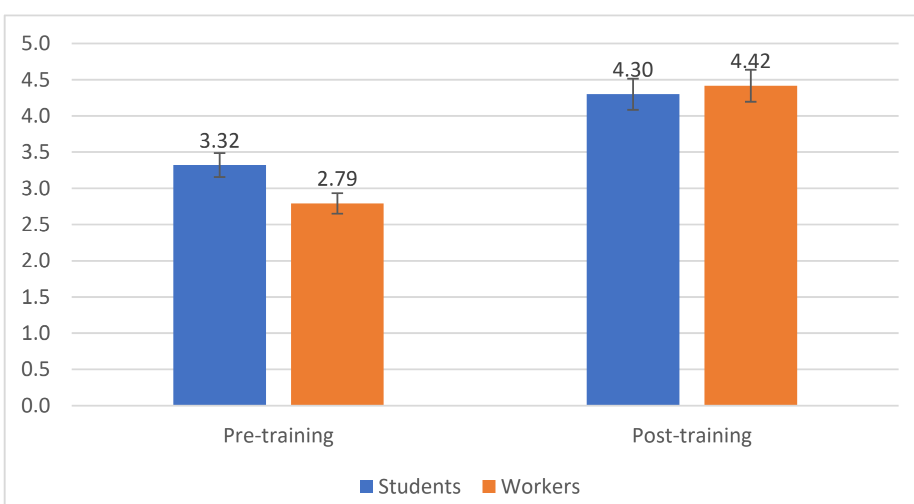

Fig. 4. Participants' average score on the robot operation self-efficacy survey.

together, our study highlights the importance of collecting data from the targeted population to obtain more accurate estimate of the impact of a program for the end-users.

5.2. Trust in the robot & self-efficacy

Our results in this study indicate that construction workers gain more trust in the robot and robot operation self-efficacy than students after experiencing VR-based training. Despite initially lower trust and self-efficacy among construction workers and students because workers and students no longer differ significantly in trust or self-efficacy after training, the training seems to be able to bring workers on par with students in terms of trust and self-efficacy. The difference in trust and self-efficacy at pre-test might be driven by the demographic differences between the two samples (and, likely, the populations they are sampled from). All the students who participated in this study were master's students in construction engineering and between 18 and 29 years old. However, the construction worker participants were from a wide range of age groups, from 18 to 29 to 60 and older. Our results support conclusions from prior work that younger adults are more eager to engage with robots than older adults [71]. Thus, younger adults in general, especially those with higher education, may have higher trust in the robot and self-efficacy even before experiencing the training.

Although our results show higher levels of trust in the robot and self-efficacy for students before the training than for construction workers, importantly, we show a larger gain from pre- to post-training in both trust and self-efficacy for construction workers than for students. These findings suggest that the previous work using students could be systematically underestimating the effect of VR-based training on these kinds of outcomes for construction workers. That is, given our findings, construction workers might have demonstrated even larger increases in trust and self-efficacy in the prior work if they had been sampled (instead of students). For example, Song et al. [22] studied the effectiveness of VR-based crane operator training (i.e., overhead, container, and tower cranes) using 108 technical high school students. They found that their VR-based training could significantly improve students' self-efficacy (Cohen's d = 1.88); however, they state that their results may not be applicable to workers with significant experience. Based on the Cohen's d measure, we can claim that our student population (Cohen's d = 1.40) has a similar effect size with Song et al.'s findings on students (Cohen's d = 1.88). Thus, it is possible that since Song and colleagues found significant improvement in self-efficacy in students, if our differences between samples in self-efficacy are representative of populations differences, their findings could possibly also be applicable to workers in the construction industry.

As robotics become more common in construction, researchers strive to understand the hurdles to robotics and automation adoption in the construction industry; thus, human-related factors in HRI, such as trust in the robot and robot operation self-efficacy, might become of even greater interest. Our study's findings contribute to the question of the extent to which results from student samples generalize to the construction worker population. If our differences between samples in trust and self- efficacy are representative of population differences, given the effect of our training went from large (in students) to even larger (in construction workers), then their observed gains could conceivably go from small (in students) to potentially significant (in construction workers). Such smaller effects observed in prior among students may therefore be underrepresenting gains in trust and self-efficacy possible with VR-based training among construction workers, at least with well-developed VR platforms and modules.

5.3. Limitations

While this study has significant implications for the research community, some limitations do exist. The current sample of students showed much larger effects of our VR-based training than prior studies reported. Our larger effect size among students may be due to demographic differences among students, or that the design of our VR-based training was perhaps more effective. Furthermore, our study has, at best, only a moderate sample size even though we observed quite large differences between our samples, and the effects were highly significant. Additionally, our sample size was not powered enough to statistically investigate how demographic variables (e.g., education level, video game experience) moderate the effectiveness of VR-based training among students and construction workers. Future studies with larger sample sizes might explore the reason behind the similarities and differences in VR-based training effectiveness among different population types. Regarding trust in the robot and self-efficacy, while realistic simulation of the construction site and the robot were included in VR-based training and the trainees were able to experience robot failures and consequences of poor strategies, we cannot be certain that VR-based training results in the same level of trust gains if the actual robot is used. Hence, future studies should test if working with the actual robot after the VR-based training has different results in terms of trust in robots and robot operation self-efficacy. Moreover, the findings of this study are limited to our specific VR-based training. Although the results may not be generalizable to all VR-based training studies, our research indicates that there might be significant differences between the effectiveness of VR-based training on construction workers and student populations. Thus, caution on population type is necessary for interpreting the results.

6. Conclusion

The present study contributes to existing research on VR-based training within the construction industry. We construct on previous research that explored the application of VR-based training for construction workers by asking the extent to which the results from student samples generalize to the construction workers population. Findings from this study suggest that VR-based training can lead to a significantly larger increase in knowledge acquisition for construction students than workers. In contrast, VR-based training improved trust in the robot and robot operation self-efficacy significantly more for construction workers than students.

These results call in to question the extent to which studies based on student samples can appropriately generalize to construction workers, which are usually the intended population for the training. If a similar difference between construction workers and students occurred with other VR-based trainings as observed for ours, given that their training appeared to be less effective than ours, no effect of VR-based training might have been observed if they had done the study with construction workers instead of students. Indeed, our effect of VR-based training went from very large (in students) to smaller (in construction workers); accordingly, it is possible that the effect of other researchers' VR-based training could go from small (in students) to non-significant (in construction workers). This suggests that, while they observed significant knowledge acquisition through VR-based training among students, their findings might not replicate using a sample of construction workers. This raises the possibility that VR-based training intended for construction workers may not actually be able to significantly improve knowledge among workers in this population. On the other hand, the larger gains that we observed for trust and self-efficacy among construction workers than students suggest that prior work examining these outcomes may have underestimated the effectiveness of VR-based training on construction workers, at least for these ancillary outcomes. Either way, future research should be cautious -given our findings- when generalizing from samples of construction students to populations of construction workers.

Declaration of Competing Interest

The authors declare that they have no known competing financial

interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.aei.2022.101837.

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