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Exploring construction workers' attention and awareness in diverse virtual hazard scenarios to prevent struck-by accidents

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ABSTRACT

Repetitive tasks in construction reduce workers' attentiveness of hazards on sites. This decline in attentiveness can be influenced by their situation awareness level. However, research on the relationship between attentiveness and situation awareness is scarce in the construction safety domain. This study employs eye-tracking techniques to investigate how visual attention changes due to variations in workers' situation awareness levels. A virtual reality-based experiment was conducted to evaluate the situation awareness level of individual workers and examine its relationship with attentiveness towards different hazards using the situation awareness global assessment technique and linear regression analysis. The experimental findings reveal that the overall trend of allocating attention toward hazards declined over time. Furthermore, the attentiveness of workers varied depending on their situation awareness levels and the type of hazardous condition. Throughout the experiment, the group with a low situation awareness failed to sustain their vigilance toward hazards as effectively as the group with a high situation awareness. The outcomes of this study will help construction safety trainers understand variations in workers' vigilance behavior over time and, thus mitigate the risk of accidents owing to inattentiveness at job sites.

1. Introduction and background

The construction industry experiences high rates of fatality injuries, with struck-by hazards being the leading cause. Despite efforts to mitigate accidents, the fatality rate remained consistent, emphasizing the urgency for improvement. Around 20,600 non-fatal struck-by injuries were recorded in the US, accounting for one-quarter of the industry's total non-fatal injuries in construction (Bureau of Labour Statistics, 2022). Previous research has focused on implementing various real-time monitoring systems, computer vision-based techniques, and remote monitoring to maintain a safe distance between workers and equipment (Khan et al., 2023; Kim et al., 2019; Tran et al., 2023, 2022). Additionally, personalized safety training and assessing safe behavior have been used to reduce risk habituation and to improve hazard identification skills (Ahn, 2021; Grégoire et al., 2022; Hussain et al., 2020). However, many struck-by accidents still occur due to workers and operators not paying attention, failing to recognize hazards, or not being careful enough to avoid risks (Hasanzadeh et al., 2018; Wang et al., 2019). Most of the construction accidents can be prevented if workers are fully aware of the situation and show attentiveness toward hazards (Görsch et al., 2020).

Attentiveness and situation awareness (SA) are interlinked factors that can prevent accidents due to unpredictable hazards (Endsley, 2017a) (Endsley, 2017a; Wickens et al., 2021). Measuring the awareness level and variation in workers' attention through direct observation is labor-intensive, time-consuming, which is practically impossible to collect in hazardous work conditions. Virtual reality (VR) technologies offer immersive training experiences that enable workers to practice safety protocols in a controlled environment, allowing them to perform activities under various hazardous situations without the risk of accidents (Choi et al., 2023; Pedro et al., 2023). For instant, Rokooei et al., (2023) mainly focuses on the design and development of a VR module for safety training in the roofing sector. Similarly, Li, (2018) discusses the popularity of VR and its real-life applications in safety training in the construction industry. Other studies have adopted VR as a complementary approach to improve workers' hazard identification skills and personalized learning experiences through virtual tours (Pedro et al., 2019; Pham et al., 2018; Roofigari-Esfahan et al., 2022). However, there has been limited exploration of VR as a behavioral intervention tool in construction safety research, particularly in the context of real-time data

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collection based on workers' actions within virtual settings.

In recent years, few studies in the context of exploring workers' attention in virtual construction environments have been performed to explore the research issue; however, these studies were limited to a single construct (e.g., attention) (Ahn, 2021; Grégoire et al., 2022). Furthermore, the design methods employed did not examine how workers' visual actions altered when performing repetitive tasks. Wolf et al., (2022) mentioned that very little research in the construction safety domain has focused on examining and analyzing inherent data collected through workers' visual actions in virtual environments. Notably, these studies did not specifically delve into the crucial link between workers' attentiveness and their level of situation awareness. With this background, the primary objective of this research was to investigate how visual attention over time is altered by changes in workers' level of situation awareness. To achieve this objective, a VR-based eye-tracking technique was utilized, allowing for precise measurement of workers' visual attention. The study presented different types of struck-by hazards in the VR environment to assess workers' awareness of the situation. Additionally, workers were engaged in repetitive simulated tasks while being exposed to random hazards, enabling the measurement of attentiveness over time.

The rest of the paper is organized as follows. First, an extensive literature review is provided to determine the roles of attentiveness and situation awareness in the construction safety domain. Section 3 outlines and describes in detail the methods for virtual content development, experimental procedure, and data collection. The acquired data is analyzed in Section 4. Subsequently, the results, discussion, and conclusions are presented, and the theoretical and practical implications of the findings are discussed in Section 5.

