



# Reducing Risk Habituation to Struck-By Hazards in a Road Construction Environment Using Virtual Reality Behavioral Intervention

Namgyun Kim, S.M.ASCE<sup>1</sup>; Brian A. Anderson<sup>2</sup>; and Changbum R. Ahn, A.M.ASCE<sup>3</sup>

**Abstract:** Repeated exposure to hazards in road construction work zones often generates worker habituation to risks associated with those hazards, a key causal factor in workplace accidents. Understanding the developmental process of risk habituation and providing effective intervention are thus critical to preventing fatalities in road construction work zones. To this end, this study investigates the efficacy of virtual reality (VR) as a behavioral intervention tool to mitigate a decline in vigilant behaviors with habituation to workplace hazards. A VR environment that simulates road construction/maintenance tasks was created and used to repeatedly expose participants to struck-by hazards in road construction operations. An accident was simulated upon the emergence of inattentiveness to hazards within the VR environment. The sustained intervention effect was examined using pretest-posttest analyses to compare the frequency and threshold of participants' vigilant behaviors. The results revealed that the VR environment elicited a reduction in attentiveness associated with risk habituation over a relatively short period of time, and the simulated accidents in the VR environment generated sustained impacts in the mitigating of the effects of habituation on attention over a week's time interval. The outcomes of this study contribute to the understanding of how workers' risk habituation can be measured in a VR environment and provide new knowledge regarding how a VR-based behavioral intervention can mitigate the attentional consequences of habituation to repeatedly exposed workplace hazards. DOI: [10.1061/\(ASCE\)CO.1943-7862.0002187](https://doi.org/10.1061/(ASCE)CO.1943-7862.0002187). © 2021 American Society of Civil Engineers.

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## Introduction

Road construction and maintenance workers are exposed to unique hazardous environments including close proximity to high-speed traffic and heavy construction equipment, which can result in potentially life-threatening accidents (Fan et al. 2014; Romano et al. 2008). Between 2011 and 2015, 609 workers were killed in road construction work zones in the US (BLS 2017). Of these road construction work-zone fatalities, being struck by a construction vehicle is the leading cause of death (Pratt et al. 2001). Specifically, runovers and backovers by construction vehicles or mobile equipment account for more than 50% of all fatal worker injuries at road construction work zones (CPWR 2018). To address these high rates of struck-by accidents, previous studies focused on developing warning systems—such as automated proximity warning systems—that employ various sensing technologies (Golovina et al. 2016, 2019; Sakhakarmi and Park 2019; Teizer et al. 2010). Although these efforts have increased somewhat the degree of workers' hazard

awareness, many struck-by accidents in road construction work zones are still rooted in workers' unsafe behaviors associated with biased/underestimated risk perception (Chan et al. 2020; Duchon and Laage 1986).

Risk habituation—lowered alertness to repeatedly exposed hazards—is one of the leading causes of struck-by fatalities in high-risk workplaces (Daalmans and Daalmans 2012; Inouye 2014; Poulton 1970; Whiting 2004). Specifically, in road construction work zones, workers' vigilant behaviors and ability to maintain a state of alertness to approaching struck-by hazards (e.g., construction equipment) are apt to diminish after frequent exposure to struck-by hazards; Workers tend to ignore potential risk associated with frequent proximity of construction vehicles (Duchon and Laage 1986; Kim and Ahn 2020; Oken et al. 2006; Weinberg and Harper 1993). To this end, understanding how road construction workers become habituated to repeated exposure to struck-by hazards and providing effective intervention are critical to reducing fatal accidents.

Although direct observation is one of the best ways to examine workers' unsafe behaviors (Glendon and Litherland 2001), it is hard to observe workers' habituation processes in a real environment as risk habituation develops over time with repeated exposure to hazards (Vance et al. 2017). Furthermore, observing risk habituation in a classroom training setting is extremely challenging due to the difficulty of simulating hazardous situations. With the advance of virtual reality (VR) technologies, previous studies in construction safety adopted VR for enhancing workers' safety knowledge and safety skills (Albert et al. 2014; Perlman et al. 2014). However, its use as a behavior intervention tool for risk habituation has not been fully explored, and many questions remain regarding how VR-based safety training can intervene in the

<sup>1</sup>Ph.D. Student, Dept. of Architecture, College of Architecture, Texas A&M Univ., College Station, TX 77843-3137. Email: [ng1022.kim@tamu.edu](mailto:ng1022.kim@tamu.edu)

<sup>2</sup>Associate Professor, Dept. of Psychological and Brain Sciences, College of Liberal Arts, Texas A&M Univ., College Station, TX 77843-4235. Email: [brian.anderson@tamu.edu](mailto:brian.anderson@tamu.edu)

<sup>3</sup>Associate Professor, Dept. of Construction Science, College of Architecture, Texas A&M Univ., College Station, TX 77843-3137 (corresponding author). ORCID: <https://orcid.org/0000-0002-6733-2216>. Email: [ryanahn@tamu.edu](mailto:ryanahn@tamu.edu)

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inattention that results from construction workers' habituation to workplace hazards.

The purposes of this study were to (1) investigate how inattention can be manifested with habituation to workplace hazards in a VR environment, and (2) examine the sustained effect of the VR-based behavioral intervention on mitigating road construction workers' inattention to struck-by hazards. The findings of this research offer new knowledge about how to elicit and measure individual workers' risk habituation to hazards, and how VR-based behavioral intervention might mitigate inattentiveness to hazards.

## Research Background

Recent studies that have focused on explaining workers' unsafe behaviors from a cognitive psychology perspective claim that workers' risk habituation is an important precursor to accidents at construction sites. The following subsections include a review of the theoretical foundation of risk habituation and discuss knowledge gaps in and challenges to reducing workers' unsafe behaviors caused by risk habituation.

### Risk Habituation and Safety

Habituation is the decrease in responsiveness to a repeated stimulus (Bukatko and Daehler 2012; Rankin et al. 2009; Thompson and Spencer 1966). The capability of a stimulus to elicit a response can be diminished when the stimulus occurs repeatedly (Lebbon and Sigurdsson 2017). Humans can be habituated to various stimuli—visual, auditory, and others (Vance et al. 2017). This habituation can be identified when measured responses decrease as a consequence of repetitive exposure to those stimuli (Grissom and Bhatnagar 2009). Thompson and Spencer (1966) have shown, however, that a decreased response to original stimuli can be recovered by presenting new or different stimuli.

Many researchers (Inouye 2014; Lund and Rundmo 2009; Perakslis 2016) have studied habituation in order to understand people's unsafe behaviors and inferred that habituation significantly contributes to biased risk perception. The term risk habituation has been defined as a decrease in risk sensitivity to repeated exposure to hazards (Daalmans and Daalmans 2012; Makin and Winder 2008). In workplaces, workers are prone to underrate the risk associated with tasks they perform frequently (Blaauwgeers et al. 2013; Curry et al. 2004; Perakslis 2016; Slovic 1987; Weyman and Clarke 2003; Whiting 2004). In other words, workers become familiarized with being repeatedly exposed to hazards in workplaces, begin to underestimate the risks, and become complacent with unsafe behaviors (Weyman and Clarke 2003; Whiting 2004). Furthermore, in real-world settings, risk habituation increases when there is no negative consequence (i.e., injury or accident) to continuous/frequent unsafe behaviors (Blaauwgeers et al. 2013).

