Impact of VR-Based Training on Human–Robot Interaction for Remote Operating Construction Robots

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Abstract: Despite the increased interest in automation and the expanded deployment of robots in the construction industry, using robots in a dynamic and unstructured working environment has caused safety concerns in operating construction robots. Improving human–robot interaction (HRI) can increase the adoption of robots on construction sites; for example, increasing trust in robots could help construction workers to accept new technologies. Confidence in operation (or self-efficacy), mental workload, and situational awareness are among other key factors that help such workers to remote operate robots safely. However, construction workers have very few opportunities to practice with robots to build trust, self-efficacy, and situational awareness, as well as resistance against increasing mental workload, before interacting with them on job sites. Virtual reality (VR) could afford a safer place to practice with the robot; thus, we tested if VR-based training could improve these four outcomes during the remote operation of construction robots. We measured trust in the robot, self-efficacy, mental workload, and situational awareness in an experimental study where construction workers remote-operated a demolition robot. Fifty workers were randomly assigned to either VR-based training or traditional in-person training led by an expert trainer. Results show that VR-based training significantly increased trust in the robot, self-efficacy, and situational awareness, compared to traditional in-person training. Our findings suggest that VR-based training can allow for significant increases in beneficial cognitive factors over more traditional methods and has substantial implications for improving HRI using VR, especially in the construction industry. **DOI: 10.1061/(ASCE)CP.1943-5487.0001016.**

Author keywords: VR-based training; Human–robot interaction (HRI); Situational awareness; Mental workload; Trust in the robot; Robot operation self-efficacy.

Introduction

Over the past two decades, both the construction industry and the scientific community have developed an increased interest in construction robotics. This interest has resulted in an increased production of scientific research and expanded deployment of robots on construction sites (Carra et al. 2018). Automation and robotics have the potential to revolutionize and address the shortcomings of the construction industry, such as stagnant productivity and safety concerns. On-site robotic systems can enhance productivity by performing highly repetitive and tedious tasks (e.g., masonry, finishing, rebar-tying); thus, construction workers can focus on more complex tasks that humans can do better than robots (Davila Delgado et al. 2019). Automation and robotics can also lower project costs by allowing construction in adverse weather conditions (e.g., various temperatures and humidity levels) (Kumar et al. 2008). Robots can also mitigate labor shortages and allow for broader workforce access by enabling underrepresented groups of workers to join the workforce, for example, enable women (who comprise only 10.3 percent of the construction workers population (US Bureau of Labor Statistics 2019) or disabled workers who cannot work on heavy tasks to engage in construction tasks. Besides, construction robots can execute hazardous and labor-intensive tasks (e.g., demolition) as well as prevent injuries and fatalities in an industry notorious for having a dangerous work climate (Castro-Lacouture 2009).

Human–robot interaction (HRI) is one of the key areas that must be explored for successful construction robotics adoption. Construction workers might not accept new automation since they might view these technologies as a way to replace them (Yahya et al. 2019). Additionally, workers might prefer traditional methods over technological solutions due to the unpredictable and dynamic nature of construction sites (Yahya et al. 2019). They often feel unsafe working around robots (Bartneck et al. 2009). Construction workers need to gain trust in the new robotic systems because building this trust among human operators or collaborators produces an increased sense of safety, a willingness to accept robot-provided information or decisions, and an inclination to work with

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robots in the future (Freedy et al. 2007; You et al. 2018). However, there are very few opportunities for construction workers to build trust before remote operating construction robots on job sites.

Even though automation and robotic systems have the potential to improve workers' safety, they can also bring about new safety concerns to construction sites. While workers and robots are separated in other industries such as automotive and manufacturing industries, robots work alongside construction workers in a constantly changing and unpredictable working environment. Hence, the safety of humans working alongside robots is a goal to achieve successful construction robotics adoption. In this regard, workers' mental workload (MWL) and situational awareness (SA) are two critical factors impacting the safe remote operation of construction robots. MWL and SA are objects of interest in cognitive engineering. They refer to the cognitive loads imposed on operators during task execution when robots and other intelligent systems are involved. MWL relates to the portion of an operator's cognitive capacity necessary to complete a given task (O'Donnell and Eggemeier 1986). SA indicates how the operator perceives the environments in which the tasks take place, comprehends its meaning, and predicts future states of the environment and the task (Endsley 1988). Despite being crucial factors of learning for construction workers to remote operate the robots safely, workers have very few opportunities to optimize their MWL and build SA before remote operating construction robots on-site.

Current training opportunities for construction workers primarily rely on passive pedagogical models (including lectures, pamphlets, and videos), with only a few examples of active training techniques being used (learner-centered instruction, apprenticeship models, and hands-on demonstrations) (Burke et al. 2006; Moon et al. 2019; Wang and Dunston 2007). Given that in-person training may not be feasible in many situations due to the safety risks it may impose on the trainees, cost and equipment requirements, and disturbance of the work on-site, virtual reality (VR)-based training is proposed as a method to provide construction workers with in-person training experiences in hazardous situations without imposing actual safety risks. In recent years, the use of VR-based training has drawn attention from construction researchers, especially in aspects related to safety and hazard identification (Albert et al. 2014; Jeelani et al. 2020; Le et al. 2015; Moore et al. 2019; Nykänen et al. 2020; Sacks et al. 2013; Xu and Zheng 2021), construction equipment operation (Bhalerao et al. 2017; So et al. 2013, 2016; Song et al. 2021; Su et al. 2013; Vahdatikhaki et al. 2019), ergonomic behavior (Akanmu et al. 2020; Diego-Mas et al. 2020), and construction task execution (Barkokebas et al. 2019; Cheng and Teizer 2013; Hafsia et al. 2018; Osti et al. 2021).

VR-based training and other extended reality (XR)-based training [i.e., augmented reality (AR) and mixed reality (MR)] have gained increasing attention in the past decade as a result of technology development and reduced implementation costs. Examples of VR-based training can be found in a variety of domains, including manufacturing (Kalkan et al. 2021), aerospace and aviation (Chandra Sekaran et al. 2018; Luong et al. 2020), healthcare (Mao et al. 2021; Mehrfard et al. 2020), military (Gluck et al. 2020), retail (Boletsis and Karahasanovic 2020), sports (Lee and Kim 2018), construction (Jeelani et al. 2020; Nykänen et al. 2020; Pooladvand et al. 2021; Song et al. 2021), among others. Existing research has identified a series of requirements that can improve the effectiveness of VR-based training. For example, one of the most important requirements refers to the levels of virtual presence that is associated with any proposed training, as existing research has shown that more feeling of presence increases the effectiveness of the training and the overall performance of the operators (Heyao and Tetsuro 2022; Song et al. 2021). Also, the realism of the virtual training environment plays an important role in the effectiveness of VR-based training and the overall user experience (Chalmers and Debattista 2009; Grant et al. 2020). Another key factor in VR-based training refers to the consideration of experiential learning [i.e., "learning through reflection on doing" (Pappa et al. 2011, p. 1003)] during the development of the training (Goulding et al. 2012). This is because including considerations about learning objectives, metrics, and outcomes during the development of the VR-based training can provide a more effective training experience.

Moreover, VR-based training has the potential to provide an opportunity for workers to build trust in automation and construction robots more specifically and trust in their ability so that workers are ready to remote operate the robot safely and efficiently on an actual construction site. VR-based training can also promote a safer interaction between humans and robots by decreasing the overall mental workload experienced by the worker while also increasing his/her SA. However, the impact of VR-based training on construction workers' trust in the robot, robot-used self-efficacy, SA, and MWL is underexplored in the construction robotics context. Thus, the present study explores the effectiveness of VR-based training on construction workers' MWL and SA, as well as their development of trust in robots and ability to use the robot (robot-use self-efficacy), compared to a more traditional, comparable in-person pedagogical model. We begin this paper with a literature review of existing studies of VR-based training from a range of trust in automation, MWL, and SA literature. Next, we present the study's methodology, which includes the VR-based training environment and the experimental design, and the study's findings. A discussion is followed by the conclusions and future directions.

Literature Review

Trust in the Robot and Robot Operation Self-Efficacy

Advancements in automation have allowed workers to collaborate with robots on various job sites; however, the dynamic, unstructured nature of construction sites has caused challenges in implementing robots on job sites (Yahya et al. 2019). Not only are construction sites inherently unpredictable, but construction workers and robots also work alongside each other rather than separately as they do in other industries (i.e., manufacturing). In addition, since robots are often designed to execute more dangerous tasks than humans in collaborative teams of humans and robots, trust in the robot plays a more pivotal role in high-risk environments, such as construction sites, than it does in more structured and relatively less risky environments (Frank et al. 2019). Therefore, construction workers must trust in the automation or robotic system they are working with and in their skills in remote operating the robots.

Lee and See (2004, p. 51) define trust as "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." The level of humans' trust depends on the characteristics of the trustee (e.g., culture, age, gender, personality), the trustor (e.g., features of the automation, capabilities of the automation), and the context of the interaction between them (e.g., team collaboration, tasks) (Chen et al. 2011; Lee and See 2004; Parasuraman et al. 2008; Sheridan 2002). Trust in human interaction with automation can be challenged by disuse and misuse. Disuse relates to the situation when humans do not accept technology and reject using it, while misuse refers to overtrusting automation excessively and inappropriately (Lee and See 2004). While trust in automation and trust in

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robots have similar fundamental characteristics, the human–robot trust may differ from the human-automation trust since robots have different characteristics than other forms of automation (Hancock et al. 2011). In this regard, researchers have been investigating factors that influence the trust in a robot (Parker and Grote 2020).

Existing studies indicate that trust in a robot can be influenced by the characteristics of humans, robots, and surrounding environment (Park et al. 2008), with the characteristics of the robot being regarded as more significant than the characteristics of humans and the environment on the development of trust (Hancock et al. 2011). On many occasions, however, there are mismatches between the perceptions of humans on the robot's characteristics and capabilities and the robot's actual characteristics and capabilities, which can lead to trust failures. For that, training the humans involved in interactions with robots has been presented as a key strategy to promote trust by reducing the differences between the expectations of humans toward the robot's capabilities and the actual robot's capabilities (Hancock et al. 2011) and to recover trust after trust failures resulting from incorrect user expectations toward the robot or user unintentional failures during the interaction (Tolmeijer et al. 2020).

Most commonly, trust is assessed subjectively with the help of questionnaires based on Likert-scales in which the subjects indicate their levels of trust in their ability to properly interact with the robot (self-efficacy) and/or the ability of the robot to achieve the task goals. Examples include proposed trust scales that account for various factors that influence HRI such as team configuration, team process, context, task, and system (Yagoda and Gillan 2012) and trust scales that assess the overall perception of the subjects on robot's capabilities using repeated measures analysis (Schaefer 2016). In one of the few attempts to measure trust in a robot objectively, Freedy et al. (2007) proposed a model that determines an overall trust score based on the human task allocation decision behavior, risk, and robot behavior and found that as robot competency decreases, the mission time and the user interventions increase. Based on the proposed formulation, the authors also proposed an analytical methodology that allows the comparison of the trust behavior of the operators to the expected behaviors of an expert, providing direct feedback on the operator's training needs relative to trust behavior.

The model proposed in Freedy et al. (2007) is based on the correlation between trust in automation and self-confidence, or self-efficacy. Robot-use self-efficacy is a human-related characteristic correlated with trust in a robot (Evers et al. 2008; Lee and Moray 1994). Self-efficacy refers to an individual's belief about his/her performance skills in a given situation (Bandura 2006). Specifically, robot-use self-efficacy refers to the workers' beliefs about their ability to use robots (Turja et al. 2019). However, self-efficacy does not equal efficacy; a person may possess the ability to perform a task successfully, but he/she may not believe that they have the power to produce the desired effect (Rosenthal-Von Der Pütten and Bock 2018).