2. Literature review

2.1. Role of attentiveness and SA in hazard recognition

Many studies have incorporated attentiveness and situation awareness as key constructs when identifying workers' abilities in hazardous situations. For instance, struck-by accidents in construction refer to incidents in which a worker is caught in or between a moving object or piece of equipment. Such accidents can be severe or even fatal and can occur when workers pay insufficient attention to their surroundings or are unaware of potential hazards in their surrounding environment (Ahn, 2021; Grégoire et al., 2022; Kim et al., 2021). Based on the causes of accidents involving being struck by objects, hazardous objects are classified into four categories: falling, flying, swinging, and rolling (OSHA, 2011). To delve further into the research issue, this section will focus on the various perspectives of attentiveness and situation awareness and describe workers' safe/unsafe behavior against risks associated with such struck-by objects. A relationship model extended from the literature is also presented to define the influencing factors that can vary the SA level and attentiveness in dynamic situations at construction workplaces.

Several studies have attempted to explore the relationship between attention and situation awareness in various disciplines. For instance, in the aviation sector, novel studies have been conducted to identify the effects of attention on pilots' situation awareness to react against adverse environmental conditions, including turbulence and crosswind (Cak et al., 2020). In the transportation sector (Henning et al., 2022; Karjanto et al., 2018), researchers have observed drivers' perceptions and attitudes during fully automated driving in alleviating motion sickness when engaging in non-driving tasks. Also, in the healthcare sector, studies have been performed to evaluate healthcare providers' clinical performances in emergency cases against infection control and equipment malfunction (Walshe et al., 2021). Other studies have presented different applications of situation awareness during military operations, including battlefields, military bases, and critical infrastructure (Munir et al., 2022). According to a recent study that reviewed 80 articles, including 20 studies from the construction industry, the combination of situation awareness and visual attention research has been the least explored area in the construction sector (Martinez-Marquez et al., 2021). This multi-dynamic model of workers' behavior to develop attentiveness toward struck-by hazards and maintain situation awareness opens doors to new ways of measuring awareness and determining workers at risk.

The attention-SA model (Endsley, 2017a; Jones and Endsley, 1996), developed by Endsley and Jones, explains how attention and situation awareness interact in dynamic environments. The model proposes that attention and situation awareness are separate but interdependent cognitive processes and play a critical role in enabling individuals to perform tasks effectively in complex and dynamic environments. According to the model, attention is a limited resource that can be channeled to focus on a specific task or aspect of the environment (Rueda et al., 2023). At the same time, situation awareness is a more general cognitive process that involves understanding the context in which a task is performed, including anticipating future events. Therefore, attention must be allotted to various sensory considerations to maintain a high situation awareness (Wickens et al., 2021). According to the Endsley model (Endsley, 2017a), balance in attention deployment is the core tenet of situation awareness in hazardous environments.

Endsley's model categorizes situation awareness into three levels: perception, comprehension, and projection (Endsley, 2017a, 1995a). Based on these levels, the decision-making loop, starting from workers' goals and objectives, is elaborated in Fig. 1 as an extended version of the Endsley's model. It shows how attentiveness and situation awareness interact in dynamic environments and how both can be developed and sustained over time. In this framework, attentiveness plays a critical role in the perception stage, enabling workers to obtain feedforward information about potential hazards from the environment through their senses and filter out distractions (Endsley and Rodgers, 1996). In the comprehension stage, workers process and interpret the information they perceive from the former stage and use their current SA levels to anticipate future events (Munir et al., 2022). They make decisions to perform actions in the projection stage. These actions lead toward results that can be used as feedback for maintaining future goals and objectives (Endsley, 1995b). Thus, the cycle continues in this way, whereby the workers' situation awareness and attentiveness are developed and maintained (Endsley, 2017a).

According to (Endsley, 2015), the three levels of situation awareness are ascending levels, not linear stages, and the occurrence of projection, comprehension, and perception in the model does not imply a strict linear progression. For example, a worker can possess SA level 2 and 3 even if they lack complete or accurate SA level 1. In such cases, workers can use their higher levels of situation awareness to guide their search for and acquisition of SA level 1 (Endsley, 2004). In other words, experienced workers may accurately project future events even if they do not fully understand or perceive the current situation. Similarly, workers may have a high level of comprehension of a hazardous situation but a low level of projection due to lack of knowledge or uncertainty. Furthermore, the cycle of situation awareness development may influence due to several personal and external factors, such as task demands, abilities, current activities, complexity of the environment, changes, and quality of information. Depending on these factors, the levels of situation awareness can vary independently, leading to different levels of situation awareness. Experienced or trained workers may have an advantage in maintaining SA due to their practical knowledge, but they may still be prone to inattentiveness if faced with repetitive tasks or high workloads.