Over many years, risk habituation resulting from repetitive exposure to hazards has been discussed as a key contributor to construction workers' unsafe behaviors (Chan et al. 2020; Kasperson et al. 1988). For instance, previous research (Sun et al. 2018, 2020) measured workers' gait pattern changes near repeatedly exposed hazards and demonstrated that repeated exposure to the same hazard could decrease workers' sensitivity to workplace risks; another study (Majekodunmi and Farrow 2009) indicated that drivers with regular exposure to lift-truck tasks underestimated the risks of driving a lift-truck.

Accident investigation reports also pointed out that workers' habituated inattention is one of the causal factors of struck-by accidents between workers on foot and construction equipment (Daalmans and Daalmans 2012; Duchon and Laage 1986; Glendon

and Litherland 2001; Pegula 2013). In many instances, construction vehicles ran over pedestrian workers because the workers were not visible to the equipment operators (Daalmans and Daalmans 2012; Duchon and Laage 1986). Even though back-up alarms or proximity warnings were presented, and the construction vehicles were traveling at a low speed, workers were struck because they did not heed the warning sounds and approaching hazards (Pegula 2013).

### VR in Safety Training

Advances in VR technologies have led to the creation of an effective and interactive training environment for hands-on experience (Chen 2010; de-Juan-Ripoll et al. 2018). VR offers several specific advantages in occupational safety training, including precise control and presentation of complex stimuli, safe learning environments, and personalized interventions (Rizzo et al. 2013; Strickland 1997). Because of these advantages, VR technologies have been adopted extensively for safety training. Previous studies in aviation (Chittaro et al. 2018), construction (Albert et al. 2014; Perlman et al. 2014), and mining (Liang et al. 2019) have demonstrated that trainees who participated in VR-based safety training achieved better learning outcomes in gaining safety-related knowledge (e.g., safety procedures and regulations) than trainees with conventional instructional media. VR has also been used to strengthen safety skills by enabling trainees to simulate and experience hazardous scenarios without risking actual injury (Li et al. 2018; Lin et al. 2020; Nilsson et al. 2019). In the construction safety field, researchers have demonstrated the effectiveness of VR-based safety training over conventional methods (Albert et al. 2017; Choi et al. 2020; Eiris et al. 2018).

More recent studies (Hasanzadeh et al. 2020; Lu and Davis 2018; Shi et al. 2019) have explored the advantages of using VR as an experimental tool for analyzing workers' unsafe behaviors in hazardous working environments. Specifically, they applied VR to study psychological factors contributing to unsafe behaviors (Bhandari et al. 2020; Choi et al. 2020; Hasanzadeh et al. 2020; Lu and Davis 2018; Shi et al. 2019). The results indicated that workers' unsafe behaviors could be attributed to a negative emotional status (Bhandari et al. 2020), the complexity of a task (Choi et al. 2020), and a high level of safety protection (Hasanzadeh et al. 2020). Although those studies demonstrated that measuring human responses toward exposed hazards in a VR environment can provide useful information about workers' unsafe behaviors, it is still not understood how workers' risk habituation can be manifested and measured in a VR environment.

### Negative Consequence Experience and Risk Habituation

Researchers have found that workers' risk habituation can be accelerated when they frequently engage in unsafe behaviors without experiencing negative consequences (i.e., injuries or accidents) in workplaces (Blaauwgeers et al. 2013; Chan et al. 2020; Duchon and Laage 1986). Although the objective risk of exposed hazards does not change, workers' perceived risk decreases according to the increase in exposure to hazards. Individual workers who have not been involved in an accident are more likely to become overconfident and engage in more unsafe behaviors (Curry et al. 2004; Young 1991). On the other hand, individuals who experienced an injury or accident in the past showed higher risk perception levels than those who did not experience such negative consequences (Burke et al. 2007; Duchon and Laage 1986). Lowered risk sensitivity may be recovered by allowing workers to indirectly experience a possible accident associated with their common workplace

tasks (Bohm and Harris 2010; Daalmans and Daalmans 2012) because emotionally negative information caused by accident experience can be more attention-grabbing and be remembered for a longer period of time (Carstensen 2006).

To investigate this, previous studies examined the feasibility of utilizing simulated accident experience to prevent workers' unsafe behaviors. Bhandari et al. (2019) demonstrated that naturalistic injury simulation could arouse workers' negative emotions to hazards in workplaces and postulated that such negative emotions might increase the level of workers' risk perception. Duffy et al. (2004) investigated the effectiveness of a VR-simulated accident on workers' safe behaviors. The results revealed that trainees who experienced a simulated equipment breakage in a VR environment exhibited improved safe decision-making performance in equipment operation tasks than those who did not experience the simulated accident. However, despite the advantage that VR presents in providing simulated accident experience, its effectiveness in mitigating construction workers' risk habituation has not yet been rigorously investigated.

### **Knowledge Gaps and Research Hypothesis**

The simulation of accident experiences affects workers' emotional state and risk perception levels, and experiencing or observing an accident in a VR environment impacts a trainee's decision and behavior in the same situation (Bhandari and Hallowell 2017; Duffy et al. 2004; Shi et al. 2019). However, the sustained impact of simulations on mitigating inattention resulting from habituation has not been rigorously investigated because it is difficult to elicit and measure behavioral consequences of habituation in a VR environment. Even in real-world settings, observing and assessing behavioral consequences of habituation presents significant challenges: direct observation of workers' behaviors in the field requires extensive time and human resources, yet still remains vulnerable to observer bias and often disregards individual differences (Glendon and Litherland 2001; Zhang and Fang 2013).

Although VR environments offer important opportunities to repeatedly expose trainees to hazardous situations, eliciting behavioral consequences of habituation over a relatively short experiment time period poses significant challenges (Vance et al. 2017, 2018). Furthermore, some trainees may not become inattentive to hazards in response to their awareness of being observed within a VR environment (i.e., demonstrating the Hawthorne effect) (Andujar and Brunet 2015; Jones 1992). Thus, few researchers have tried to observe and measure behavioral consequences of habituation in a VR environment. In response to this challenge in examining whether inattention to hazards can be manifested in VR environments as a result of habituation, the following hypothesis was constructed:

*Hypothesis 1:* Workers' vigilant behaviors in response to struck-by hazards will decrease in frequency and latency with repeated exposure to struck-by hazards as measured in the VR environment.

Habituation is a form of learning. Therefore, the inattentiveness to hazards resulting from habituation can be reduced by implementing an effective behavioral intervention (Rankin et al. 2009). In particular, providing time-sensitive feedback once habituation is observed and measuring the effectiveness of interventions are critical steps in the implementation of an effective behavioral intervention (Skinner 1963, 1984; Zohar and Erev 2007). Although it is difficult to deliver time-sensitive feedback on inattention to hazards in traditional safety training in classroom settings or while a task is being undertaken, VR environments can be used to generate time-sensitive feedback. However, the effectiveness of VR-simulated accident experiences as a behavioral intervention has rarely been

evaluated in the form of direct behavior measurements. Moreover, a sustained impact of experiencing VR-simulated accidents on mitigating workers' inattention to hazards (e.g., neglecting approaching hazards when focusing on a construction task) has not been rigorously measured. To this end, the following hypothesis was constructed and tested:

*Hypothesis 2:* Experiencing VR-simulated accidents as negative consequences of workers' inattention to workplace hazards increases workers' vigilant behaviors, and this effect can be sustained for a prolonged period of time.