VR has been used to study and enhance trust in automation in different fields, including drivers' and pedestrians' trust in autonomous vehicles (Jayaraman et al. 2019; Miller et al. 2016; Morra et al. 2019; Sportillo et al. 2019). In construction applications, the study of trust in HRI is rare and has been limited to the study of perceived safety in HRI teams because of physical separation between workers and robots and its impacts on promoting team identification and trust (You et al. 2018). As of this date, to the best of our knowledge, there is no study in the construction industry that has focused on understanding the impact of immersive VR-based training on construction workers' trust in the robot and robot operation self-efficacy. Since the development of trust in the robot and robot operation self-efficacy is crucial for the adoption of construction robotics, this study investigates VR-based training's impact in enhancing the aforementioned factors in construction workers compared to traditional in-person training.

Mental Workload

Since more than 70% of all accidents in the construction industry are related to workers' activities, it is crucial to mitigate human-related factors affecting the safety conditions in this industry (Chen et al. 2016). Construction workers' ability to perceive hazards can help them to avoid dangerous conditions. Among the human factors that relate to hazard perception is mental workload (MWL) (Gao and Wang 2020; Di Stasi et al. 2009; Tevell and Burns 2000). One of the most accepted definitions of the MWL associated with a task is "the level of attentional resources required to meet both objective and subjective performance criteria, which may be mediated by task demands, external support and past experience" (Young and Stanton 2001, p. 507).

The study of MWL has become a topic of interest due to the increasing cognitive demand requirements resulting from the deployment of more complex human-machine and human–robot systems in diverse fields, including aviation, surgery, manufacturing, and construction. In many studies, MWL has been recognized as a key factor that affects operator's performance during human-machine and human–robot interactions (Dybvik et al. 2021; Memar and Esfahani 2018; Moore et al. 2015; O'Donnell and Eggemeier 1986; Tao et al. 2019). Most commonly, these studies have shown that decreasing the cognitive loads imposed on the operator during task execution usually results in improved performance. Although most of the studies focus on mental overload, when task requirements overcome operator capabilities, mental underload is another situation that leads to reduced performance. As presented by Young and Stanton (2001), instead of trying to remove the operator from as many tasks as possible when deploying automated systems, the designer should try to optimize the design of the tasks to take advantage of both the technology and the operator's skills, which can be accomplished through the use of adaptive interfaces and dynamic task allocation. In such cases, human factors such as operator's workload and levels of fatigue, and physiological data such as heart rate variability, can be used to dynamically allocate tasks to the humans and robots involved in the interaction to alleviate the negative effects of workload, fatigue, and stress (Landi et al. 2018; Pini et al. 2016).

Various techniques can be used to assess MWL during task execution, including subjective measures [e.g., NASA-Task Load Index (TLX) and the subjective workload assessment technique (SWAT)], physiological measures (e.g., heart rate, eye-gazing, electrodermal response), and objective measures based on task performance (primary and/or secondary tasks) (Young and Stanton 2004). Developed by the Ames Research Center (Biferno 1985), the NASA-TLX is a standard, questionnaire-based, subjective measure of the overall workload experienced by a human working in a human-machine or human–robot system. It is one of the most used measures of task load and considers six subscales: mental demand, physical demand, temporal demand, level of performance, effort, and frustration. Even though a variety of physiological measures has been used to predict MWL in many domains (Grimmer et al. 2021; Sakib et al. 2021; Singh et al. 2021; Yauri et al. 2021), the use of subjective assessments alone has been preferred in many studies (Sugiono et al. 2017; Yurko et al. 2010), especially due to their simplicity of application and nonintrusive nature. Also, for MWL specifically, existing studies show that while most of the physiological measures used in MWL research can detect changes in MWL levels, the validity of these measures is dependent on the application at hand, requiring a proper selection of the physiological measures for each task scenario (Charles and Nixon 2019; Tao et al. 2019).

In construction applications, some of these techniques have been used, sometimes combined, to assess the levels of MWL that workers experience when working alongside machines and robots (Akyeampong et al. 2014), assess the reliability of using physiological data to predict MWL (Sakib et al. 2021), or to adjust robot behavior during the interaction (Liu et al. 2021). Current efforts to understand the implications of VR-based training on MWL have shown that there are significant differences between the levels of MWL experienced by the subjects when operating simulated drones and real drones, being the MWL higher in the simulated condition (Sakib et al. 2021). Yet, it is still not clear whether the same results can be obtained when using VR-based training to train construction workers on the operation of more complex construction machines and robots given the requirements of longer training sessions, more unstructured environments, and the relatively more complex control interfaces and mechanisms found in these machines/robots.

Despite the increasing body of research on the cognitive impacts of the deployment of intelligent systems and robotics on-site and in the use of immersive environments for construction workers' training, the impacts of VR-based training on the cognitive loads experienced by construction workers during the actual remote operation of a construction robot has not yet been fully explored. In this paper, the cognitive loads experienced by two groups of construction workers with VR-based versus in-person training are measured using NASA-TLX and compared to assess the effectiveness of VR-based training to reduce MWL during the remote operation of a construction robot.

Situational Awareness

Another crucial human factor in applications involving human–robot systems is SA, which, according to Endsley (1995a), forms the basis for decision making and performance in the operation of complex systems. As is the case with the MWL, current studies have increasingly focused on SA to investigate new systems design and training programs in various fields (Endsley 2021). The most accepted definition of SA centers on the operator's "perception of the elements of the environment within a volume of time and space, the comprehension of their meaning and the projection of their status in the near future" (Endsley 1988, p. 792). This definition clearly presents three phases in the process of an operator acquiring SA: perception, comprehension, and projection. These three phases are defined in the hierarchical model of SA in decision making proposed by Endsley (1995b), which defines the Level 1 SA (lowest level) as the perception of the environment and its elements, Level 2 SA as the holistic comprehension of these elements and their implications for the task goals, and Level 3 SA (highest level) as the projection of the future states of these elements in the environment.

Various tools and metrics have been proposed to assess workers' SA, which include process measures, performance measures, and direct SA measures, which are further differentiated among situation awareness rating technique (SART), situation awareness global assessment technique (SAGAT), and situation present assessment technique (SPAM) (Endsley 2021). Among these, SAGAT is one of the most used techniques for measuring SA and involves randomly freezing the task simulation and asking the subject questions about the current situation as a means to determine his/her knowledge about the situation considering the three levels of SA (perception, comprehension, and prediction) (Endsley 1988, 2021). After multiple queries taking place at various moments during the simulation, a composite SAGAT score is calculated, and it represents an objective measure of SA because the perceptions of the operator (as represented by his/her answers to the queries) are compared to the actual conditions of the simulation (Endsley 1988).

In construction applications, SA has commonly been studied from the perspectives of hazard identification and/or operating performance of complex machines and equipment, especially cranes and excavators (Cheng and Teizer 2014; Fang et al. 2018; Hong et al. 2020; Wallmyr et al. 2019). Existing results show that increasing an operator's SA with the help of an assistance system based on visual cues, for example, can improve the overall operator's safety performance and task performance (Fang et al. 2018; Fang and Cho 2017). Relative to the use of VR-based training to increase construction workers' SA, Vahdatikhaki et al. (2019) claimed that current VR-based simulators for construction operation training put too much emphasis on the development of photo- and physics-realistic scenarios and less emphasis on the development of context-realistic scenarios, limiting the ability of the trainees to increase their SA and skills. As is the case with the operation of actual construction equipment, increasing the worker's SA during training in a simulated environment can also improve the worker's safety behavior and help workers to visualize potential risks associated with their actions after the training sections (Cheng and Teizer 2013).

Many studies show that physical and mental loads and environmental and task requirements also affect the worker's SA and, consequently, the ability of these workers to identify safety hazards during task execution. Task complexity, for example, has been associated with reduced performance and SA and increased mental workload (Fang et al. 2018), which may require specific training scenarios to mitigate the reduction of the operator's SA levels during more complex tasks (Choi et al. 2020). Finally, for similar levels of task complexity, construction workers' SA is significantly affected by different levels of MWL, with SA decreasing for higher levels of MWL (Kim et al. 2021).

Although construction sites represent one of the most hazardous working environments (US Bureau of Labor Statistics 2020) and there have been an increased number of robots deployed on construction sites [International Data Corporation (IDC 2020)], there is still a lack of research into the potential of VR-based training on enhancing the workers' self-efficacy, SA, and mental workload during the remote operation of real construction robots. Thus, this study investigates the impact of VR-based training on construction workers' self-efficacy, mental workload, and SA as compared to traditional in-person training.

Methods

Construction Robot Test-Case

A remote-operated demolition robot is selected based on the industry acceptance trends, level of technology development, frequency of use in construction projects, and potential impact on enhancing construction productivity and safety. Remote-operated demolition robots constitute about 90% of the total market for all construction robots (Association for Advancing Automation 2020). One reason for the fast adoption of remote-operated robots by the construction industry is the unhealthy and dangerous nature of demolition tasks (Corucci and Ruffaldi 2016). The use of handheld demolition tools is associated with an average of 32 missed days for workers due to fractures, injuries, and the effects of excessive vibration and strain (Brokk Inc. 2020). Moreover, using remote-operated demolition

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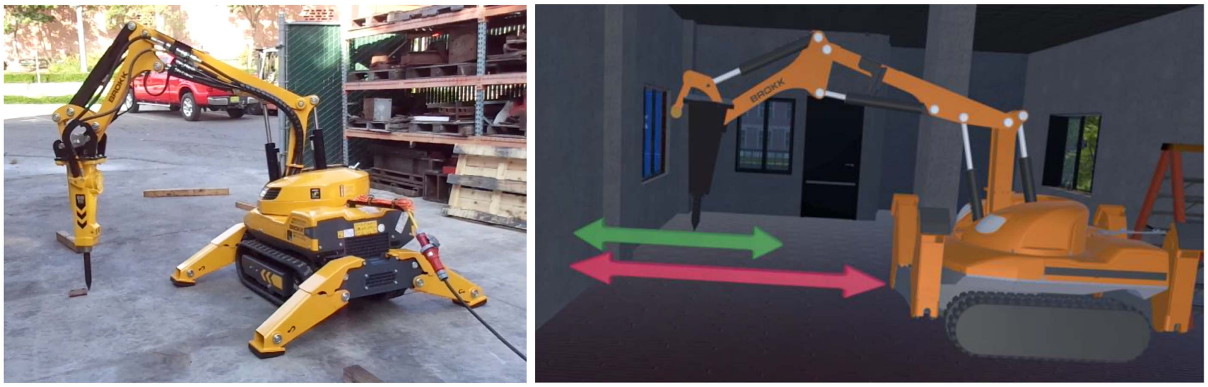


(a) (b)

Fig. 1. (a) Brokk110 (image by Burcin Becerik-Gerber); and (b) Brokk110 in VR environment.

allows operators to conduct demolition from a safer distance, resulting in increased safety for the operators (Corucci and Ruffaldi 2016).

While there are different models and shapes of demolition robots, in this study, Brokk110 with a 19.5 kW smart power electrical system and a 360-degree working radius is used [Figs. 1(a and b)] (Brokk Inc. 2020). Since a human worker controls the robot directly, the human role in this interaction is to be the operator. Since one operator interacts with one demolition robot, the team composition is one human to one robot. The communication between the human and the robot is based on digital codes through the robot's controller (buttons and joysticks). Hence, the interaction type is physical and synchronous since the operator and the robot work simultaneously.