Although a few studies have discussed attention as a function of workers' situation awareness in the construction domain, empirical evidence to test this hypothesis has not been concluded due to the absence of a reliable method for measuring attention. Among these studies, a seminal one by (Hasanzadeh et al., 2018) utilized eye-tracking mobile devices to present a real construction site-based experiment

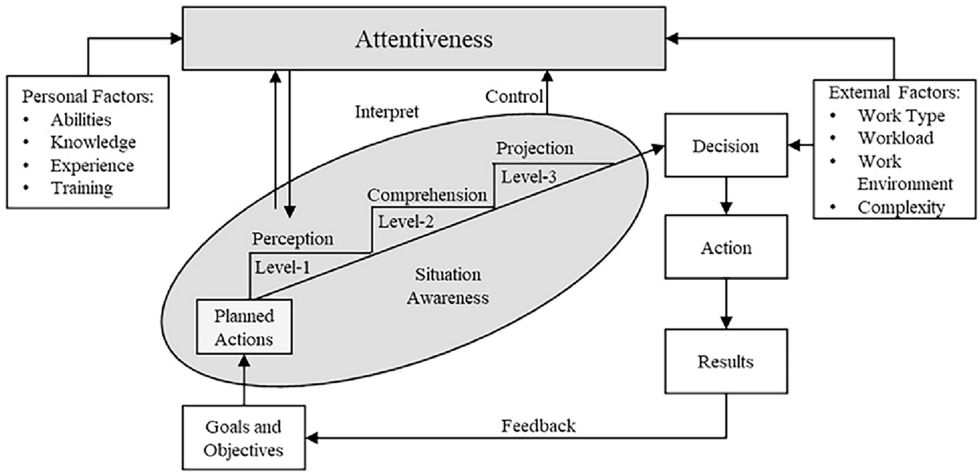

Fig. 1. Role of attentiveness in situation awareness (an extended model from Endsley's theory) (Endsley, 1995a).

under tripping hazards. In another study, eye movement, measured through visual scanning, directly measured human attentional behavior (Li et al., 2022). However, these techniques are not practically feasible under high-impact hazards, such as struck-by, as they pose safety limitations for subjects. Fortunately, advancements in VR technologies have led to the development of new head-mounted displays with eye-tracking features. Thus, eye-tracking technology when used in combination with VR can provide a continuous measure of attentiveness and, thus, provide a better way of assessing situation awareness metrics sequentially. A detailed discussion about the various means of evaluating situation awareness and using VR for measuring workers' attentiveness under the auspices of literature has been presented in the next section.

2.2. Measuring situation awareness and attentiveness

The accurate measurement of situation awareness levels in specific contexts is challenging. Choi et al., (2020) divided the methods in the literature for situation awareness assessment into three categories: situation awareness investigation based on past accident scenarios; the direct system of performance-based measures, and the use of simulated environments via direct experimental techniques (Endsley, 2017a; Jones and Endsley, 1996). Post-accident and performance measurement techniques can be either self-rating or observer-rating under real-world contexts. The limitations of these measurement methods stem from various factors, such as subjectivity and the potential inability to capture comprehensive situation awareness (Choi et al., 2020; Endsley, 2017a). While variables and conditions can be controlled when measuring situation awareness in a simulated environment, the opportunity to undertake testing in a safe and low risk setting, the ability to repeat measurements, and the potential for realizing cost-effectiveness may not be possible or practical in a real-world setting.

In cognitive science, situation awareness is typically assessed using either subjective or objective measures. Subjective measures can offer insights into workers' individual experiences of situation awareness. However, these measures have been identified to be quite sensitive to many potential factors, such as self-perception and memory biases. On the other hand, objective measures involve collecting data on a person's behavior or performance in a real-world or simulated environment to acquire an objective assessment of their situation awareness. Salmon et al., (2006) suggested that the available situation awareness measurement techniques are inadequate for performing assessments in dynamic environments. However, a combination of different techniques i.e., multiple-measure approaches, can prove effective in comprehensively understanding workers' situation awareness.

The situation awareness global assessment technique (SAGAT), a systematic knowledge assessment technique also known as the freeze-probe technique, has been widely adopted in various application domains for accurately measuring situation awareness in simulated environments (Choi et al., 2020; Coolen et al., 2019; Zhang et al., 2020). In this technique, the simulation is paused at predetermined points and resumed as the experiment progresses. During an evaluation, workers are asked to complete the questionnaire and identify what their perspectives are based on their knowledge of the situation at each frozen moment (Endsley, 1995a, 1988). SAGAT is a valuable tool that can be adopted to measure construction workers' situation awareness in a controlled environment with struck-by risks, as it offers the following main advantages over post-trail and subjective measures: 1) covers all situation awareness assessment levels; 2) information can be objectively evaluated; and 3) worker's situation awareness immediately after experiencing a situation can be measured (Choi et al., 2020; Endsley, 1988; Salmon et al., 2006). SAGAT is a global measure to acquire workers' knowledge about situations, as it includes different levels for situation awareness measurement defined by Endsley's model of SA evaluation. Each level, with its definition and example, is presented in Table 1.