### **Research Methods**

To test the aforementioned hypotheses, an experiment was designed to collect participants' behavior data in a VR-simulated hazardous environment. Specifically, a VR environment to simulate road construction and maintenance operations was developed and used in the experiment. To design a close-to-real simulation, the developed VR environment and the scenario were reviewed and validated by three experienced safety managers (one executive vice president of safety, one regional safety manager, and one project safety manager) of a nationwide road construction/maintenance company. The following sections describe the development process of the VR environment, the experimental settings, and the data analysis process.

#### **Immersive Virtual Road Construction Environment and Experimental Setting**

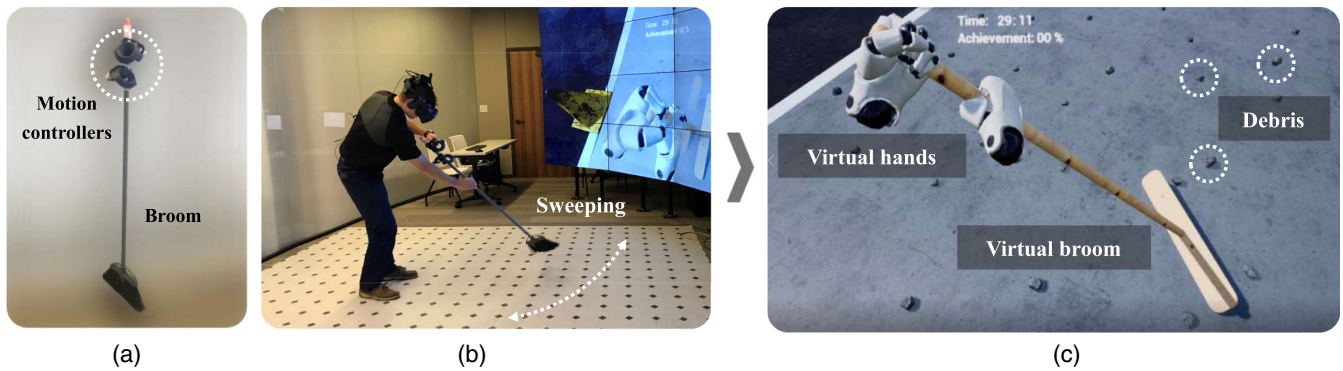
##### **Scenario and Immersive VR Environment Development**

To build a scenario that effectively triggers participants' risk habituation, the experimental scenario focused on repeated exposure of workers to potential struck-by hazards associated with construction vehicles, with associated warning signals (i.e., auditory warning alarms). A road maintenance working environment in which participants would be part of an asphalt milling crew was selected for the experimental scenario and designed. All virtual components included in this research were drawn using 3ds Max (version 2019) and Maya (version 2019). The immersive virtual environment was created using Unreal Engine 4 (UE4).

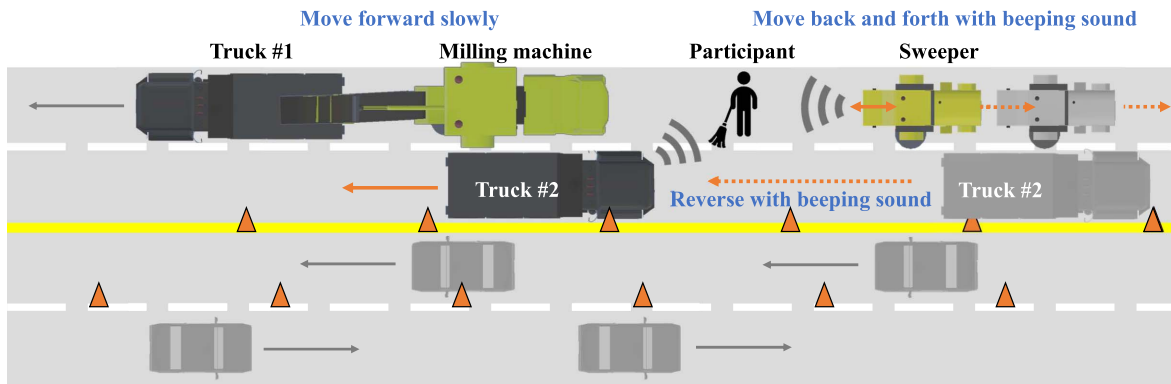
When working at a construction site, workers tend to direct most of their attentional resources to a specific task and become less attentive to surrounding workplace hazards (Chen et al. 2016; Huang and Watanabe 2012; Wickens 2008). Thus, in this study, the participants' task was designed to accelerate their habituation over a short time period while promoting active participation in the task. In the VR environment, a participant was asked to simulate a cleaning crew's task in a road maintenance workplace. The participant was tasked with removing all debris and cleaning the entire surface of the road with a broom. The level of immersiveness in any VR environment plays a crucial role in VR-based safety training (Jeelani et al. 2017). To achieve a high level of immersiveness, the participant's physical sweeping movement was captured via motion controllers attached to an actual broomstick and simulated in the VR environment with a virtual broom (Fig. 1).

As shown in Fig. 2, the movement of virtual construction machines was designed to respond to a participant's behavior. The back-and-forth movement of a sweeper that moves behind a participant is controlled according to its distance from a participant. The sweeper begins to reverse and turns off its warning alarm when it reaches the designated distance to a participant, thereby repeatedly exposing a participant to potential struck-by hazards without interfering with the participant's task. Next to the lane where a





**Fig. 1.** Interactive system for immersive tasking experience: (a) integration of HMD motion controllers with a broom; (b) participant's sweeping action with the broom; and (c) and movement of debris in the VR module in response to a participant's sweeping action.



**Fig. 2.** Struck-by hazards in the developed VR environment. A participant is exposed to repeated encounters with a sweeper machine (moving back and forth away and toward a participant) and trucks (periodically approaching and passing by a participant). These machines generate auditory warning alarms and require a participant to continuously pay attention to struck-by risks.

participant is executing the sweeping task, dump trucks intermittently pass by very close to the participant. More importantly, all of the construction machines generate operating sounds and auditory warning signals (i.e., beeping sounds), and these warning sounds are carefully simulated so that a participant can recognize the direction and proximity to the approaching hazard based on the warning sounds, similar to a real-world jobsite setting.

### Risk Habituation Measurement

This research defines vigilant behavior as hazard-checking behavior—an eye and/or head movement a participant makes to observe approaching hazards. Evaluating and perceiving the risk posed by a hazard in workplaces require selective (in this case, visual) attention because in order to properly respond to a hazard, workers must pay attention to it (Desimone and Duncan 1995; Jeelani et al. 2018; Nakayama et al. 2004; Rensink et al. 1997). Although orientation to a hazard may not always lead to workers' comprehension of the risks associated with the hazard (Eiris et al. 2018; Hasanzadeh et al. 2019), visual attention is an essential prerequisite for improved comprehension (Rensink et al. 1997). Visual attention is closely associated with eye movement (Hoffman and Subramaniam 1995), and visually checking of potential hazards is an important safety behavior worth promoting. Thus, measuring the decline in participants' visual attention to an approaching hazard provides a concrete and empirically rigorous way to monitor the development of risk habituation.