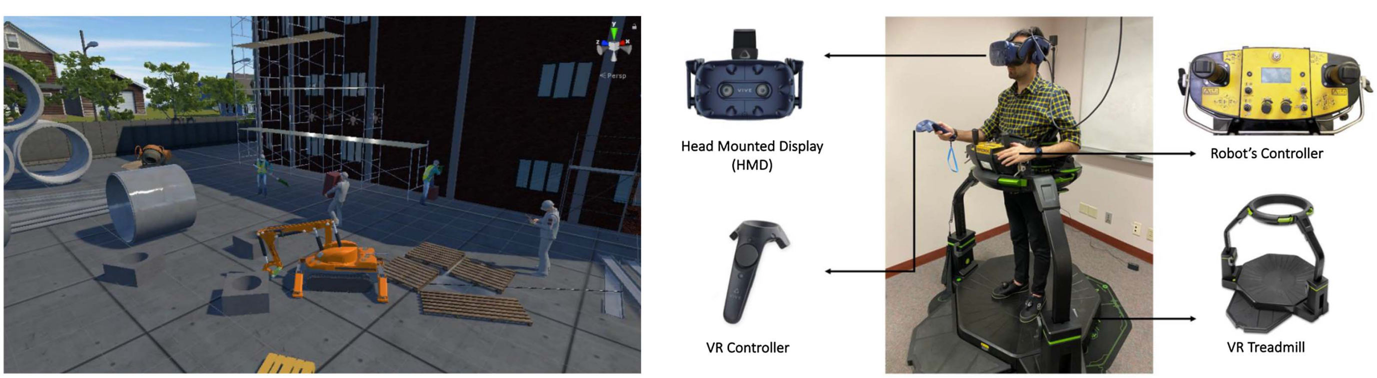
VR-Based Training (Experimental Condition)

VR System Setup

The VR-based training used in this study is developed on the Unity3D game engine platform. VR-based training occurs in a four-floor building and a simulated construction site [Fig. 2(a)], which are modeled in Revit 2019. The construction site model and the digital 3D model of the robot are exported in FBX format and imported to the Unity3D game engine using the PiXYZ plugin. We have simulated the robot's model through physics simulation in the Unity3D game engine. Brokk110's technical specifications, such as mass, drag, angular drag, and mesh colliders of various components, are used to model the rigid body properties of the robot in the VR environment. Additionally, multiple joints of the 5-degrees-of-freedom (DOF) robot (e.g., fixed, hinge, and configurable joints) have been modeled to provide an accurate movement similar to the actual robot. Connected bodies, anchors, break force, and break torque are assigned based on specifications acquired from the robot's manufacturing company. Additionally, we have written scripts in the C# programming language to simulate various robot components' movement and rotation (considering relative axis and speed). The virtual model of the robot has been tested and verified by an expert from the robot's manufacturing company. In addition, a set of construction equipment is added to the virtual environment (VE) from the Unity3D asset store.

The system [Fig. 2(b)] consists of VR-based training on a PC with an NVIDIA GeForce GTX 1080 graphics card. The trainee needs to wear a head mounted display (HMD) as the immersive VE visualization tool. The trainee uses a VR controller to experience the VR-based training (e.g., going to the next/previous step in the learning scenario, replaying the narrative voice, and interacting with objects in the VE). While the HMD gives the trainee a first-person view, the headphone connected to the HMD provides sound effects. Two base stations track the HMD and VR controller. In addition to the VR equipment, the trainee uses the demolition robot's actual controller unit to remote operate the simulated robot in the VR-based training environment. The robot's controller is connected to the computer using Arduino Pro micro serial connection.

Since the trainee needs to use the robot's controller during the training, it is essential to use a controller-free navigation method in



(a) (b)

Fig. 2. (a) Construction site in VR environment; and (b) VR-based training system setup (images by Pooya Adami).

the VE so that the trainee does not need a controller to walk within the VE. Therefore, the locomotion technique used in this VR-based training is a walk-in-place treadmill. Virtuix Omni is used as the VR treadmill, designed to allow participants to walk within the VR-based training environment without boundary since they are walking on a treadmill, as opposed to a room-scale VR environment that would limit the participants to the boundary of the room that the experiment takes place. The treadmill has a bowl-shaped surface that requires the user to wear low friction shoes for movement. The simulator can track the trainee's position, speed, and length of stride using inertial sensors.

Learning Modules

The VR-based training designed for this study, which consists of seven learning modules (in both English and Spanish languages), aims to enhance construction workers' trust in the robot (remotely operated demolition robot) and robot operation self-efficacy and to decrease their MWL with a higher level of SA in remote operating the robot. The content of the VR-based training and its delivery (i.e., activities and engagement features with the content) was developed based on adult learning theory (andragogy) and content experts' feedback through several iterations. The content of VR-based training followed the typical in-person training. Before conducting the experiment, we ran a pilot study to identify and fix technical problems. A detailed description of the development process of learning modules can be found in Adami et al. (2020).

The final version of the VR-based training consisted of seven modules, each of which ended with a diagnostic assessment to ensure that workers learned the content covered in each module before moving on to the next one. The training aimed to help workers learn the robot's purpose and applications (module 1) [Fig. 3(a)], safety features by interacting with the robot in the VR environment (module 2), how to use the controller to remote operate the robot (module 3), how to start the robot (Module 4) [Fig. 3(b)], and how to position the robot to remote operate safely (Module 5) [Fig. 3(c)], how to move the robot, and use the outriggers and arms (Module 6) [Fig. 3(d)], and how to demolish (Module 7).

Trainees acquired the necessary learning material to remotely operate the robot by completing the guided activities. Module 1 aimed to begin building trust in the robot in workers by introducing the robot, its purpose, and its components using visualization and active learning techniques since workers' unfamiliarity with robots is one of the obstacles in the adoption of construction robotics (Yahya et al. 2019). Highlighting and animating different components of the robot presented the movement range of each component to the trainee, helping them to trust in the robot in construction sites that can be dynamic and unpredictable.

Module 2 aimed to help workers increase their SA in the remote operation of the robot by providing safety instructions (cable safety management (e.g., the cable should not be on a wet surface), definition and boundary conditions of the risk zone, and workplace inspection (e.g., keep robot out of dust and flying rocks, turn off the robot in the event people enter the operating zone) through an interactive learning method. By programming various objects in the virtual construction sites, trainees were able to interact with them to deliver the assigned tasks in the learning module (e.g., change the place of the power cable, pick up the loose objects lying on the robot, emergency stop of the robot to prevent collision with other construction workers violating the danger zone). Therefore, trainees were prepared for the potential hazards that they might face during the remote operation of the robot.

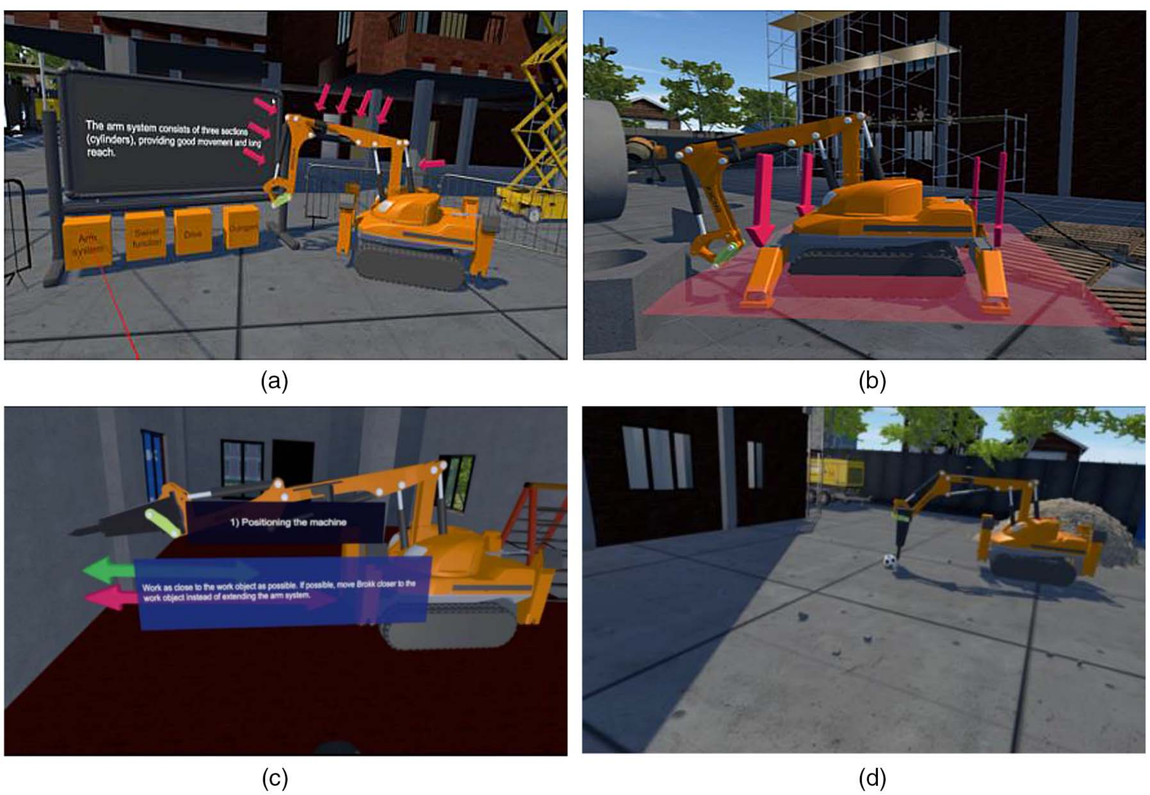


Fig. 3. (a) Highlights and animations illustrating the range of each component's movement (Module 1); (b) Illustration of prestartup check-ups (Module 4); (c) Trainee learns correct positioning of the robot (Module 5); and (d) Trainee practices using the control unit by kicking a soccer ball (Module 6).

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Moreover, module 3 provided opportunities to test different functions of the robot's controller to help workers improve their confidence and self-efficacy in remote operating the robot. Different functions of the actual controller (buttons and joysticks) were programmed in the VR-based training, and the movement of the robot with 5 DOF was simulated to provide the trainee a realistic experience of robot remote operation. Module 3 was the only nonimmersive learning module since the learner would need to see the controller and movement of the robot.

After a chance to build self-efficacy, learners wear HMD for the remaining learning modules to remote operate the robot in an immersive VE using the actual controller in real life (not visible in VR). The VR modules provided the opportunity to implement different strategies for moving the robot and for demolition to experience the consequences of dangerous or wrong strategies. Additionally, the last three modules (modules 5, 6, and 7) give the trainee opportunities to increase his/her SA (e.g., managing the power cable while moving the robot), trust in the robot, robot operation self-efficacy (e.g., practicing moving the robot and demolishing a concrete block), and manage MWL by getting additional practice with the robot in the VR environment. By modeling the destruction of different structural elements in the VE, trainees were able to remote operate the robot using various strategies to demolish different objects in the VR-based training. On average, the workers in the VR-based training spent 120 min completing all the modules.

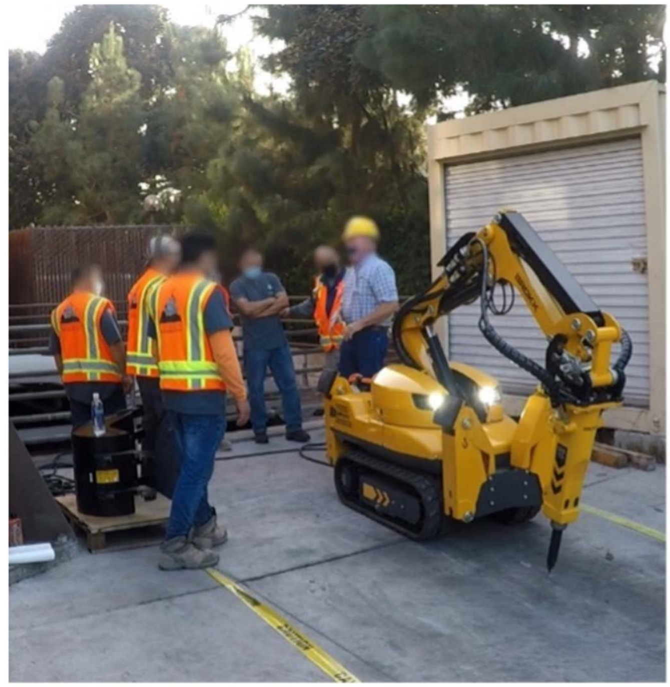

Fig. 4. In-person training session.