Since attentiveness is crucial to perceive the situation of the surrounding environment, visual attention plays a vital role in avoiding jobsite struck-by incidents in dynamic work environments (Ahn, 2021; Grégoire et al., 2022). To ensure a safe and timely response to potential hazards, workers must pay visual attention to perceived risks posed by hazards (Jeelani et al., 2018). The promising feature of VR is it creates simulated job sites that replicate real-world environments. This allows workers to practice and develop their skills in safe and controlled

Table 1
Summary of Situation Awareness (SA) levels extracted through Endsley's theory.

SA Levels	Definitions	Examples
Level 1 SA: Perception	To perceive the status, attributes, and dynamics of relevant elements in the environment.	A worker must be familiar with the struck-by hazard, its name, type, impact, and frequency.
Level 2 SA: Comprehension	To build a holistic picture of the situation based on knowledge and comprehending the significance of objects and events.	A worker must comprehend the situation by the location, direction, and time of the struck-by object.
Level 3 SA: Projection	To project the future course of actions of the elements in the environment, at least in the near term.	By their own motion and the relative movement of nearby objects, a worker can decide whether that object is likely to strike in the given manner.

settings. Researchers have widely accepted eye-tracking measurement methods using VR technology to assess workers' attentiveness in various domains, including construction (Fathy et al., 2023; Jeelani et al., 2018; Kim et al., 2022; Martinez-Marquez et al., 2021).

One of the novel approaches through which visual attention (eye-tracking data) can be evaluated is identifying attentional deficits to automate workers' personalized safety training (Jeelani et al., 2018). For instance, through the virtual simulation of accidents using VR, (Kim et al., 2022) assessed workers' eye movements by measuring where and for how long they were looking (fixation duration) at electric hazards. (Ahn, 2021) used fixation count to identify an attentiveness deficit in workers consistently ignoring road machinery at a road construction site, highlighting the potential risks associated with this hazard. Previous efforts to enhance construction hazard awareness have utilized eye-tracking technology, mainly for qualitative analyses such as studying visual paths or search strategies using heat maps or gaze plots (Zhu et al., 2022). However, there has been limited exploration of the quantitative aspect of eye-tracking, particularly in terms of extracting trends over time of being attentive toward specific situations by relative information of eye fixation. This study utilizes a VR-based inherent eye-tracking technique to evaluate the variation in workers' attentional behavior towards hazards in different struck-by situations.

When performing repetitive tasks in dynamic and complex environments, workers may struggle to maintain a constant level of SA due to "attention tunneling." This phenomenon causes them to focus too much on their task, resulting in decreased hazard scanning behavior around them (Bedny and Meister, 2010). Situation awareness as described by (Endsley, 1995a) is a not a simple construct but covers various variables involved in the workers' behavior, with particular attention to its cognitive elements. However, this ability of being attentive may vary depending on the type of task involved and hazard type. Workers may rely heavily on habitual responses, which can limit their awareness of relevant factors (Grégoire et al., 2022). In instances of unexpected events, workers must actively seek out and integrate new information for an accurate understanding of the situation (Endsley, 2017a). Similarly, in high-risk or complex operations, workers must anticipate future events and make proactive decisions based on incomplete or ambiguous information. Therefore, workers may face unique challenges in each hazard condition. By measuring Endsley's levels of SA (perception, comprehension, and projection) in different hazard conditions, a comprehensive understanding of how individuals and groups adapt to different types of challenges can be achieved.

It is crucial to note that attentiveness, a key aspect of situational awareness, assists workers in detecting and recognizing potential dangers (Liang et al., 2021), thereby enabling them to take necessary actions to prevent accidents. Therefore, measuring workers' awareness about situation combined with studying their visual attention provides an opportunity to identify workers at risk for struck-by accidents. Interestingly, despite its importance, no study has yet measured the influence of SA level on workers' attentiveness under hazardous conditions or how workers' attention varies at different SA levels. (Hasanzadeh et al., 2018) investigated how SA affects tripping-hazard detection at an actual construction site. However, it is not possible to perform experiments to simulate struck-by hazards and analyze SA due to the associated safety risks. Additionally, in the aforementioned study, the subjective measure of SA, was used and limited to self-report measures, which can be influenced by biases and inaccuracies, thus failing to provide a comprehensive picture of an individual's situation awareness.