To measure the decline in participants' visual attention to the hazard, an eye-movement tracking system was integrated into the developed VR environment. A participant's eye movement (i.e., gaze behavior) was measured via an eye tracker embedded in the head-mounted display (HMD) with a peak frequency of 45 Hz. The eye tracker embedded in the HMD projects a ray from a participant's viewpoint and documents the name of the object that is hit by the ray, thereby indicating what the participant is looking at (Seele et al. 2017). The projected ray and name of the fixated object were invisible to the participants in the actual experiment, but were used by the researchers to analyze the data.

The developed behavior monitoring system documents (1) the threshold for exhibiting vigilant behaviors, and (2) the frequency of vigilant behaviors. The raw data from the experiment were preprocessed as follows:

1. The threshold for exhibiting vigilant behaviors (checking distance): One exposure to the hazard was defined as one reciprocal movement of the sweeper. During the experiment, when a participant looked back and gazed at the sweeper to check its proximity for the first time at each exposure, the distance between the participant and the sweeper was documented. In order to remove individual differences in the range of checking distance, the min-max normalization was applied to normalize extracted checking distance values without distorting the raw data. In this way, the entire range of values in each participant's checking

distance from minimum checking distance to maximum checking distance is normalized to a range from 0 to 1. For instance, if a certain participant's minimum and maximum checking distance were 8.5 and 18.1 m, those values were mapped to 0 and 1, respectively.

2. The frequency of vigilant behaviors (checking rate): During the experiment, when a participant checked the proximity of the sweeper, it was counted as a vigilant behavior. If a participant showed multiple checking actions during one exposure, it was still counted as one vigilant behavior. The checking rate of each participant was computed as the frequency of vigilant behaviors across the entire exposure to hazards using the following equation:

$$CR_i = \frac{TC_{\text{Success}}}{TE_{\text{Total}}} \quad (1)$$

where  $TC_{\text{Success}}$  = total number of successes in checking the hazards by a participant  $i$ ; and  $TE_{\text{Total}}$  = total number of hazard exposures of a participant  $i$ .

In order to avoid data manipulation, if a participant did not check the proximity of the sweeper until the sweeper reached the minimum distance where it starts to back up, that exposure was not included in the analysis of checking distance. Therefore, the analysis of checking rate supplements the results of the analysis of checking distance by enabling the observation of how frequently a participant neglected the approaching hazards.

### Experiencing a Negative Consequence: VR-Simulated Accident

The developed VR environment includes a module that simulates struck-by accidents upon a participant's risk habituation. The accident simulation involves visual scenes (from the first-person point of view), sounds, and haptic feedback via the motion controllers. Furthermore, visual scenes were dramatized to emphasize aversive feedback to a participant. Struck-by accidents caused by two types of equipment—a sweeper and dump trucks—were designed. The accident with the sweeper is triggered by participant's inattention to the hazards. When a participant fails to check on the approaching sweeper more than 11 times, the sweeper makes erratic movements and moves forward toward the participant until it either collides virtually with the participant or the participant moves out of the way. Although 11 instances of ignoring serve as a benchmark that is ultimately to some degree arbitrary, it is reflective of a participant's frequent ignorance of the approaching hazard during the 20 min of exposure in the experiment and therefore provides a proxy for habituation. Thus, the number 11 was used to trigger

the simulated struck-by accident. The participant can avoid the accident if the participant recognizes the proximity of the equipment and succeeds in avoiding the collision by moving out of the working lane. The participant is also exposed to the risk of being struck by the truck during the experiment. About 15 min after the start of the experiment, one of the trucks, intermittently passing the participant in the adjacent lane, quickly changes its direction and moves backward in the lane where the participant is working. This accident is also avoidable if the participant perceives the proximity of the truck and avoids the collision by dodging the truck that is heading toward them. Again, these struck-by hazards in the simulation involve warning sounds when they are approaching the participant.

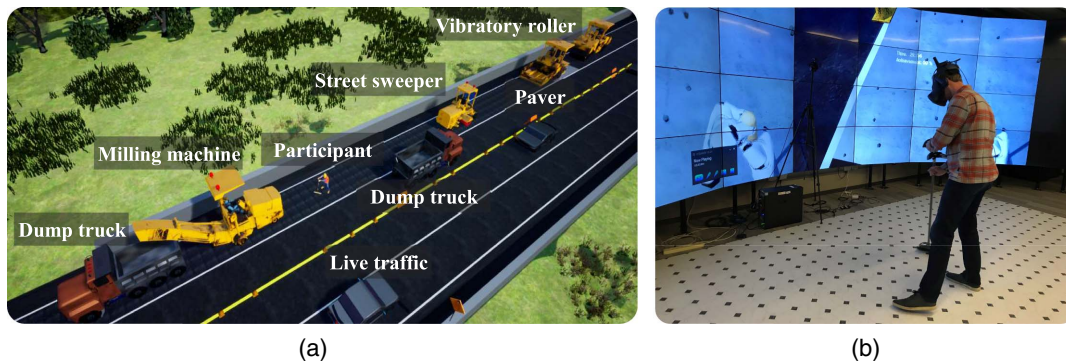
## Experimental Procedure and Hypotheses Testing

### Experimental Procedure

A total of 32 participants (26 males and 6 females;  $M_{\text{age}} = 21.09$  and  $SD_{\text{age}} = 3.04$ ) were recruited and participated in the experiment. All of the participants were undergraduate and graduate students at Texas A&M University (TAMU) majoring in construction/engineering. Half of the participants had working experience at a construction jobsite; 31% of the participants had less than 1 year of working experience, and 19% of the participants had more than 1 year and less than 5 years of working experience at a construction jobsite. In addition, 90% of the participants had some experience with VR technology.

The study proposal was approved by the Institutional Review Board (IRB) at Texas A&M University (IRB 2019-1270D). The approved informed consent form was provided to participants prior to their participation, and signed informed consent forms were obtained from all participants. The experiment was performed in the Building Information Modeling-Computer Aided Virtual Environment (BIM-CAVE) at Texas A&M University, as shown in Fig. 3.

Prior to commencing the experiment, in order to control for the prior safety knowledge of all of the recruited participants, all participants watched a highway worker safety training video for asphalt paving work provided by the Associated General Contractors of America (AGC 2019) and were instructed on how to perform the task in the VR environment. Before the actual experiment, all participants completed a practice session, became familiarized with the VR environment, and learned how to carry out the task; the practice session did not include any struck-by hazards or simulated accidents. During the experiment, the following instructions were given to all participants: Follow the milling machine while performing the sweeping task, sweep away all of the debris from the



**Fig. 3.** Experimental environment: (a) overview scene of the immersive virtual road construction environment; and (b) experiment conducted at TAMU BIM-CAVE.

working lane, and pay attention to approaching equipment and warning signals for safety purposes.