In-Person Training (Control Condition)

The in-person training provided to the workers in the control group was designed based on an existing workshop provided by an expert trainer who trains workers on how to remote operate the demolition robot. The contents of in-person training and VR-based training were the same and done in a parallel manner. Unlike the VR-based training, there was no assessment during the in-person training sessions. Each phase of the in-person training ended with learners asking questions from the trainer. Moreover, each trainee had the opportunity to practice the instructions of remote operating the robot under the trainer's supervision at the end of the training after the trainer finished presenting the instructions.

The in-person training began with the trainer giving an overview of the demolition robot and its intended usage (same content as VR-based training, Module 1), the basic make-up of the demolition robot (e.g., essential parts and what they do) (VR-based training, module 1), followed by the trainer presenting safety management (e.g., electrical hazards, workplace inspection, operator positioning, and risk zone) (VR-based training, Module 2), and a pre-start checklist (e.g., inspecting the power cable and hydraulic oil level, and looking for oil leaks).

In the second phase of the in-person training, the trainer showed how to start the robot (VR-based training, Module 4) and used the demolition robot to demonstrate the pre-start checklist and how to use the robot's controller (VR-based training, Module 3), correct the operator's positioning, show how to position the robot to remote operate safely (VR-based training, Module 5), what to do in an emergency, how to use the robot's different components (e.g., arms, hammer, outriggers) (VR-based training, Module 6) and how to use the robot to demolish a concrete block (VR-based training, Module 7).

Participants in this condition attended one of four in-person training sessions. Accordingly, each session was attended by about six workers, and the same professional trainer conducted all in-person training sessions (Fig. 4). Specifically, the training was delivered by an experienced trainer who had been delivering this training for many years and spoke English and Spanish. Workers spent 120 min in the in-person training. As in the actual training provided to construction workers by the robotics company, each participant had some time during the training to remote operate the robot under the supervision of the professional trainer.

Procedures and Measures

Participants were randomly assigned to one of the two conditions: 25 participants were asked to complete the VR-based training, while the other 25 were asked to complete the in-person training. First, participants' backgrounds and demographics were measured by a set of survey items. Specifically, participants were asked to report their gender, age group, race, and the language they were comfortable speaking. Moreover, the survey measured participants' education level, employment status, and experience in the construction industry. Participants also reported if they have any experience in using VR or demolition robots.

Before starting either type of training, participants were required to complete two surveys that measure trust in the robot and robot operation self-efficacy. The measure of trust in the robot was modified from the automated trust scale (Jian et al. 2000) to measure participants' attitudes toward interaction with the robot, specifically. The modified survey used in this study has used items and words proposed in the automated system scale. Modifications were made to adapt the survey to the demolition robot. The modified survey consists of 21 sentences about participants' trust in the reliability, integrity, safety of the robot, and participants' beliefs about the robot's influence on their careers. Participants rated the sentences on a 5-point Likert scale that ranges from completely disagree to completely agree. For example, participants were asked to rate the sentences such as "I can trust the robot," "The robot is reliable," and "The robot provides safety/security" with a number from 1 to 5 indicating their disagreement (1) or agreement (5) with each sentence. The robot operation self-efficacy survey was modified from the validated robot-use self-efficacy scale (Turja et al. 2019). It consisted of two sentences ("I am confident in the robot," and "I feel confident around the robot") measuring participants' self-efficacy

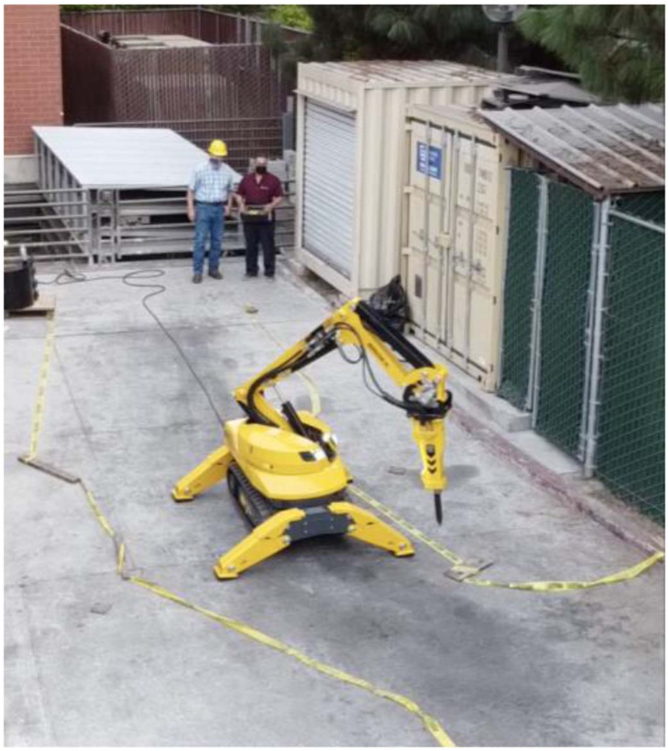

Fig. 5. Performance assessment.

and confidence in their ability to remote operate the robot. As with the trust in the robot survey, participants rated the sentences on a 5-point Likert scale ranging from completely disagree to completely agree.

Once the surveys were completed, participants began their assigned training. After both groups completed their training, they were asked to retake the trust in the robot and robot operation self-efficacy surveys. Then, participants were asked to complete a performance assessment, remote operating the actual robot, in which each worker's SA and MWL were assessed (Fig. 5). First, they had to start the robot, running the sequence of prestartup safety checks (e.g., hydraulic oil level, oil leakage, cable position). After starting the controller and the robot, participants moved the robot in the direction indicated on the ground. They had to use the controller's function and follow the safety guidelines to move the robot efficiently and safely. Participants then demonstrated the demolition position of the robot's arm system on a simulated concrete block. After showing the demolition process, participants were asked to move the robot in reverse to the starting position and go through the complete shutdown procedure.

To measure situational awareness, we employed a modified version of the SAGAT. While moving the actual robot to the simulated concrete block in the performance assessment session, participants were asked to pause the remote operation and answer the SA survey. This survey consisted of eight questions evaluating the trainee's perception, comprehension, and projection. In the perception section, participants answered questions related to the perception of the cable's location relative to the robot, the outriggers, and sharp edges (e.g., "Is the cable behind the robot?", "Is the cable close to the outriggers?", and "Is the cable close to sharp objects?"). In the comprehension section, the trainer asked participants if the robot had sufficient distance from various objects and if the angles between the arms were in the correct range (e.g., "Is the distance between the robot and the element to be demolished sufficient for a proper operation?", "Are the angles between the arms of the machine in the correct position?"). Finally, in the projection section, participants discussed whether the robot proceeded to the correct position and the trainer observed whether the arm trajectory hit the operator or any objects (e.g., "Is the robot proceeding to the right position?", "Will the arm trajectory hit the operator?", "Will the arm trajectory hit any objects?"). Participants' answers were rated by the expert trainer. Finally, to measure participants' MWL, we employed the NASA-TLX. After the remote operation of the actual robot, participants were asked to complete the MWL survey. In this survey, participants reported their mental demand, physical demand, temporal demand, performance, effort, and frustration level while remote operating the robot based on a Likert scale that ranges from very low to very high (e.g., "How much mental activity was required to perform your job (thinking, deciding, calculating, remembering, looking, searching, etc.)?"). The NASA-TLX asks the subject to use a rating between 0 and 100 for a group of questions in each of these subscales, and these ratings are used to determine the weights during the comparisons of the level of importance the subject assigned to each subscale (Vidulich and Tsang 2012).

Participants

Fifty participants were recruited to complete the experiment at the University of Southern California. All participants were construction workers aged 18 or older working on a construction job at the university campus. 25 construction workers were randomly assigned to VR-based training, while the other 25 workers completed the traditional in-person training. One of the VR-based training workers resigned in the middle of the training since he was not comfortable using VR equipment (controllers and VR treadmill); hence, we used the data of 24 VR-based training participants in our analysis. Table 1 presents the demographics of participants in these two conditions.

No statistically significant relationships were found between worker's gender and race and the training to which they were assigned, $\chi2(1,\mathrm{N}=49)=0.31$, $\mathrm{p}=0.576$ for gender, and $\chi2(1,\mathrm{N}=49)=1.06$, $\mathrm{p}=0.302$ for race. Participants in these two conditions were also not statistically different in terms of their age group $\chi2(1,\mathrm{N}=49)=0.98$, $\mathrm{p}=0.808$, experience in the construction $\chi2(1,\mathrm{N}=48)=0.47$, $\mathrm{p}=0.792$, and experience with using a demolition robot $\chi2(1,\mathrm{N}=49)=0.98$, $\mathrm{p}=0.322$. In addition, workers in each training condition had similar levels of prior experience with VR $\chi2(1,\mathrm{N}=49)=1.18$, $\mathrm{p}=0.277$. Both groups also had similar levels of initial trust in the robot ($\mathrm{Mdiff}=-0.22$, $\mathrm{SD}=0.17$, $\mathrm{p}=0.20$), and self-efficacy ($\mathrm{Mdiff}=-0.14$, $\mathrm{SD}=0.29$, $\mathrm{p}=0.628$). Hence, we can confidently state that, taken altogether, randomization was successful and workers in both training programs were similar in terms of their demographics, as well as baseline trust and beliefs.

Analysis

The data collected, both pretraining and posttraining, were used to understand the impact of VR-based training compared to in-person training on four dependent variables: trust in the robot, robot operation self-efficacy, SA, and mental workload. For each of the first two outcomes, we conducted 2×2 mixed factorial ANOVAs with time (pretraining versus posttraining) as the within-subject factor and training type (VR-based training versus in-person training) as the between-subject factor. Additionally, we conducted independent sample t-tests with training type (VR-based training versus in-person) as the independent variables for each of the latter two

Table 1. Demographics of workers in the two conditions

Indicator	In-person training (N = 25)	Virtual reality-based training (N = 24)
Worker characteristic	—	—
Male	23	23
Hispanic/Latinx	24	23
Speaks English comfortably	12	12
Highest level of education	—	—
Less than a high school diploma	10	8
High school	12	12
College degree	3	4
Age	—	—
18–29	7	8
30–39	7	7
40–49	4	2
50 or older	7	7
Experience in the construction industry[a]	—	—
Less than 5 years	10	12
5–10 years	8	5
11–20 years	3	5
More than 20 years	3	2
No experience with a demolition robot	24	24
No experience with the Brokk machines	25	24
No experience with virtual reality	24	21
No experience with virtual reality training	25	23

[a]One of the trainees did not answer this item in the demographic survey.

outcomes. We then ran additional tests to check for moderation by demographic factors: in separate mixed ANOVAs, we tested for moderation by (1) language (Spanish versus English), (2) age, (3) level of education, and (4) experience in the construction industry.

Results

Analyses for the trust ratings (range: 0–5) are presented in Table 2. Using the Kolmogorov–Smirnov method, we verified that there were no significant violations of normality ($p = 0.200$). The time (pretraining versus posttraining) by training type interaction is statistically significant for trust in the robot [$F(1, 47) = 25.94$, $p < 0.001$, Cohen's $d > 1.0$], with the VR-based training increasing trust more (1.38) than the in-person training (0.52). The reliability of this scale (Cronbach's alpha) was 0.91. None of the demographic variables significantly moderated this effect (all $Fs < 1.15$, $ps > 0.29$).

The analyses for the robot operation self-efficacy ratings (range: 0–5) are presented in Table 3. Using the Kolmogorov–Smirnov method, we verified that there were no significant violations of normality ($p = 0.183$). The time (pretraining versus posttraining) by training type interaction is statistically significant for self-efficacy [$F(1, 47) = 10.43$, $p < 0.002$, Cohen's $d > 1.0$], with VR-based training increasing self-efficacy more (1.62) than the in-person training (0.74). The reliability of this scale (Cronbach's alpha) was 0.69. Again, none of the demographic variables significantly moderated this effect (all $Fs < 3.22$, $ps > 0.14$).