These gaps motivated an investigation of interplay between attention and situation awareness, with the following research question: "Do construction workers with distinct SA levels deploy attention over time differently when exposed to different types of struck-by hazards?". This research delves deeper through a series of following targeted steps. The study begins by examining how SA levels vary with the type of struck-by hazard encountered, aiming to observe changes in critical SA levels for individuals in diverse hazardous scenarios. To further elucidate the temporal dynamics of attention, the study analyzes whether overall attention declines over time for all participants, regardless of their SA level. To explore these questions, we test the following two primary hypotheses:

> H1: There is no significant difference in attention allocation over time between workers with high and low SA when performing repetitive tasks.
>
> H2: Within the high SA group, there is no significant difference in attention allocation over time between participants exhibiting high levels of perception, comprehension, and projection.

Results from these tests uncover the correlation between visual attention and workers' SA levels, investigating whether improvement in distinct SA levels may influence attentiveness under various hazardous environments. Consequently, the theoretical findings of this study assess whether these enhancements can translate into sustained attention allocation over time. It is anticipated that these insights would aid construction practitioners to determine which construction workers are at greater risk and to develop effective techniques for increasing their attentiveness toward recognizing hazards, driving workers' SA, and decreasing the probability of human error.

3. Research methods

The objectives of this research were achieved through the following steps (Fig. 2). 1) A VR-based hazardous environment with the simulated scenario of the repetitive task was designed by incorporating the exposure of different struck-by hazards in an outdoor building construction work area. 2) The experiment was conducted in two modules to measure the participants' SA level and attentiveness over time. Both modules were reviewed by three construction safety managers and two professors from the construction engineering department. To replicate a close-to-real environment, the suggested modifications were introduced in the design and then validated again to proceed with the final experiment. 3) Data on the participants' situation awareness was collected during the experiment as they proceeded with the simulation using SAGAT in the first module. Next, the workers' attentiveness was measured in the second module by documenting their head/eye movement within the virtual environment while they performed a repetitive task. 4) The collected data was analyzed to discuss the results in detail.

The following sections explain the participant selection, development process, experimental procedures, data collection, and analysis.

3.1. Participant Selection

Thirty-four students (twenty-six males and eight females) were recruited from the construction and architecture departments of Chung-Ang university to participate in the formal experiment. In this study, achieving an adequate sample size was pivotal for robust data analysis. The determination of an optimal sample size involves various considerations, including the strength of relationships between variables, effect size, and data variability (Chander, 2017). Considering these variables alongside the high frequency of data collection, a sample size of 34 participants was established, ensuring a substantial number of observations. Additionally, a power analysis using G*Power version 3.1.9.4 (Kang, 2021) was conducted. This analysis affirmed the adequacy of our sample size for detecting a medium effect size at a significance level of $\alpha = 0.05$, further reinforcing the statistical robustness of our study.

The selection criteria for recruitment were the individuals' interest and knowledge of construction engineering. Students with a minimum of three years of construction education were allowed to participate in the experiment. Furthermore, to ensure familiarity with construction safety hazards and their interests, all the subjects were required to fill out a simple form for identifying hazards at construction job sites. All