During the experiment, participants could have experienced the VR-simulated accident if they had become inattentive to struck-by hazards and failed to avoid one of these hazards. If the accident occurred, the experiment was discontinued immediately. If the accident did not occur, the experiment was aborted approximately 20 min after the experiment start time. A follow-up interview to collect feedback about the experience in the VR environment was conducted. To investigate the sustained effect of experiencing VR-simulated accidents in mitigating inattention to hazards, each participant undertook two sessions separated by a week's interval; 1 week is considered acceptable to measure the long-term effect of an intervention (Anderson et al. 2011; Prabhakaran and Molesworth 2011; Wang and Thomas 1992).

The second session was carried out using the same procedure but without the practice session and safety training session (i.e., watching the highway worker safety training video). Each session took approximately 1–1.5 h per participant, including VR-based training and other pre/post surveys.

### Hypotheses Testing

Hypothesis 1 was tested through the following steps: (1) bivariate linear regression analysis; and (2) multilevel modeling (MLM) analysis. The bivariate linear regression models predicting checking distance from a length of exposure time to the hazards were conducted using the following equation:

$$\hat{y}_i = B_0 + B_1T + r \quad (2)$$

where  $\hat{y}_i$  = checking distance at exposure time  $T$ ;  $B_0$  = intercept of the regression line at  $T = 0$ ; and  $B_1$  = slope of the regression that indicates the change in checking distance  $\hat{y}_i$  for each 1-min increase in exposure time  $T$ . If the test result of the coefficient  $B_1$  is significantly negative, the manifestation of participants' risk habituation can be determined. Analysis results were presented with standard error (SE) of the coefficient  $B_1$ .

In addition, a two-level MLM analysis was conducted in order to examine the association between the variances in the within-subject level predictor (exposure time) and the variances in the between-subject level predictor (checking rate). MLM analysis has been used extensively in psychology research to investigate a change in cognitive processes (Maxwell et al. 2017) and is widely used for analyzing repeated measurements in longitudinal data with different numbers of observations per participant (Peugh 2010; Volpert-Esmond et al. 2018). In this study, a variable on the first level of the model (within-subject level) was exposure time. The second level (between-subject level) variable was the checking rate of each participant. A total number of observations for exposure time at the first level is nested in a participant at the second level. Because checking rate was calculated only one time per person in each trial, checking rate is modeled as a subject-level predictor. The following equations were used for MLM analysis:

The Level 1 within-subject-level model is

$$y_{ij} = B_{0j} + B_{1j}T_{ij} + B_{2j}A_{ij} + B_{3j}T \times A_{ij} + r_{ij} \quad (3)$$

where  $y_{ij}$  = sum of the participant intercept;  $j$  = participant ( $j = 1, 2, 3, \dots, n$ ); and  $i$  = each observation ( $i = 1, 2, 3, \dots, n$ ) within a participant;  $B_{0j}$  = intercept in participant  $j$ ;  $B_{1j}$  = slope that represents the predicted decrease in checking distance by 1 min increase in exposure time  $T$  in participant  $j$ ;  $B_{2j}$  = slope that represents the predicted change in checking distance by 1% increase in checking rate  $A$ ; and  $B_{3j}$  = slope of the interaction term of exposure time  $T$  and checking rate  $A$ .

The Level 2 between-subject-level model is

$$B_{0j} = \gamma_{00} + \gamma_{01}A_j + v_{0j} \quad (4)$$

Eq. (4) represents the intercept of the participant level, where  $A_j$  = checking rate – checking rate of participant  $j$ ;  $\gamma$  = regression coefficients at the participant level;  $\gamma_{00}$  = intercept over participant when all predictors are zero;  $\gamma_{01}$  = intercept of checking rate  $A$  of participant  $j$ ; and  $v_{0j}$  = participant level error in the intercept

$$B_{1j} = \gamma_{10} + \gamma_{11}A_j + v_{1j} \quad (5)$$

Eq. (5) represents the slope of the participant level, where  $\gamma_{10}$  = slope of a participant;  $\gamma_{11}$  = regression coefficient of checking rate  $A$ ; and  $v_{1j}$  = participant level error in the slope. Eqs. (3)–(5) were integrated into Eq. (6). Using the lme4 package in R version 4.0 (Bates et al. 2014; R Core Team 2020), the MLM analysis was conducted. As the continuous variable, exposure time  $T$  was scaled and mean-centered

$$y_{ij} = (\gamma_{11}A_j + \gamma_{10} + v_{1j})T_{ij} + (\gamma_{01}A_j + \gamma_{00} + v_{0j}) + r_{ij} \quad (6)$$

The result of the significance test for the MLM model indicates how differences in checking rate affected the decrease in checking distance.

Hypothesis 2 was tested using (1) multiple regression analysis estimating checking distance at hazard exposure time and accident experience in the first session, and (2) a paired-samples  $t$ -test evaluating the intervention effect on the increase in checking rate for both accident groups. Multiple regression analysis was employed to evaluate whether and how a participant's experience of VR-simulated accidents in the first session affected their attentiveness in the second session. A participant's experience of VR-simulated accidents in the first session was added as a categorical variable (dummy-coded as 0 for the without-accident group and 1 for the with-accident group) in the following regression equation:

$$\hat{y} = B_0 + B_1T + B_2A + B_3TA + r \quad (7)$$

where  $\hat{y}$  = dependent variable (checking distance) at exposure time  $T$  and accident experience  $A$ ;  $B_0$  = simple intercept of the regression line in the without-accident group ( $A = 0$ );  $B_1$  = change in the simple intercept for each 1-min increase in exposure time  $T$ ;  $B_2$  = difference in simple intercepts, comparing the with-accident group ( $A = 1$ ) with the without-accident group ( $A = 0$ ); and  $B_3$  = difference in simple slopes, comparing the with-accident group ( $A = 1$ ) with the without-accident group ( $A = 0$ ).

In addition, paired-sample  $t$ -tests were conducted to examine the intervention effect of experiencing VR-simulated accidents in the first session on checking rate in the second session (pre-treatment vs. post-treatment). Analysis results were presented as mean  $\pm$  standard deviation (SD). The magnitude of the effect of the intervention was measured using Cohen's effect sizes ( $d$ ), with the following criteria: 0.2 = small effect, 0.5 = moderate effect, and 0.8 = large effect (Cohen 2013; Koral et al. 2018). Among the 32 participants, some never showed vigilant behaviors (four participants in the first session, and one participant in the second session). The data collected from such participants were excluded from the analysis of checking distance for testing Hypothesis 1; these data were only included in the analysis of checking rate for testing Hypothesis 2.

To ensure a desired level of statistical power to test the hypotheses, a posterior statistical power analysis was performed using the *pwr* package in R (Champely et al. 2017). The results of the posterior statistical analysis revealed that the numbers of samples in this study provide a minimum desired level of statistical power, 0.50, to test the hypotheses at the 0.05 significance level.



## Results

### Hypothesis 1 Testing

Hypothesis 1 was confirmed by testing the bivariate models for predicting checking distance from the length of exposure time to the hazard. The models were significant,  $R^2 = 0.16$ ,  $F(1, 441) = 83.83$ , and  $p < 0.001$  (for the first session),  $R^2 = 0.10$ ,  $F(1, 694) = 79.67$ , and  $p < 0.001$  (for the second session). Exposure time to the hazard negatively predicted checking distance,  $B_1 = -0.023$  and  $p < 0.001$  for the first session and  $B_1 = -0.014$  and  $p < 0.001$  for the second session. The results of both sessions indicate that the participants' action to check the proximity of the sweeper was slowed with prolonged exposure time to the hazard (Table 1; Fig. 4).