Analyses for SA measurement (range: 0–1) are presented in Table 4. Using the Kolmogorov–Smirnov method, we verified that there were no significant violations of normality ($p = 0.291$). The results reveal that VR-based training participants (mean SA rating = 0.98) have significantly greater situational awareness compared to participants who completed in-person training (mean SA rating = 0.86) [$t(47) = 3.449$, $p < 0.001$, Cohen's $d > 1.0$]. None of the demographic variables significantly moderated this effect (all $Fs < 1.15$, $ps > 0.29$).

Finally, the analyses for the MWL during the remote operation of the robot are presented in Table 5. Using the Kolmogorov–Smirnov method, we verified that there were no significant violations of normality ($p = 0.053$). Although VR-based training participants [mean MWL rating (range: 0–100) = 45.20] have shown lower MWL than in-person training participants (mean MWL rating = 53.73), we could not find a significant difference between VR-based and in-person training [$t(1, 47) = 1.77$, $p = 0.915$, Cohen's $d > 1.0$]. Cronbach's alpha for this scale was 0.77, indicating good reliability. Again, none of the demographic variables significantly moderated this effect (all $Fs < 3.22$, $ps > 0.14$).

Discussion

This study aimed to understand the impact of VR-based training on construction workers' trust in the robot, robot operation

Table 2. Means and standard deviations (SD) of trust in the robot based on individual differences

Measures	VR-based training mean (SD)		In-person training mean (SD)	
	Before	After	Before	After
Overall	2.81 (0.36)	4.19 (0.50)	2.88 (0.33)	3.40 (0.37)
Language	—	—	—	—
English	2.79 (0.37)	4.33 (0.39)	2.95 (0.27)	3.45 (0.34)
Spanish	2.83 (0.31)	4.06 (0.49)	2.80 (0.39)	3.35 (0.39)
Age groups	—	—	—	—
18–29	2.78 (0.32)	4.27 (0.40)	3.04 (0.32)	3.39 (0.24)
30–39	2.83 (0.35)	4.23 (0.44)	2.77 (0.24)	3.50 (0.25)
40–49	2.83 (0.25)	4.20 (0.83)	2.75 (0.58)	3.58 (0.61)
50–69	2.83 (0.45)	4.04 (0.63)	2.88 (0.26)	3.20 (0.36)
Education levels	—	—	—	—
Less than a high school diploma degree	2.82 (0.37)	4.05 (0.50)	2.75 (0.44)	3.47 (0.43)
High school diploma degree	2.91 (0.28)	4.25 (0.54)	2.99 (0.23)	3.32 (0.32)
College degree	2.49 (0.32)	4.32 (0.48)	2.86 (0.25)	3.49 (0.29)
Experience groups	—	—	—	—
Less than 5 years	2.76 (0.38)	4.11 (0.46)	2.96 (0.40)	3.49 (0.49)
5–10 years	2.95 (0.25)	4.31 (0.76)	2.86 (0.28)	3.40 (0.26)
More than 10 years	2.78 (0.35)	4.25 (0.34)	2.84 (0.31)	3.44 (0.28)

Table 3. Means and standard deviations of robot operation self-efficacy based on individual differences

Measures	VR-based training mean (SD)		In-person training mean (SD)	
	Before	After	Before	After
Overall	2.79 (0.69)	4.42 (0.65)	2.82 (0.74)	3.56 (0.60)
Language	—	—	—	—
English	2.96 (0.66)	4.50 (0.56)	3.08 (0.42)	3.50 (0.60)
Spanish	2.63 (0.71)	4.33 (0.75)	2.58 (0.91)	3.61 (0.62)
Age groups	—	—	—	—
18–29	3.05 (0.63)	4.55 (0.40)	2.86 (0.85)	3.42 (0.45)
30–39	2.71 (0.56)	4.59 (0.44)	2.64 (0.85)	3.79 (0.39)
40–49	3.00 (0.10)	4.50 (0.83)	2.63 (0.83)	3.88 (0.85)
50–69	2.42 (0.92)	4.33 (0.63)	3.07 (0.19)	3.79 (0.69)
Education levels	—	—	—	—
Less than a high school diploma degree	2.56 (0.50)	4.31 (0.50)	2.45 (0.44)	3.65 (0.67)
High school diploma degree	2.88 (0.77)	4.41 (0.82)	3.08 (0.23)	3.50 (0.60)
College degree	3.00 (0.82)	4.62 (0.48)	3.00 (0.25)	3.50 (0.50)
Experience groups	—	—	—	—
Less than 5 years	2.79 (0.58)	4.45 (0.49)	2.90 (0.70)	3.45 (0.68)
5–10 years	3.08 (0.66)	4.25 (0.98)	2.93 (0.42)	3.43 (0.41)
More than 10 years	2.50 (0.89)	4.50 (0.63)	2.83 (0.93)	4.00 (0.54)

Table 4. Means and standard deviations (SD) of SA assessment based on individual differences

Measures	VR-based training mean (SD)	In-person training mean (SD)
Overall	0.98 (0.04)	0.86 (0.16)
Language	—	—
English	0.99 (0.04)	0.85 (0.22)
Spanish	0.97 (0.06)	0.87 (0.09)
Age groups	—	—
18–29	0.98 (0.04)	0.89 (0.09)
30–39	0.98 (0.05)	0.91 (0.06)
40–49	1.00 (0.00)	0.91 (0.06)
50–69	0.96 (0.06)	0.75 (0.27)
Education levels	—	—
Less than a high school diploma degree	0.95 (0.06)	0.86 (0.09)
High school diploma degree	0.99 (0.03)	0.85 (0.22)
College degree	1.00 (0.00)	0.88 (0.13)
Experience groups	—	—
Less than 5 years	0.97 (0.05)	0.80 (0.22)
5–10 years	0.97 (0.05)	0.92 (0.06)
More than 10 years	0.97 (0.05)	0.88 (0.13)

Table 5. Means and standard deviations (SD) of MWL assessment based on individual differences

Measures	VR-based training mean (SD)	In-person training mean (SD)
Overall	45.20 (16.48)	53.74 (17.18)
Language	—	—
English	41.04 (21.49)	46.39 (10.76)
Spanish	49.38 (8.28)	60.51 (19.51)
Age groups	—	—
18–29	47.13 (10.76)	41.07 (10.39)
30–39	40.83 (27.83)	54.99 (5.79)
40–49	39.17 (2.36)	55.83 (18.27)
50–69	49.45 (8.00)	63.93 (23.65)
Education levels	—	—
Less than a high school diploma degree	48.33 (13.51)	58.25 (22.46)
High school diploma degree	44.44 (19.01)	51.94 (12.70)
College degree	41.25 (16.42)	45.83 (13.09)
Experience groups	—	—
Less than 5 years	47.78 (8.36)	51.25 (10.30)
5–10 years	38.33 (21.63)	55.83 (19.31)
More than 10 years	46.96 (23.50)	58.89 (23.40)

self-efficacy, SA, and mental workload as compared to a traditional in-person training approach. Based on our analyses, VR-based training had significantly impacted the first three measures when compared with traditional in-person training. This section provides a discussion on the significance of these findings.

Trust in the Robot and Robot Operation Self-Efficacy

This study demonstrates that VR-based training is capable of increasing construction workers' trust in the robot and robot operation self-efficacy while remote operating a demolition robot significantly more than in-person training. One of the key factors contributing to this success is the nature of the VR environment. The VR environment provides an immersive experience for the trainees to work with the robot and familiarize themselves with the robot's functions. Our results confirm that a VE can help trainees to focus their attention on the information relevant to the training to gain confidence in using new technology (Sportillo et al. 2019). Besides, our VR-based training allowed the trainee to work with the robot in different scenarios to get a clearer understanding of the robot's behavior in different tasks. This helped humans to gain trust in the robot by managing humans' expectations of the robot's actions. Moreover, the reliable representation of each strategy's consequences boosted workers' self-efficacy in working with the robot, as seen in Koppula et al. (2016). A vital drawback of VR-based training is that developing a VR-based training, including accurate robot and various scenarios simulation, may need significant effort, time, computing power, and cost. However, with the increase of VR-based applications and technology improvement, the aforementioned negative factors can be mitigated considerably. Moreover, developing VR-based training is a one-time effort compared to the traditional in-person training that requires an actual robot and a professional trainer for each training session.

Autor (2015) claimed that, while many middle-skill jobs are susceptible to being fully automated, others will demand workers acquire a mixture of tasks to adapt to new technologies. Our results indicate that VR-based training could help workers overcome the fear of robotics use in the construction industry. Construction workers worry that new robotic systems will take their jobs; thus, they remain reluctant to accept new technologies. This is especially true about demolition robots that will directly replace humans who manually demolish the site. VR-based training demonstrated the potential to increase workers' trust in the robot and robot operation self-efficacy, leading to the acceptance of the new robots (e.g., demolition robots) in the construction industry. This produces significant implications for improving HRI using VR.

VR-based training can be used as a platform to motivate and attract construction workers to increase their vocational skills and adaptability for the future of work in the construction industry. Different scenarios in our VR environment present the abilities a demolition robot provides to a construction worker. The efficacy of implementing robots in dangerous tasks while covering the same learning contents as in-person training impacts workers' attitudes toward trust in the robot. This is one of the limitations of in-person training in which workers are limited in practicing dangerous tasks with the robot during the training due to ethical, financial, and safety concerns. Also, since construction robots are not common yet, training to use these new robots safely and effectively is a niche and varies widely between different instructors (G. Lucas, unpublished data, 2019). However, VR-based training provides consistency, efficiency, and scalability in training in the construction industry.

As suggested by Lee and See (2004), our results confirm that when training provides crucial information concerning the purpose and methods of implementing new technology in interactive contexts, trust in the new technology increases. In contrast to the in-person training in which trainees are limited in interacting with the real robot, VR-based training enables learning the robot's implementation in an interactive context. Workers can observe the robot's behavior and accumulate knowledge of underlying processes during interaction with the robot. This feature increases the human mental model of the robot and establishes more trust in automation (Holmes 1991). Hence, the worker's trust in the robot and robot operation self-efficacy increases significantly more in VR-based training than in in-person training.

Situational Awareness and Mental Workload

The SAGAT scores between VR-based training conditions and in-person training conditions show that VR-based training participants had significantly more SA than in-person training participants while remote operating the demolition robot. Similar to our findings related to trust in the robot and robot operation self-efficacy, we suspect that the higher SAGAT score for the VR-based training condition relates to the opportunities that the VR environment provides to trainees. While in-person training participants did not have significant freedom in remote operating the robot mainly due to safety concerns, VR-based training participants could remote operate the robot in different scenarios and implement different strategies. This advantage provided an opportunity of experiencing different situations and consequences of wrong decisions while remote operating the robot. For example, participants experienced the consequences of ignoring power cable management during robot operation and losing the cable by putting it under outriggers or on sharp objects. In addition, they experienced the consequence of not paying attention to the correct position of the demolition robot's arm system while moving the robot and tilting the robot resulting in its failure. Thus, VR-based training participants had a higher perception of the power cable position, comprehension of the robot's distance from surrounding objects and workers, and projection of the demolition robot's trajectory during remote operation. Our findings confirm the statement that applying immersive visualization techniques in a training environment can increase workers' SA in complex and dynamic environments (Cheng and Teizer 2014). Although VR-based training can increase workers' SA, it can have physical side effects such as dizziness, eyestrain, or nausea on its users. However, by giving break times to trainees to take off HMD, the probability of experiencing adverse side effects can be decreased.