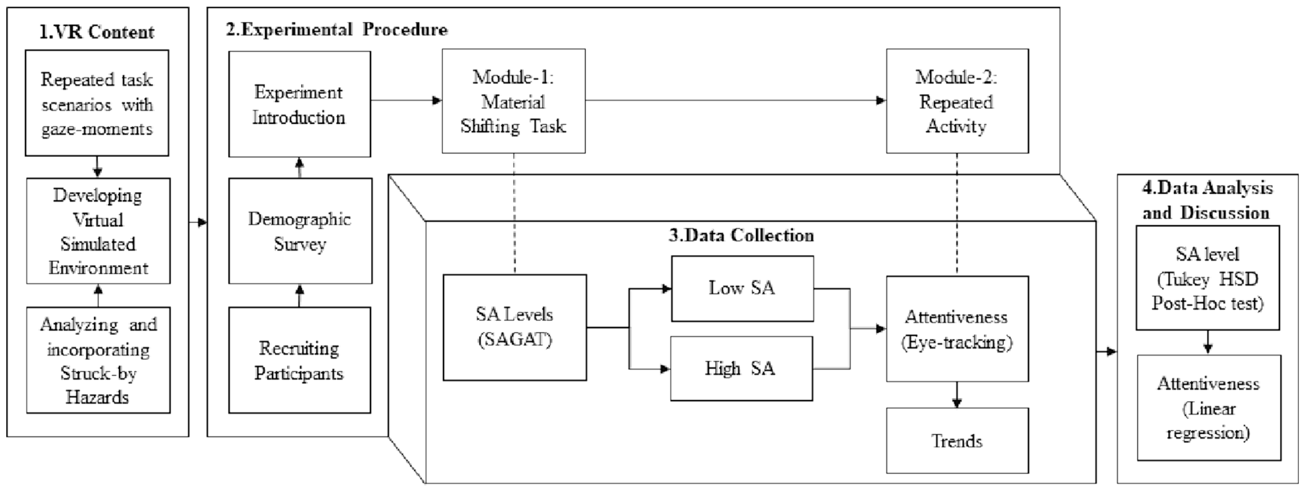

Fig. 2. Research method and experimental procedure.

participants provided written informed consent before participating in this study. None of the participants had any prior experience in the construction industry. However, all had previous experience with VR technology in different domains. As this study measured the participants' cognitive abilities and how they maintained SA during simulation, it was essential to familiarize them with the devices used in the experiment. Therefore, a small introductory session was added before the formal experiment to acquaint the participants with the HMD and the virtual environment. The detail description of demographics is shown in Table 2. The VR experimental laboratory setting, and the user's point-of-view perspective are shown in Fig. 4(a) and (b). A step-by-step procedure for both the experiment modules is presented in the following sub-sections.

3.2. *Virtual simulated environment and Scenario development*

A virtual experimental setting with multi-physical simulated objects was developed based on the struck-by accident reports extracted from OSHA's database for Fatality and Catastrophe Investigation Summaries (OSHA, n.d.) and the instructor guide of Construction Focus Four: Struck-by Hazards issued by the OSHA Directorate of Training and Education (OSHA, 2011). A total of 233 struck-by-accidents were identified in the last ten years using the advanced search option and the term "struck-by accident" as the keyword. The identified cases were analyzed based on the struck-by object type, as classified in the instructor guide (e.g., flying, swinging, rolling, and falling) to further examine the impact and frequency of the accidents. The study of these accident cases revealed the same finding as that of the Data Bulletin of the Center for Construction Research and Training (Brown et al., 2022)), which is that rolling objects (struck-by vehicles) contribute to a major proportion of fatal injuries among all the categories while both swinging and flying objects contribute to major injuries with a high occurrence rate.

Based on the analysis of accident cases associated with hazard type, the task of shifting the material from the origin to the assigned stock area was designed to proceed with the first module of the virtual experiment. Three simulated models (Fig. 3) for potential hazards associated with heavy construction equipment (1-excavator, 2-crane) and motor vehicle (3-truck) were added along the path of material shifting. Each model possessed different characteristics of struck-by hazards; for instance, the excavator as a swinging object, the crane as flying, and the truck as a rolling struck-by hazard. To enable the participants to work in an immersive setting, the operating sounds of the struck-by objects and different noises associated with the construction site were carefully simulated with different amplitudes and frequencies, similar to an actual work-site environment. The purpose of allocating hazards at various spots on the path was to investigate changes in workers' SA, as it can vary at different points and times during the simulation. The construction site layout and the path to be followed for material delivery in the first module are shown in Fig. 3.

In the next step, an outdoor construction area (close to the track) for the rolling object was selected to perform the task for module 2. This task was designed based on two of the accident cases from the OSHA accident database (OSHA, n.d.) as follows:

- *"An employee was walking through the yard. A semi-truck hit the employee. The employee was killed."* (OSHA, 2022a)
- *"An employee was walking outdoors between two warehouses when a coworker stuck the employee with a rolling object. The employee was pronounced dead."* (OSHA, 2022b)

Furthermore, to perceive the risk of workplace hazards, selective attention was required to ensure an appropriate response to a hazard (Jeelani et al., 2018), meaning that workers must pay visual attention to hazards to avoid accidents. Therefore, a random and continuous moment of rolling hazard, as a virtual model, was simulated on the track to document the participants' visual actions. Additionally, to engage the workers in the construction activity, the same task as that performed in module 1 of shifting material, was included for a short span of distance by crossing the track, as illustrated in Fig. 4. This way, a program to document the time and location of to-and-fro movements of the truck

Table 2
Demographic characteristics of the participants.