The results of MLM analysis are presented in Table 2. The coefficient  $B_3$ , interaction of exposure time and checking rate, approached significance ( $p = 0.074$ ). Exposure time and checking rate had a positive interaction, meaning that the checking rate moderates the relationship between exposure time to hazard and checking distance. This result indicates that the participants with lower checking rates tended to have faster decay patterns of checking distance over exposure time compared with participants with higher checking rates.

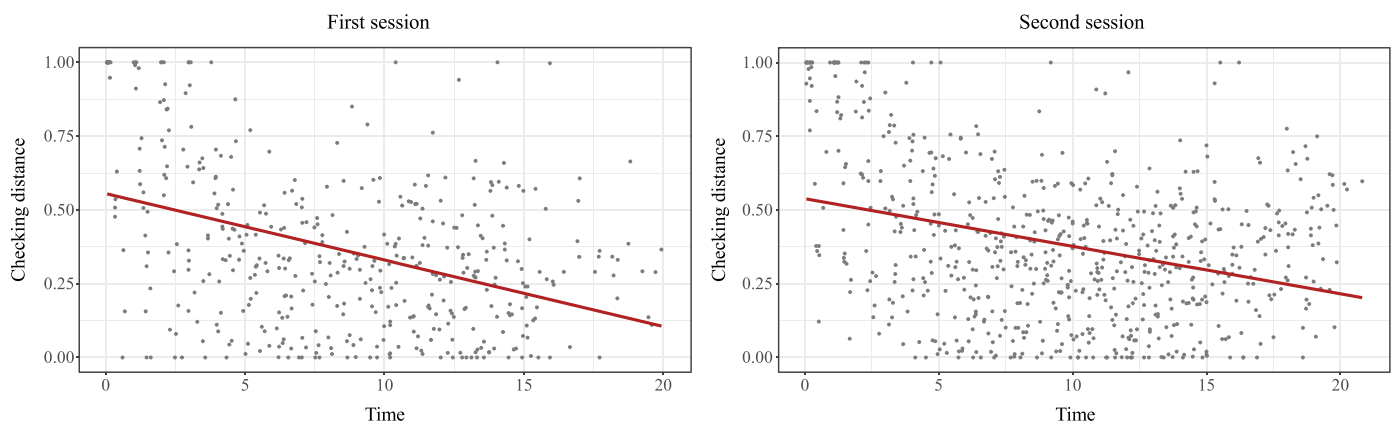
Fig. 5 shows the difference in checking distance between the participants who showed different checking rates. The slope of lines indicates the effect of checking rate (between-subject level predictor) on the strength of the relation between checking distance and exposure time (within-subject level predictor) at the mean for the checking rate, one standard deviation above the mean checking rate, and one standard deviation below the mean of the checking rate.

The result of the follow-up interview supports the testing results of Hypothesis 1. In order to identify the reason for participants' decreasing vigilance with respect to hazards in the experiment, participants in the with-accident group were asked to answer why

**Table 1.** Regression coefficient, indicating the influence of exposure time on the decrease in checking distance

Session	Predictors	$B_1$	SE	$p$ -value
First	Exposure time	-0.023	0.002	<0.001*
Second	Exposure time	-0.016	0.003	<0.001*

Note: \*Significant at the  $p = 0.05$  level; and SE = standard error.



**Fig. 4.** Checking distance when subjects looked back to check the proximity of the sweeper.

they stopped to check the proximity of the construction equipment. Most of them replied that they were focusing just on sweeping out the debris on the road and believed that the construction vehicles were moving around normally and posed no threat. Therefore, they forgot to look back to assess the proximity of the equipment.

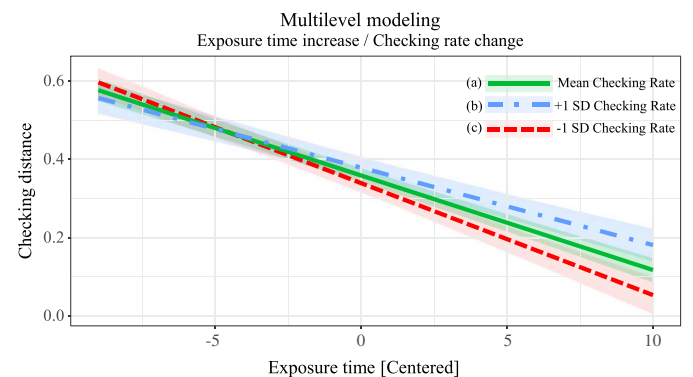
### Hypothesis 2 Testing

During the experiment, VR-simulated accidents occurred in response to a participant's habituated behaviors. As indicated in Table 3, in the first session, 24 out of 32 participants experienced VR-simulated accidents triggered by their inattention to hazards (i.e., the with-accident group) and eight participants did not experience simulated accidents (i.e., the without-accident group). In the

**Table 2.** Fixed effects of the multilevel model on the checking distance of the exposure time and checking rate

Predictors	Estimates	SE	$p$ -value
$B_0$ , intercept	0.30	0.06	<0.001*
$B_1$ , exposure time	-0.04	0.01	<0.001*
$B_2$ , checking rate	0.10	0.09	0.244
$B_3$ , exposure time $\times$ checking rate	0.02	0.01	0.074

Note: \*Significant at the  $p = 0.05$  level; and SE = standard error.



**Fig. 5.** Slopes for the effect of exposure time (centered at the mean) on checking distance at the mean of checking rate; one standard deviation above the mean of checking rate; and one standard deviation below the mean of checking rate.

second session, 58% of the with-accident group did not engage in accidents. However, 75% of the without-accident group engaged in accidents during the second session.

The multiple linear regression model for testing Hypothesis 2 was significant,  $R^2 = 0.11$ ,  $F(3, 686) = 28.41$ , and  $p < 0.001$  (Table 4). The result indicated a significant interaction between exposure time in the second session and VR-simulated accident experience in the first session,  $B_1 = 0.008$  and  $p < 0.001$ . The result confirmed that experiencing the VR-simulated accident as a negative consequence of the participant's inattention significantly mitigated the effects of risk habituation (Fig. 6).

The checking rates from the second session were compared with the checking rates from the first session. For the with-accident

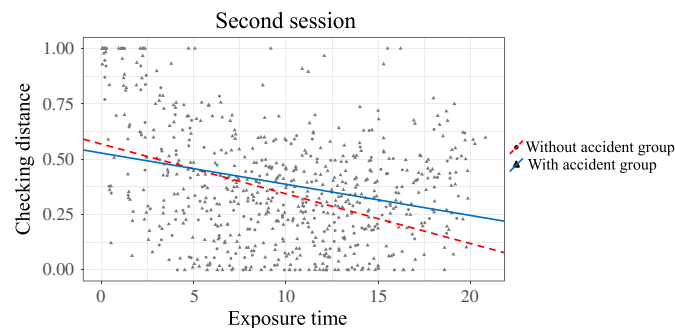
**Table 3.** Classified results according to the accident occurrence during the experiment

First session	<i>n</i>	Second session (total = 32)		
		Without accident	With accident	Subtotal
Without accident	8	2	6	8
With accident	24	14	10	24
Subtotal	32	16	16	32

**Table 4.** Regression coefficients, indicating the influence of accident experiencing on the checking distance

Session	Coefficient	$B_1$	SE	<i>p</i> -value
Second	Exposure time	-0.022	0.004	<0.001*
	Experiencing accident in the first session	0.004	0.022	0.369
	Exposure time $\times$ experiencing accident in the first session	0.008	0.004	0.048*

Note: \*Significant at the  $p = 0.05$  level; and SE = standard error.