Although the NASA-TLX MWL survey scores indicate that VR-based training participants experienced a lower average MWL than in-person training participants, it failed to show a significant difference between these two conditions. Therefore, in this study, we cannot claim that VR-based training reduces construction workers' MWL significantly compared to the traditional in-person training method. One of the factors impacting the lower average level of MWL in VR-based training participants is that trainees had the opportunity to remote operate the robot in different scenarios in the VR environment, while in-person training participants were limited in remote operating the robot. So, part of how VR can help reduce the MWL is by allowing more time to practice with the robot. However, again the collected data from the NASA-TLX measurement method did not show a significant difference between the two groups. Since VR-based training participants were on VR treadmill (walk-in-place treadmill), they had not experienced the actual physical demand and effort in remote operating the demolition robot; therefore, they experienced the physical demand and effort for the first time during the assessment, which may have impacted their MWL. One of the reasons we did not produce a significant difference may have stemmed from the sample size. We suggest that future studies investigate the impact of VR-based training on construction workers' mental workload on larger sample sizes.

Limitations

While this study presents VR-based training implications for human-related factors (i.e., trust in the robot, robot operation self-efficacy, SA, and MWL) in robotic remote operation in the construction industry, some limitations exist. There are differences in VR-based and in-person training mechanisms, while some represent an important limitation of in-person training. In traditional training, each worker only gets a limited amount of time to work with the robot since the overall time is limited due to the cost of traditional training, and there are multiple workers in a session to be efficient with time and money. On the other hand, VR-based training is not subject to these kinds of practical constraints. By providing VR equipment and computing devices, trainees have the opportunity to experience the training individually and work with the robot for a more extended period than the traditional training. Additionally, during in-person training, workers cannot explore different strategies in remote operating the robot on their own because it represents a risk to safety and the equipment. In contrast, VR-based training not only provides more opportunities for workers to practice with the robot, but they can also safely explore different aspects of operation without risk to safety or equipment. These are natural differences between the two kinds of training and indeed represent several of the reasons why VR-based training was suggested as a new training method to study in the first place.

The goal of the current study was not to tease apart the different mechanisms by which VR-based training has its effect but rather investigate the impact of VR-based training as a whole compared to the traditional in-person training. Therefore, the limitation is that the study does not have experimental control to test "why" [i.e., the mechanism(s) by which] VR training has better outcomes than in-person training. Indeed, VR-based training presents possibilities for overcoming these kinds of limitations of standard in-person training sessions, and we wanted to harness the power of all these natural differences between the two conditions. Hence, instead of having various VR conditions that each differ from in-person training on only one variable (thus would have better experimental control), we opted for only two conditions that differed in all of the ways VR training and in-person training would naturally differ. Future research should investigate the mechanisms by which VR-based training improves outcomes over in-person training and therefore would need to isolate those mechanisms experimentally. In these kinds of follow-up studies, the experimental conditions would be better controlled (i.e., various VR conditions that each differ from in-person training on only one variable).

Conclusion

The research reported in this paper investigated the impact of VR-based training on four human-related factors (i.e., trust in the robot, robot operation self-efficacy, SA, and MWL) in the remote operation of a robot compared to traditional in-person training. While the advancement of construction robotics can enhance productivity and safety in the construction industry, it also has brought about new challenges. The unstructured and unpredictable nature of construction sites has hindered the adoption of construction robotics. Moreover, sharing workspace between workers and robots in dynamic and hazardous construction sites has introduced new safety concerns. Therefore, it is crucial to enhance human-related factors such as trust in the robot, robot operation self-efficacy, SA, and MWL while remote operating robots on construction sites to address new safety concerns and facilitate the implementation of robotics in the construction industry. Despite the vast body of research on the effectiveness of VR-based training in the construction industry, the impact of VR-based training in building trust, self-efficacy, SA, and optimizing MWL in the remote operation of construction robotics is not well studied.

Thus, to study the impact of VR-based training on these factors, immersive VR-based training was developed. Fifty construction workers were assigned randomly to complete either the VR-based training or in-person training. Construction workers were asked to complete trust in the robot and robot operation self-efficacy surveys before and after completing their assigned training. In addition, their SA was evaluated during the remote operation of the actual robot by a professional trainer. Finally, they completed a MWL survey using the NASA-TLX measurement method immediately after the remote operation of the actual robot.

The quantitative results show that VR-based training can significantly increase workers' trust in the robot and robot operation self-efficacy compared to a traditional training method such as in-person training. Moreover, VR-based training participants have significantly more SA while remote operating the construction robot. Although VR-based training participants had lower mean ratings of MWL than in-person training participants, we did not find any significant difference in participants' MWL between the two conditions in this study.

One of the key factors contributing to this success is the nature of the VR environment. The accurate simulation and visualization of the robot and the construction site allowed the trainee to work with the robot in various scenarios to get a clear understanding of the robot's behavior in different tasks. VR-based training participants could find the opportunity to remote operate the robot in different scenarios, implementing different strategies to experience the consequences without exposure to danger. These findings produce multiple implications for improving HRI using VR, especially in the construction field.

Admittedly, there are also limitations in this study that need to be addressed in future studies. For example, as we had a limited sample size to test for moderation by demographics, we were underpowered to find any differences among different demographic groups such as different age groups, experience levels, and education levels. These factors could be more thoroughly tested in future studies with larger samples.

Data Availability Statement

Some or all data, models, or codes that support the findings of this study [experiment data (unidentifiable personal information), developed codes that enable interaction with the robot in VR-based training] are available from the corresponding author upon reasonable request.

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References

Adami, P., T. Doleck, B. Becerik-Gerber, Y. Copur-Gencturk, L. Soibelman, and G. Lucas. 2020. "An immersive virtual learning environment for worker-robot collaboration on construction sites." In *Proc., 2020 Winter Simulation Conf. (WSC)*, 2400–2411. New York: IEEE.

Akanmu, A. A., J. Olayiwola, O. Ogunseiju, and D. McFeeters. 2020. "Cyber-physical postural training system for construction workers." *Autom. Constr.* 117 (Sep): 103272. https://doi.org/10.1016/j.autcon.2020.103272.

Akyeampong, J., S. Udoka, G. Caruso, and M. Bordegoni. 2014. "Evaluation of hydraulic excavator human-machine interface concepts using NASA TLX." *Int. J. Ind. Ergon.* 44 (3): 374–382. https://doi.org/10.1016/j.ergon.2013.12.002.

Albert, A., M. R. Hallowell, B. Kleiner, A. Chen, and M. Golparvar-Fard. 2014. "Enhancing construction hazard recognition with high-fidelity augmented virtuality." *J. Constr. Eng. Manage.* 140 (7): 4014024. https://doi.org/10.1061/(ASCE)CO.1943-7862.0000860.

Association for Advancing Automation. 2020. "Demolition robots disrupt a labor-intensive industry." Accessed January 15, 2021. https://www.automate.org/a3-content/service-robots-demolition.

Autor, D. H. 2015. "Why are there still so many jobs? The history and future of workplace automation." *J. Econ. Perspect. Am. Econ. Assoc.* 29 (3): 3–30. https://doi.org/10.1257/jep.29.3.3.

Bandura, A. 2006. "Guide for constructing self-efficacy scales." In *Self-efficacy beliefs of adolescents*, edited by F. Pajares and T. C. Urdan, 307–337. Greenwich, CT: Information Age Publishing.

Barkokebas, R., C. Ritter, V. Sirbu, X. Li, and M. Al-Hussein. 2019. "Application of virtual reality in task training in the construction manufacturing industry." In Vol. 36 of *Proc., Int. Symp. on Automation and Robotics in Construction*, 796–803. Edmonton, AB, Canada: IAARC Publications. https://doi.org/10.22260/ISARC2019/0107.

Bartneck, C., D. Kulić, E. Croft, and S. Zoghbi. 2009. "Measurement instruments for the anthropomorphism, animacy, likeability, perceived intelligence, and perceived safety of robots.” *Int. J. Soc. Rob.* 1 (1): 71–81. https://doi.org/10.1007/s12369-008-0001-3.

Bhalerao, B. N., P. S. Dunston, and R. W. Proctor. 2017. “Use of PC-based simulators to train basic control functions of a hydraulic excavator: Audiovisual instruction contrasted with hands-on exploration.” *Int. J. Hum. Comput. Interact.* 33 (1): 66–74. https://doi.org/10.1080/10447318.2016.1232230.

Biferno, M. A. 1985. *Mental workload measurement event-related potentials and ratings of workload and fatigue*. NASA Contractor Rep. No. 177354. Moffett Field, CA: National Aeronautics and Space Administration.

Boletsis, C., and A. Karahasanovic. 2020. “Immersive technologies in retail: Practices of augmented and virtual reality.” In Vol. 4 of *Proc., 4th Int. Conf. on Computer-Human Interaction Research and Applications (CHIRA)*, 281–290. Setúbal, Portugal: SciTePress. https://doi.org/10.5220/0010181702810290.

Brokk. 2020. “How remote-controlled demolition equipment can boost efficiency and profits.” Accessed January 15, 2020. https://www.brokk.com/us/news/brokk-articles/profitable-processing/.

Burke, M. J., S. A. Sarpy, K. Smith-Crowe, S. Chan-Serafin, R. O. Salvador, and G. Islam. 2006. “Relative effectiveness of worker safety and health training methods.” *Am. J. Public Health* 96 (2): 315–324. https://doi.org/10.2105/AJPH.2004.059840.

Carra, G., A. Argiolas, A. Bellissima, M. Niccolini, and M. Ragaglia. 2018. “Robotics in the construction industry: State of the art and future opportunities.” In *Proc., ISARC 2018—35th Int. Symp. on Automation and Robotics in Construction*, 866–873. Taipei, Taiwan: IAARC Publications. https://doi.org/10.22260/ISARC2018/0121.

Castro-Lacouture, D. 2009. “Construction automation.” In *Springer handbook*, edited by S. Y. Nof, 1063–1078. Berlin: Springer.

Chalmers, A., and K. Debattista. 2009. “Level of realism for serious games.” In *VS-GAMES*. New York: IEEE.

Chandra Sekaran, S., H. J. Yap, K. E. Liew, H. Kamaruzzaman, C. H. Tan, and R. S. Rajab. 2018. “Haptic-based virtual reality system to enhance actual aerospace composite panel drilling training.” In *Structural health monitoring of biocomposites, fibre-reinforced composites and hybrid composites*. Duxford, UK: Woodhead Publishing.

Charles, R. L., and J. Nixon. 2019. “Measuring mental workload using physiological measures: A systematic review.” *Appl. Ergon.* 74 (Jan): 221–232. https://doi.org/10.1016/j.apergo.2018.08.028.

Chen, J., X. Song, and Z. Lin. 2016. “Revealing the ‘Invisible Gorilla’ in construction: Estimating construction safety through mental workload assessment.” *Autom. Constr.* 63 (Mar): 173–183. https://doi.org/10.1016/j.autcon.2015.12.018.

Chen, J. Y. C., M. J. Barnes, and M. Harper-Sciarini. 2011. “Supervisory control of multiple robots: Human-performance issues and user-interface design.” *Part C Appl. Rev.* 41 (4): 435–454. https://doi.org/10.1109/TSMCC.2010.2056682.

Cheng, T., and J. Teizer. 2013. “Real-time resource location data collection and visualization technology for construction safety and activity monitoring applications.” *Autom. Constr.* 34 (Sep): 3–15. https://doi.org/10.1016/j.autcon.2012.10.017.

Cheng, T., and J. Teizer. 2014. “Modeling tower crane operator visibility to minimize the risk of limited situational awareness.” *J. Comput. Civ. Eng.* 28 (3): 4014004. https://doi.org/10.1061/(ASCE)CP.1943-5487.0000282.

Choi, M., S. Ahn, and J. Seo. 2020. “VR-based investigation of forklift operator situation awareness for preventing collision accidents.” *Accid. Anal. Prev.* 136 (Mar): 105404. https://doi.org/10.1016/j.aap.2019.105404.