Demographic Factors	Number (n = 34)	Percentage (%)
Gender		
Male	26	76 %
Female	8	24 %
Age (Mean = 23.4 Years)		
20 – 24	15	44 %
25 – 29	12	35 %
30 – 34	5	15 %
> 35	2	6 %
Education Level		
Undergraduate	29	85 %
Graduate	5	15 %
Construction Education (Mean = 4.6 Years)		
3 – 5	29	85 %
5 – 10	3	9 %
>10	2	6 %
Familiarity with VR Technology (Scale 1–10)		
5 – 7	18	53 %
8 – 10	16	47 %

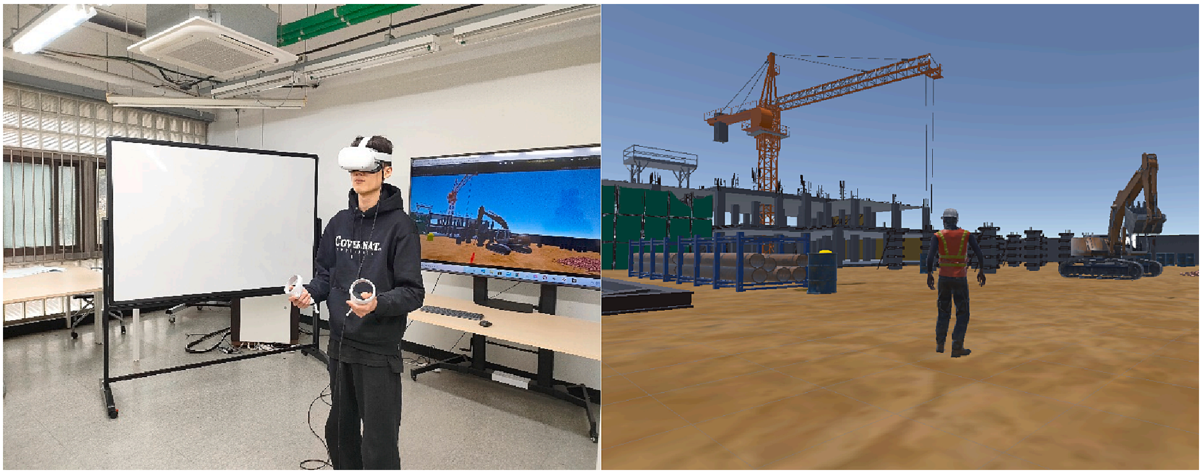

Fig. 3. (a) VR laboratory experimental settings and (b) user's point-of-view perspective showing struck-by hazards.

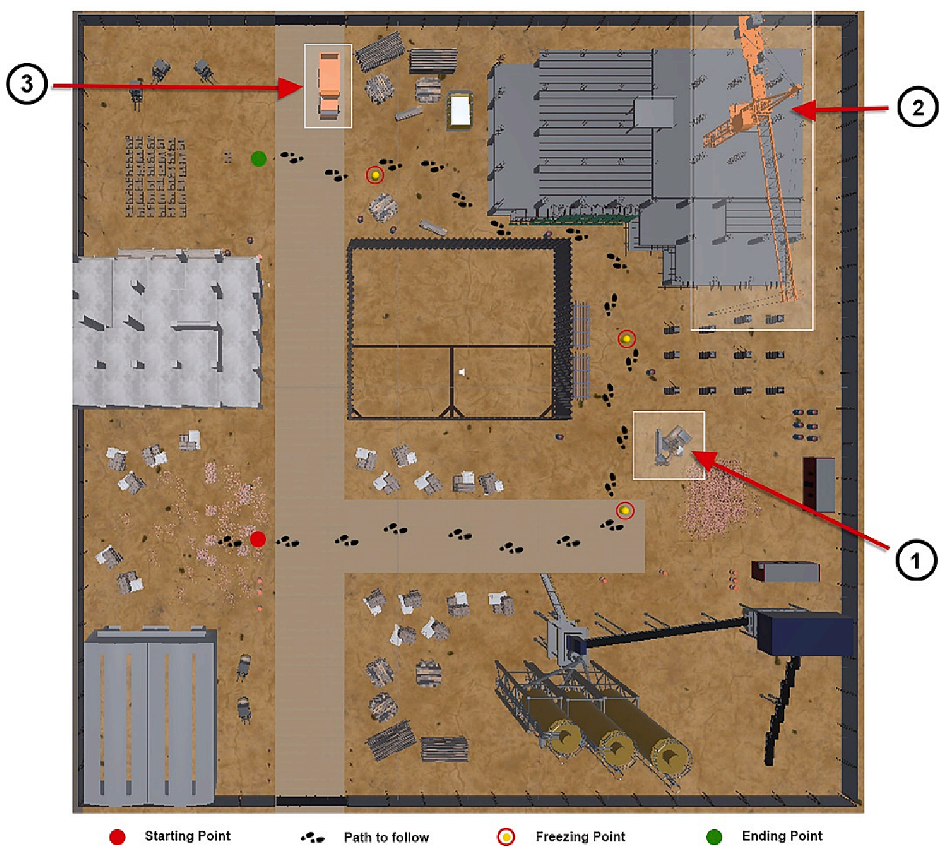

Fig. 4. Virtual construction site layout.

with respect to the workers' motions was incorporated into the simulation without interfering with the workers' task.