**Fig. 6.** Slopes for the effect of exposure time are plotted separately for different groups according to whether or not the VR-simulated accidents were experienced in the first session.

group, there was a significant difference in checking rate for the first session ( $M = 0.38$  and  $SD = 0.26$ ) and the second session ( $M = 0.70$  and  $SD = 0.27$ );  $t(24) = -6.03$  and  $p < 0.001$ . The effect size ( $d$ ) was  $-1.22$ , considered large by Cohen (2013). However, in the without-accident group, there was no significant difference in the checking rates between the first session ( $M = 0.71$  and  $SD = 0.15$ ) and the second session ( $M = 0.78$  and  $SD = 0.20$ );  $t(8) = -1.25$  and  $p = 0.25$ . The effect size ( $d$ ) was  $-0.38$ , considered small (Table 5; Fig. 7).

Hypothesis 2 was confirmed by the results of the preceding tests. The multiple regression analysis results indicate that the with-accident group showed slower habituation tendencies than the without-accident group in the second session. Importantly, the results of the paired-sample  $t$ -test demonstrate that experiencing the VR-simulated accidents significantly improved subsequent checking rate. These findings confirmed that the VR-simulated accidents mitigated the effects of construction workers' risk habituation resulting from repeated exposure to struck-by hazards and that the mitigation effects were sustained over a prolonged period of time.

## Discussion

The results indicate that participants' habituation to struck-by hazards and corresponding inattention can be significantly affected by an increase in exposure time, and that the constructed VR environment effectively elicited such habituation over a relatively short period of time. Vigilant behaviors in response to approaching construction vehicles decreased over time. Participants' responses to the follow-up interview questions supplement the results of the experiment. Participants who experienced the simulated accident reported that they had stopped paying attention to the proximity of equipment behind them because it appeared to be moving normally and did not appear to be posing any threat. Although the participants were warned about potential struck-by hazards and were required to pay attention to approaching equipment for safety purposes, during the experiment they got used to repeated exposure to struck-by hazards and concentrated only on the sweeping task. This result implies that performing the sweeping task may contribute to workers' narrowly focused attention and their ignoring struck-by hazards, thereby accelerating the development of risk habituation in the VR environment.

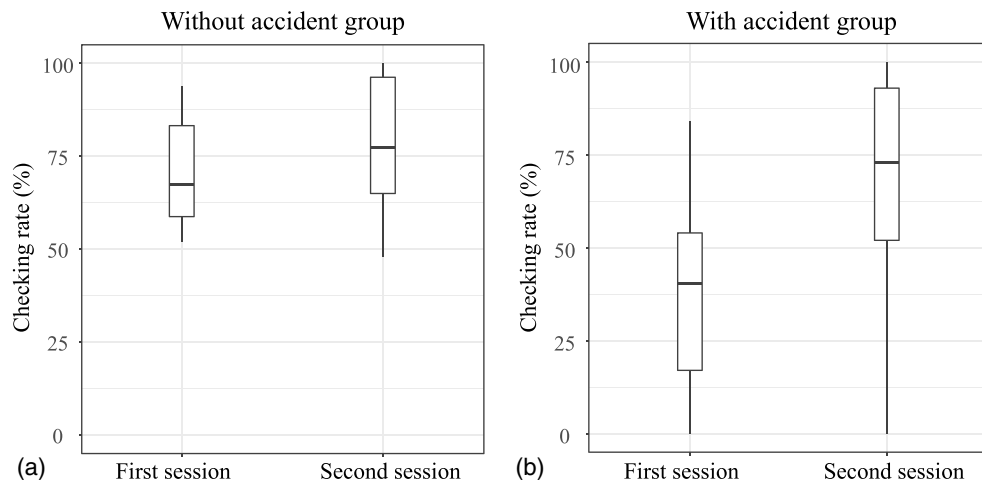
The outcomes also demonstrate that experiencing VR-simulated struck-by accidents significantly mitigated risk habituation as measured in the VR environment, and that the mitigation effects are sustained over a prolonged period of time. In spite of a week's interval between the two experimental sessions, the participants' experience of the VR-simulated accidents in the first session significantly affected their vigilant behaviors—checking distance and checking rate—in the second session. Although the participants' checking distance still exhibited a decreasing tendency, the participants who experienced VR-simulated accidents in the first session showed slower risk habituation tendencies than the participants who did not experience a simulated accident. In the follow-up

**Table 5.** Effect of experiencing VR-simulated accident on the checking rate: paired sample  $t$ -test and effect size

VR accident experience	Checking rate				<i>t</i>	<i>p</i> -value	Cohen's <i>d</i> (effect size)
	First		Second				
	<i>M</i>	SD	<i>M</i>	SD			
Without accident group	0.71	0.15	0.78	0.20	-1.253	0.250	0.37 (small)
With accident group	0.38	0.26	0.70	0.27	-6.031	<0.001*	1.22 (large)

Note: \*Significant at the  $p = 0.05$  level.





**Fig. 7.** Intervention effect on the change in frequency of vigilant behaviors: (a) change in checking rate of the group who did not experience a VR-simulated accident in the first session; and (b) change in checking rate of the group who experienced a VR-simulated accident in the first session.

interview, 90% of the participants who (1) experienced the accidents in the first session; and (2) did not experience the accidents in the second session agreed that the experience of VR-simulated accidents affected their attitude toward hazards. As a consequence, they paid more attention to the repeatedly exposed hazards and succeeded in avoiding accidents. Some participants said that after being run over by a construction vehicle in the VR environment, they were more cautious and aware of their surroundings instead of just focusing on the assigned task. This implies that demonstrating VR-simulated accidents soon after the onset of habituation not only mitigates workers' risk habituation in the future but may positively affect workers' attitudes toward workplace hazards and promote safe behaviors.

We also examined the relationship between an individual's personality traits and their risk habituation tendencies. During the experiment, the association between individual participants' personality traits and risk habituation tendency was analyzed using the Big-Five personality traits survey, which measures the five dimensions of personality traits—Extraversion, Agreeableness, Conscientiousness, Neuroticism, and Openness (Goldberg 1990; John and Srivastava 1999). The results demonstrated a significant positive association between the Agreeableness trait and a high checking rate,  $R^2 = 0.39$ ,  $F(28) = 3.52$ ,  $p < 0.05$ ,  $\beta = 0.003$ , and  $p < 0.05$  (Appendix).