Corucci, F., and E. Ruffaldi. 2016. *Toward autonomous robots for demolitions in unstructured environments*, edited by E. Menegatti, N. Michael, K. Berns, and H. Yamaguchi, 1515–1532. Berlin: Springer.

Davila Delgado, J. M., L. Oyedele, A. Ajayi, L. Akanbi, O. Akinade, M. Bilal, and H. Owolabi. 2019. “Robotics and automated systems in construction: Understanding industry-specific challenges for adoption.” *J. Build. Eng.* 26 (Nov): 100868. https://doi.org/10.1016/j.jobe.2019.100868.

Diego-Mas, J. A., J. Alcaide-Marzal, and R. Poveda-Bautista. 2020. “Effects of using immersive media on the effectiveness of training to prevent ergonomics risks.” *Int. J. Environ. Res. Public Health* 17 (7): 2592. https://doi.org/10.3390/ijerph17072592.

Di Stasi, L. L., V. Álvarez-Valbuena, J. J. Cañas, A. Maldonado, A. Catena, A. Antolí, and A. Candido. 2009. “Risk behaviour and mental workload: Multimodal assessment techniques applied to motorbike riding simulation.” *Transp. Res. Part F Psychol. Behav.* 12 (5): 361–370. https://doi.org/10.1016/j.trf.2009.02.004.

Dybvik, H., M. Løland, A. Gerstenberg, K. B. Slåttsveen, and M. Steinert. 2021. “A low-cost predictive display for teleoperation: Investigating effects on human performance and workload.” *Int. J. Hum. Comput. Stud.* 145 (Jan): 102536. https://doi.org/10.1016/j.ijhcs.2020.102536.

Endsley, M. R. 1988. “Situation awareness global assessment technique (SAGAT).” In *Proc., National Aerospace and Electronics Conf. (NAECON)*, 789–795. New York: IEEE.

Endsley, M. R. 1995a. “Measurement of situation awareness in dynamic systems.” *Hum. Factors* 37 (1): 65–84. https://doi.org/10.1518/001872095779049499.

Endsley, M. R. 1995b. “Toward a theory of situation awareness in dynamic systems.” *Hum. Factors* 37 (1): 32–64. https://doi.org/10.1518/001872095779049543.

Endsley, M. R. 2021. “A systematic review and meta-analysis of direct objective measures of situation awareness: A comparison of SAGAT and SPAM.” *Hum. Factors* 63 (1): 124–150. https://doi.org/10.1177/0018720819875376.

Evers, V., H. Maldonado, T. Brodecki, and P. Hinds. 2008. “Relational vs. group self-construal: Untangling the role of national culture in HRI.” In *Proc., 3rd ACM/IEEE Int. Conf. on Human-Robot Interaction (HRI)*, 255–262. New York: Association for Computing Machinery. https://doi.org/10.1145/1349822.1349856.

Fang, Y., and Y. K. Cho. 2017. “Effectiveness analysis from a cognitive perspective for a real-time safety assistance system for mobile crane lifting operations.” *J. Constr. Eng. Manage.* 143 (4): 5016025. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001258.

Fang, Y., Y. K. Cho, F. Durso, and J. Seo. 2018. “Assessment of operator’s situation awareness for smart operation of mobile cranes.” *Autom. Constr.* 85 (Jan): 65–75. https://doi.org/10.1016/j.autcon.2017.10.007.

Frank, M., R. Ruvald, C. Johansson, T. Larsson, and A. Larsson. 2019. “Towards autonomous construction equipment-supporting on-site collaboration between automatons and humans.” *Int. J. Prod. Dev.* 23 (4): 292–308. https://doi.org/10.1504/IJPD.2019.105496.

Freedy, A., E. DeVisser, G. Weltman, and N. Coeyman. 2007. “Measurement of trust in human-robot collaboration.” In *Proc., 2007 Int. Symp. on Collaborative Technologies and Systems*, 106–114. New York: IEEE. https://doi.org/10.1109/CTS.2007.4621745.

Gao, S., and L. Wang. 2020. “Effects of mental workload and risk perception on pilots’ safety performance in adverse weather contexts BT.” In *Engineering psychology and cognitive ergonomics. Cognition and design*, edited by D. Harris and W.-C. Li, 278–291. Berlin: Springer.

Gluck, A., J. Chen, and R. Paul. 2020. “Artificial intelligence assisted virtual reality warfighter training system.” In *Proc., 2020 IEEE Int. Conf. on Artificial Intelligence and Virtual Reality*, 386–389. New York: IEEE.

Goulding, J., W. Nadim, P. Petridis, and M. Alshawi. 2012. “Construction industry offsite production: A virtual reality interactive training environment prototype.” *Adv. Eng. Inf.* 26 (1): 103–116. https://doi.org/10.1016/j.aei.2011.09.004.

Grant, B. L., P. C. Yielder, T. A. Patrick, B. Kapralos, M. Williams-bell, and B. A. Murphy. 2020. “Audiohaptic feedback enhances motor performance in a low-fidelity simulated drilling task.” *Brain Sci.* 10 (1): 21. https://doi.org/10.3390/brainsci10010021.

Grimmer, J., L. Simon, and J. Ehlers. 2021. “The cognitive eye: Indexing oculomotor functions for mental workload assessment in cognition-aware systems.” In *Proc., Extended Abstracts of the 2021 CHI Conf. on Human Factors in Computing Systems*, 1–6. New York: Association for Computing Machinery. https://doi.org/10.1145/3411763.3451662.

Hafsia, M., E. Monacelli, and H. Martin. 2018. “Virtual reality simulator for construction workers.” In *Proc., Virtual Reality Int. Conf.—Laval Virtual, VRIC ’18*. New York: Association for Computing Machinery.

Hancock, P. A., D. R. Billings, K. E. Schaefer, J. Y. C. Chen, E. J. De Visser, and R. Parasuraman. 2011. “A meta-analysis of factors affecting

trust in human-robot interaction." *Hum. Factors* 53 (5): 517–527. https://doi.org/10.1177/0018720811417254.
Heyao, H., and O. Tetsuro. 2022. "Assessing the sense of presence to evaluate the effectiveness of virtual reality wildfire training." In Vol. 133 of *Advances in networked-based information systems. NBiS 2021*, edited by L. Barolli, H. C. Chen, and T. Enokido. Basel, Switzerland: Springer. https://doi.org/10.1007/978-3-030-84913-9_28.
Holmes, J. G. 1991. "Trust and the appraisal process in close relationships." In Vol. 2 of *Advances in personal relationships: A research annual*, 57–104. Oxford, UK: Jessica Kingsley Publishers.
Hong, Z., Q. Zhang, X. Su, and H. Zhang. 2020. "Effect of virtual annotation on performance of construction equipment teleoperation under adverse visual conditions." *Autom. Constr.* 118 (Oct): 103296. https://doi.org/10.1016/j.autcon.2020.103296.
IDC (International Data Corporation). 2020. "Worldwide spending on robotics systems and drones forecast to reach $128.7 Billion in 2020, according to new IDC spending guide." Accessed April 29, 2021. https://www.idc.com/getdoc.jsp?containerId=prUS45800320.
Jayaraman, S. K., C. Creech, D. M. Tilbury, X. J. Yang, A. K. Pradhan, K. M. Tsui, and P. J. Robert Lionel. 2019. "Pedestrian trust in automated vehicles: Role of traffic signal and AV driving behavior." In *Frontiers in robotics and AI*, 117. Lausanne, Switzerland: Frontiers.
Jeelani, I., K. Han, and A. Albert. 2020. "Development of virtual reality and stereo-panoramic environments for construction safety training." *Eng. Constr. Archit. Manage.* 27 (8): 1853–1876. https://doi.org/10.1108/ECAM-07-2019-0391.
Jian, J.-Y., A. M. Bisantz, and C. G. Drury. 2000. "Foundations for an empirically determined scale of trust in automated systems." *Int. J. Cognit. Ergon.* 4 (1): 53–71. https://doi.org/10.1207/S15327566IJCE0401_04.
Kalkan, Ö. K., Ş. Karabulut, and G. Höke. 2021. "Effect of virtual reality-based training on complex industrial assembly task performance." *Arabian J. Sci. Eng.* 46 (12): 12697–12708. https://doi.org/10.1007/s13369-021-06138-w.
Kim, S., H. Lee, S. Hwang, J.-S. Yi, and J. Son. 2021. "Construction workers' awareness of safety information depending on physical and mental load." *J. Asian Arch. Build. Eng.* 1–11. https://doi.org/10.1080/13467581.2021.1908899.
Koppula, H. S., A. Jain, and A. Saxena. 2016. "Anticipatory planning for human-robot teams." In *Experimental robotics*, edited by M. A. Hsieh, O. Khatib, and V. Kumar, 453–470. Berlin: Springer.
Kumar, V. S. S., I. Prasanthi, and A. Leena. 2008. "Robotics and automation in construction industry." In *Proc., AEI 2008: Building Integration Solutions*, 1–9. Reston, VA: ASCE.
Landi, C. T., V. Villani, F. Ferraguti, L. Sabattini, C. Secchi, and C. Fantuzzi. 2018. "Relieving operators' workload: Towards affective robotics in industrial scenarios." *Mechatronics* 54 (Apr): 144–154. https://doi.org/10.1016/j.mechatronics.2018.07.012.
Le, Q. T., A. Pedro, and C. S. Park. 2015. "A social virtual reality based construction safety education system for experiential learning." *J. Intell. Rob. Syst.* 79 (3): 487–506. https://doi.org/10.1007/s10846-014-0112-z.
Lee, H. T., and Y. S. Kim. 2018. "The effect of sports VR training for improving human body composition." *Eur. J. Image Video Process* 2018 (1): 1–5. https://doi.org/10.1186/s13640-018-0387-2.
Lee, J. D., and N. Moray. 1994. "Trust, self-confidence, and operators' adaptation to automation." *Int. J. Hum. Comput. Stud.* 40 (1): 153–184. https://doi.org/10.1006/ijhc.1994.1007.
Lee, J. D., and K. A. See. 2004. "Trust in automation: Designing for appropriate reliance." *Hum. Factors* 46 (1): 50–80. https://doi.org/10.1518/hfes.46.1.50.30392.
Liu, Y., M. Habibnezhad, and H. Jebelli. 2021. "Brainwave-driven human-robot collaboration in construction." *Autom. Constr.* 124 (Apr): 103556. https://doi.org/10.1016/j.autcon.2021.103556.
Luong, T., F. Argelaguet, N. Martin, and A. Lecuyer. 2020. "Introducing mental workload assessment for the design of virtual reality training scenarios." In *Proc., 2020 IEEE Conf. on Virtual Reality and 3D User Interfaces (VR)*, 662–671. New York: IEEE.
Mao, R. Q., L. Lan, J. Kay, R. Lohre, O. R. Ayeni, D. P. Goel, and S. A. Darren de. 2021. "Immersive virtual reality for surgical training: A systematic review." *J. Surg. Res.* 268 (Dec): 40–58. https://doi.org/10.1016/j.jss.2021.06.045.
Mehrfard, A., J. Fotouhi, T. Forster, G. Taylor, D. Fer, D. Nagle, M. Armand, N. Navab, and B. Fuerst. 2020. "On the effectiveness of virtual reality-based training for surgical robot setup." *Comput. Methods Biomech. Biomed. Eng.: Imaging Visualization* 9 (3): 243–252. https://doi.org/10.1080/21681163.2020.1835558.
Memar, A. H., and E. T. Esfahani. 2018. "Physiological measures for human performance analysis in human-robot teamwork: Case of tele-exploration." In Vol. 6 of *IEEE access*, 3694–3705. New York: IEEE.
Miller, D., M. Johns, B. Mok, N. Gowda, D. Sirkin, K. Lee, and W. Ju. 2016. *Behavioral Measurement of Trust in Automation: The trust fall*. Los Angeles: SAGE.
Moon, S., B. Becerik-gerber, and L. Soibelman. 2019. "Advances in informatics and computing in civil and construction engineering. Advances in informatics and computing in civil." In *Construction engineering*. Berlin: Springer.
Moore, H. F., R. Eiris, M. Gheisari, and B. Esmaeili. 2019. "Hazard identification training using 360-degree panorama vs. Virtual reality techniques: A pilot study." In *Proc., Int. Conf. on Computing in Civil Engineering*, 55–62. Reston, VA: ASCE. https://doi.org/10.1061/9780784482421.008.
Moore, L. J., M. R. Wilson, J. S. McGrath, E. Waine, R. S. W. Masters, and S. J. Vine. 2015. "Surgeons' display reduced mental effort and workload while performing robotically assisted surgical tasks, when compared to conventional laparoscopy." *Surg. Endoscopy* 29 (9): 2553–2560. https://doi.org/10.1007/s00464-014-3967-y.
Morra, L., F. Lamberti, F. G. Prattico, S. Rosa La, and P. Montuschi. 2019. "Building trust in autonomous vehicles: Role of virtual reality driving simulators in HMI design." In *Proc., IEEE Transactions on Vehicular Technology*, 9438–9450. New York: IEEE.
Nykänen, M., et al. 2020. "Implementing and evaluating novel safety training methods for construction sector workers: Results of a randomized controlled trial." *J. Saf. Res.* 75: 205–221. https://doi.org/10.1016/j.jsr.2020.09.015.
O'Donnell, R. D., and F. T. Eggemeier. 1986. "Workload assessment methodology." In Vol. 2 *Handbook of perception and human performance*, 1–49, Oxford, UK: Wiley.
Osti, F., R. de Amicis, C. A. Sanchez, A. B. Tilt, E. Prather, and A. Liverani. 2021. "A VR training system for learning and skills development for construction workers." *Virtual Reality* 25 (2): 523–538. https://doi.org/10.1007/s10055-020-00470-6.
Pappa, D., I. Dunwell, A. Protopsaltis, L. Pannese, S. Hetzner, S. de Freitas, and G. Rebolledo-Mendez. 2011. "Game-based learning for knowledge sharing and transfer: The e-VITA approach for intergenerational learning." In *Handbook of research on improving learning and motivation through educational games: Multidisciplinary approaches*, edited by P. Felicia, 974–1003. Hershey, PA: IGI Global.
Parasuraman, R., T. B. Sheridan, and C. D. Wickens. 2008. "Situation awareness, mental workload, and trust in automation: Viable, empirically supported cognitive engineering constructs." *J. Cognit. Eng. Decis. Making* 2 (2): 140–160. https://doi.org/10.1518/155534308X284417.
Park, E., Q. Jenkins, and X. Jiang. 2008. "Measuring trust of human operators in new generation rescue robots." In *Proc., JFPS Int. Symp. on Fluid Power*, 489–492. Tokyo: Japan Fluid Power System Society. https://doi.org/10.5739/isfp.2008.489.
Parker, S. K., and G. Grote. 2020. "Automation, algorithms, and beyond: Why work design matters more than ever in a digital world." *Appl. Psychol*. https://doi.org/10.1111/apps.12241.
Pini, F., M. Ansaloni, and F. Leali. 2016. "Evaluation of operator relief for an effective design of HRC workcells." In *Proc., IEEE Int. Conf. on Emerging Technologies and Factory Automation*. New York: IEEE.
Pooladvand, S., H. Taghaddos, A. Eslami, A. Nekouvaght Tak, and U. Hermann. 2021. "Evaluating mobile crane lift operations using an interactive virtual reality system." *J. Constr. Eng. Manage.* 147 (11): 4021154. https://doi.org/10.1061/(ASCE)CO.1943-7862.0002177.
Pütten, A. R. V. D., and N. Bock. 2018. "Development and validation of the self-efficacy in human-robot-interaction scale (SE-HRI)." *ACM Trans. Hum. Rob. Interact.* 7 (3): 1–30. https://doi.org/10.1145/3139352.

Sacks, R., A. Perlman, and R. Barak. 2013. “Construction safety training using immersive virtual reality.” *Construct. Manage. Econ.* 31 (9): 1005–1017. https://doi.org/10.1080/01446193.2013.828844.

Sakib, M. N., T. Chaspari, and A. H. Behzadan. 2021. “Physiological data models to understand the effectiveness of drone operation training in immersive virtual reality.” *J. Comput. Civ. Eng.* 35 (1): 04020053. https://doi.org/10.1061/(ASCE)CP.1943-5487.0000941.

Schaefer, K. E. 2016. “Measuring trust in human robot interactions: Development of the ‘trust perception scale-HRI.” In *Robust intelligence and trust in autonomous systems*, edited by A. Wagner, D. Sofge, R. Mittu, and W. F. Lawless, 191–218. Berlin: Springer.

Sheridan, T. B. 2002. *Humans and automation: System design and research issues*. New York: Wiley.

Singh, G., C. P. C. Chanel, and R. N. Roy. 2021. “Mental workload estimation based on physiological features for pilot-UAV teaming applications.” *Front. Hum. Neurosci.* 15: 1–20. https://doi.org/10.3389/fnhum.2021.692878.

So, J. C. Y., L. M. Macrowski, P. S. Dunston, R. W. Proctor, and J. E. Goodney. 2016. “Transfer of operator training from simulated to real hydraulic excavators.” In *Proc., Construction Research Congress 2016*, 1968–1977. Reston, VA: ASCE. https://doi.org/10.1061/9780784479827.196.

So, J. C. Y., R. W. Proctor, P. S. Dunston, and X. Wang. 2013. “Better retention of skill operating a simulated hydraulic excavator after part-task than after whole-task training.” *Hum. Factors* 55 (2): 449–460. https://doi.org/10.1177/0018720812454292.

Song, H., T. Kim, J. Kim, D. Ahn, and Y. Kang. 2021. “Effectiveness of VR crane training with head-mounted display: Double mediation of presence and perceived usefulness.” *Autom. Constr.* 122: 1–11. https://doi.org/10.1016/j.autcon.2020.103506.

Sportillo, D., A. Paljic, and L. Ojeda. 2019. “On-road evaluation of autonomous driving training.” In *Proc., 2019 14th ACM/IEEE Int. Conf. on Human-Robot Interaction (HRI)*, 182–190. New York: IEEE. https://doi.org/10.1109/HRI.2019.8673277.

Su, X., P. S. Dunston, R. W. Proctor, and X. Wang. 2013. “Influence of training schedule on development of perceptual–motor control skills for construction equipment operators in a virtual training system.” *Autom. Constr.* 35 (1): 439–447. https://doi.org/10.1016/j.autcon.2013.05.029.

Sugiono, S., D. Widhayanuriyawan, and D. P. Andriani. 2017. “Investigating the impact of road condition complexity on driving workload based on subjective measurement using NASA TLX.” In *Proc., 2nd Int. Conf. on Design, Mechanical and Material Engineering (D2ME 2017)*, edited by R. Das and A. K. T. Lau. Malang, IN: Univ. Brawijaya.

Tao, D., H. Tan, H. Wang, X. Zhang, X. Qu, and T. Zhang. 2019. “A systematic review of physiological measures of mental workload.” *Int. J. Environ. Res. Public Health* 16 (15): 2716. https://doi.org/10.3390/ijerph16152716.

Tevell, M., and P. C. Burns. 2000. “The effects of perceived risk on mental workload.” In *Proc., Human Factors and Ergonomics Society Annual Meeting*, 682. Thousand Oaks, CA: SAGE.

Tolmeijer, S., A. Weiss, M. Hanheide, F. Lindner, T. M. Powers, C. Dixon, and M. L. Tielman. 2020. “Taxonomy of trust-relevant failures and mitigation strategies.” In *Proc., 2020 ACM/IEEE Int. Conf. on Human-Robot Interaction, HRI ’20*, 3–12. New York: Association for Computing Machinery.

Turja, T., T. Rantanen, and A. Oksanen. 2019. “Robot use self-efficacy in healthcare work (RUSH): Development and validation of a new measure.” *AI Soc.* 34 (1): 137–143. https://doi.org/10.1007/s00146-017-0751-2.

US Bureau of Labor Statistics. 2019. *Women in the labor force: A databook. (Report 1084)*. Washington, DC: US Bureau of Labor Statistics.

US Bureau of Labor Statistics. 2020. *National census of fatal occupational injuries in 2019*. USDL-20-2265. Washington, DC: US Bureau of Labor Statistics.

Vahdatikhaki, F., K. El Ammari, A. K. Langroodi, S. Miller, A. Hammad, and A. Doree. 2019. “Beyond data visualization: A context-realistic construction equipment training simulators.” In *Automation in construction*. New York: Elsevier.

Vidulich, M. A., and P. S. Tsang. 2012. “Mental workload and situation awareness.” In *Handbook of human factors and ergonomics*, edited by G. Salvendy, 243–273. New York: Wiley.

Wallmyr, M., T. A. Sitompul, T. Holstein, and R. Lindell. 2019. “Evaluating mixed reality notifications to support excavator operator awareness BT.” In *Human-computer interaction—INTERACT 2019*, edited by D. Lamas, F. Loizides, L. Nacke, H. Petrie, M. Winckler, and P. Zaphiris, 743–762. Berlin: Springer.

Wang, X., and P. S. Dunston. 2007. “Design, strategies, and issues towards an Augmented Reality-based construction training platform.” *J. Inf. Technol. Constr.* 12 (25): 363–380.

Xu, Z., and N. Zheng. 2021. “Incorporating virtual reality technology in safety training solution for construction site of urban cities.” *Sustainability* 13 (1): 243. https://doi.org/10.3390/su13010243.

Yagoda, R. E., and D. J. Gillan. 2012. “You want me to trust a ROBOT? The development of a human-robot interaction trust scale.” *Int. J. Soc. Rob.* 4 (3): 235–248. https://doi.org/10.1007/s12369-012-0144-0.

Yahya, M. Y. B., Y. L. Hui, A. B. M. Yassin, R. Omar, R. O. Anak Robin, and N. Kasim. 2019. “The challenges of the implementation of construction robotics technologies in the construction.” In *Proc., MATEC Web of Conf.*, 5012. Les Ulis, France: EDP Sciences.

Yauri, J., A. Hernández-Sabaté, P. Folch, and D. Gil. 2021. “Mental workload detection based on EEG analysis.” In *Artificial Intelligence Research and Development: Proc., 23rd Int. Conf. of the Catalan Association for Artificial Intelligence (CCIA)*, edited by M. Villaret, T. Alsinet, C. Fernández, and A. Valls, 268–277. Amsterdam, Netherlands: IOS Press. https://doi.org/10.3233/FAIA210144.

You, S., J. H. Kim, S. H. Lee, V. Kamat, and L. P. Robert. 2018. “Enhancing perceived safety in human–robot collaborative construction using immersive virtual environments.” *Autom. Constr.* 96 (Sep): 161–170. https://doi.org/10.1016/j.autcon.2018.09.008.

Young, M. S., and N. A. Stanton. 2001. “Mental workload: Theory, measurement, and application.” In *International encyclopedia of ergonomics and human factors*, edited by W. Karwowski, 507–509. London: Taylor & Francis.

Young, M. S., and N. A. Stanton. 2004. “Mental workload.” In *Handbook of human factors and ergonomics methods*, edited by N. Stanton, A. Anthony, K. Hedge, E. S. Brookhuis, and H. W. Hendrick. Boca Raton, FL: CRC Press.

Yurko, Y. Y., M. W. Scerbo, A. S. Prabhu, C. E. Acker, and D. Stefanidis. 2010. “Higher mental workload is associated with poorer laparoscopic performance as measured by the NASA-TLX Tool.” *J. Soc. Simul. Healthcare* 5 (5): 267–271. https://doi.org/10.1097/SIH.0b013e3181e3f329.