Although the sample size was not sufficient to generalize the findings on personality traits, this result highlights that behavioral measurements in VR safety training would support additional research on individual differences in safety behaviors. Although there has been significant interest in the relationship between personality traits and safety behaviors, most of the existing studies on this topic were limited by the challenges posed by trying to measure safety behaviors (in practice or during training) and thus relied on the measurement of outcomes resulting from unsafe behaviors (e.g., injury experience or violation) (Landeweerd et al. 1990; Sing et al. 2014); However, such data on behavior outcomes are generally the outcome of rare events (e.g., accidents) and less sensitive to variation in personality traits. In this context, leveraging behavioral measurements—in particular, measurements related to habituation—in immersive VR environments would help researchers more thoroughly investigate the factors contributing to individual differences in safety behaviors.

With regard to practical applications, adopting the proposed VR-based behavioral intervention might benefit construction safety efforts. Although direct observation of workers' risk habituation in the field requires extensive human resources, time, and funds, the developed VR-environment enables direct measurement of the development of risk habituation at a lower cost and in less time. Furthermore, measuring workers' behavioral responses in the VR environment may help researchers and safety practitioners to identify which workers are more vulnerable to risk habituation or more risk-prone than other workers, thereby facilitating tailored safety training. Tailored safety training can help workers determine their risk habituation tendencies toward repeatedly exposed hazards and enable workers to understand when and how they engage in risky workplace behaviors. Consequently, the proposed VR-based behavioral intervention holds the potential to motivate workers to correct their habituated behaviors on their own.

Although the development of VR-based safety training incurs higher upfront costs than conventional safety training, once a VR training environment is developed, there is very little residual operating cost. Furthermore, with the advance of VR technologies, the cost of incorporating VR into construction safety training is steadily falling. A VR-based behavioral intervention tool can be established using a consumer-grade VR HMD and VR environment development tools that can be used free of charge for educational/training purposes. Thus, the proposed method can be implemented as a means to offset the limitations posed by conventional safety training without incurring significant costs.

In the impending era of fully automated vehicles (AVs), construction vehicles will be equipped with technologies that detect obstacles and automatically brake to avoid accidents. Those systems would be effective in helping to prevent fatal struck-by accident between construction vehicles and pedestrian workers. However, the many cases of accidents between AVs and pedestrians to date have revealed that those technologies are not yet fully capable of preventing accidents (Yang et al. 2021). Thus, before and even after the era of fully automated construction vehicles, it will still be critically important to improve workers' awareness of struck-by hazards in order to prevent unsafe behaviors that can cause struck-by accidents.

Several limitations in the proposed approach should be noted. First, although half of the participants had working experience in a construction field, all the participants were undergraduate and

graduate students. Thus, participants' responses to the exposed hazard in a VR environment might be different from that of experienced construction workers. Second, the sample size was limited and unevenly distributed. During the experiment, the designed intervention was demonstrated in response to participants' inattention to workplace hazards. Therefore, the number of participants who did not experience VR-simulated accidents was relatively small.

Third, the perceived complexity of a task might be closely related to risk habituation (Duchon and Laage 1986). When carrying out a task in the VR environment, an individual participant may perceive the difficulty of the sweeping task differently. Although all participants participated in a practice session, individual differences in the perceived difficulty of the task may have affected participants' responses to the hazards. However, that issue was not addressed in this study.

Fourth, despite having watched the safety training video and been given safety directions, some participants never showed any vigilant behavior during the experiment. The collected data from these participants were used only to analyze the frequency of vigilant behaviors (checking rate). Fifth, the practice session did not include performing the evasive maneuver using the controls to avoid approaching equipment in the VR environment. Thus, some participants might have trouble avoiding an accident, regardless of their attention to approaching equipment.

Sixth, although a person's peripheral vision plays a critical role in detecting the motion of an object and recognizing potential hazards in the surrounding environment (Loomis et al. 2008; Younis et al. 2019), the eye-tracking system adopted in this research measured only a participant's visual attention by sensing the movement of foveal (central) vision (Connor et al. 2004). Therefore, if participants were checking the exposed hazard just by using their peripheral vision, in this study, those behaviors were not considered to be vigilant behaviors. Furthermore, previous literature shows that the effect of safety training decreases with repeated participation (Minowa et al. 2015). Therefore, the effect of experiencing VR-simulated accidents in mitigating risk habituation may also decrease with repeated participation. Additional studies are needed to examine the relationship between a decrease in the training effect and the number of participations in the proposed VR intervention.

Lastly, the findings of this study may be somewhat limited by the laboratory conditions using VR environment, and the improvement in vigilant behavior resulting from the VR-intervention might not translate to behavior in a real-life construction environment or may not be sustained beyond the timeframe investigated. Therefore, it will need to pursue further validation in field experiments.

## Conclusion

This study investigated how repeated exposure to a hazard affects workers' vigilant behaviors in a VR environment. Subsequently, the sustained effect of VR-based behavioral intervention on mitigating workers' risk habituation was examined. In particular, this research focused on risk habituation toward struck-by hazards related to mobile construction vehicles. The experiment results reveal that the proposed VR environment can elicit workers' risk habituation, and that the behavioral intervention demonstrating VR-simulated accidents significantly mitigates workers' risk habituation. The outcomes of this study contribute to the understanding of how a decline in workers' vigilant behaviors—the attentional consequences of habituation to repeatedly exposed hazards—can be quantitatively measured and mitigated by a VR-based behavioral intervention, thereby offering a new perspective on understanding construction workers' inattentive behaviors

in workplaces and potentially improving safety management in construction sites.

To generalize these research findings, additional studies will be needed. Adopting the proposed approach to other construction trades (e.g., fall risk-associated trades and electrocution risk-associated trades) will help investigate the risk habituation of workers who are frequently/continuously exposed to a specific hazard. For example, roofers are consistently exposed to fall hazards. They become familiarized with working from a height and, over time, begin to engage in unsafe behaviors (Hasanzadeh et al. 2020). The process of habituation to fall risks could also be investigated in a VR environment by expanding on the proposed approach.

Collecting physiological responses (e.g., electrodermal activity and electroencephalography) and integrating them with physical responses in a VR environment presents an additional promising application in preventing risk habituation. Because measuring skin response or brain activity can generate information related to workers' emotional arousal resulting from exposure to hazardous situations, combining these multimodality data sets might help unveil whether or not workers consciously or unconsciously exhibit a broader range of consequences of habituation to repeatedly exposed hazards. Additionally, incorporating the measurement of mental workload associated with the assigned task would be useful to examine the relationship between perceived mental workload and a reduction in workers' attentiveness associated with risk habituation. Thus, these approaches may have broader impacts in preventing fatalities and injuries associated with risk habituation in the construction industry.

## Appendix. Regression Coefficients Indicating the Influence of Personality Traits on Checking Rate

Predictors	Estimates	SE	<i>p</i> -value
Extraversion	−0.025	0.022	0.262
Agreeableness	0.038	0.014	0.014*
Conscientiousness	−0.012	0.018	0.519
Neuroticism	−0.021	0.011	0.069
Openness	−0.033	0.017	0.054

Note: \*Significant at the  $p = 0.05$  level; and SE = standard error.

## Data Availability Statement

Data generated or analyzed during the study are available from the corresponding author by request. Information about the *Journal's* data-sharing policy can be found here: [http://ascelibrary.org/doi/10.1061/\(ASCE\)CO.1943-7862.0001263](http://ascelibrary.org/doi/10.1061/(ASCE)CO.1943-7862.0001263).

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