For developing the virtual construction site to effectively trigger workers' SA and attentiveness toward hazards, Unity 3D game engine (Version 2020.3) with C# - based scripting API was used. The virtual environment comprised different visual scenes and haptic feedback in terms of the participants' motions and sound effects. The environment was explicitly built to show the active outdoor building construction site with various tasks being performed simultaneously. Different material stocks and scattered tools were included at different locations on the ground to make it more real. All the 3D objects included in this experiment were either developed using 3D Studio Max (Version 2020) or acquired through commercially available models at the Unity Asset Store. To set up an experimental setting that would allow the collection of users' eye-tracking data and movements, Oculus Rift 2 was used as a VR head-mounted display (HMD) with the peak frequency of 45 Hz. A brief procedure for conducting the experiment and data collection is presented in the following section.

3.3. Experimental procedure and data collection

A pilot test was conducted involving laboratory members to validate the experimental design. Following this, the main study was structured into two distinct modules, details of which are outlined in the subsequent sections.

Module 1: Situation Awareness

The situation awareness global assessment technique (SAGAT), developed and validated by Endsley (Endsley, 2017b), was adopted for this module to assess the real-time SA of the participants. SAGAT is based on freeze-on-line probe techniques in which a simulated environment, employing a system of interest, is paused at a pre-defined number of times. At each pause, participants are asked different questions about the situation. In this context, the SA levels defined in Fig. 1 were utilized for assessing the participants' SA. Level 1 SA, called perception, pertains to whether the workers perceived any hazard in proximity. Comprehension, as level 2 SA, relates to whether the workers comprehended situations in which potential hazards when moved posed a threat, and the projection in level 3 SA relates to the workers' anticipation of whether there was any chance of being struck by a hazard.

The participants were asked to complete a material shifting activity in a VR environment, in an outdoor construction area along a pre-defined path, as shown in Fig. 5. The simulation was designed to pause automatically upon the participants' arrival at the designated area during the task, referred to as "freeze moments". The total task duration was approximately 09 min, with each freeze moment lasting around 125 s. Three freeze moments were introduced just when the participants reached the targeted hazard. At each moment, the participants had to remove the HMD to fill out the questionnaire. The series of questions was based on the principles of a systematic information requirement assessment technique called goal-directed task analysis (GDTA), which is a cognitive task analysis technique used to identify major goals and decisions that drive performance in hazardous situations (Nasser-Dine et al., 2021; Sharma et al., 2019). This technique was used to determine the best way to support the decision-making process of a particular role and assess an individual's SA in relation to the module's goal and the potential challenges that may arise during the simulation session.

During each freeze moment, participants were presented with an average of 18 to 20 questions. The questionnaire was divided into three sections, each corresponding to a different level of situational awareness (SA) at the hazard location. Participants were required to complete all three sections, which focused on SA Level 1 - Perception, SA Level 2 - Interpretation/Comprehension, and SA Level 3 - Projection.

In the first section of each hazard scenario, participants were asked about their immediate surroundings, including their position in relation to the hazard, the task they were performing, visibility of the hazard, impact of hazard movement, and the presence of other workers. The second level focused on workers' understanding of the hazard, assessing their awareness of its proximity, movement, potential hazards, impact on tasks, recognition of operator signals, adherence to safety guidelines, and awareness of safety equipment usage. The third level explored workers' ability to anticipate future actions, evaluating their capacity to predict the hazard's future location and movement, anticipate potential hazards, plan for contingencies, adjust tasks considering the hazard's movement, foresee the operator's next moves, and identify potential hazards related to the hazard's activity. To ensure that the questions were not redundant or repetitive, multiple variants were considered and presented in a randomized order for each situation. Fig. 5 displays a table showcasing the SAGAT questionnaire, highlighting the different SA levels and their respective objectives. Detailed questions used in the experiment can be found in Appendix A.

To evaluate participant performance, two different approaches were considered. First, the sum of scores gained in each section for all freeze moments was calculated. This provided an insight into how well participants performed in the context of specific SA levels across different situations. Second, the overall score obtained in all three sections for all freeze moments was combined to provide an overview of participants' overall SA performance in the whole experiment. By using both aspects, a more comprehensive understanding of participant performance in SA was obtained. The analysis of the SAGAT scores correlating with all three dimensions of SA levels at each hazard is presented in the Data Analysis and Results section in detail.

Module 2: Attentiveness

In this module, the participants were asked to perform the repetitive task of shifting material from the stock area to the construction site. The

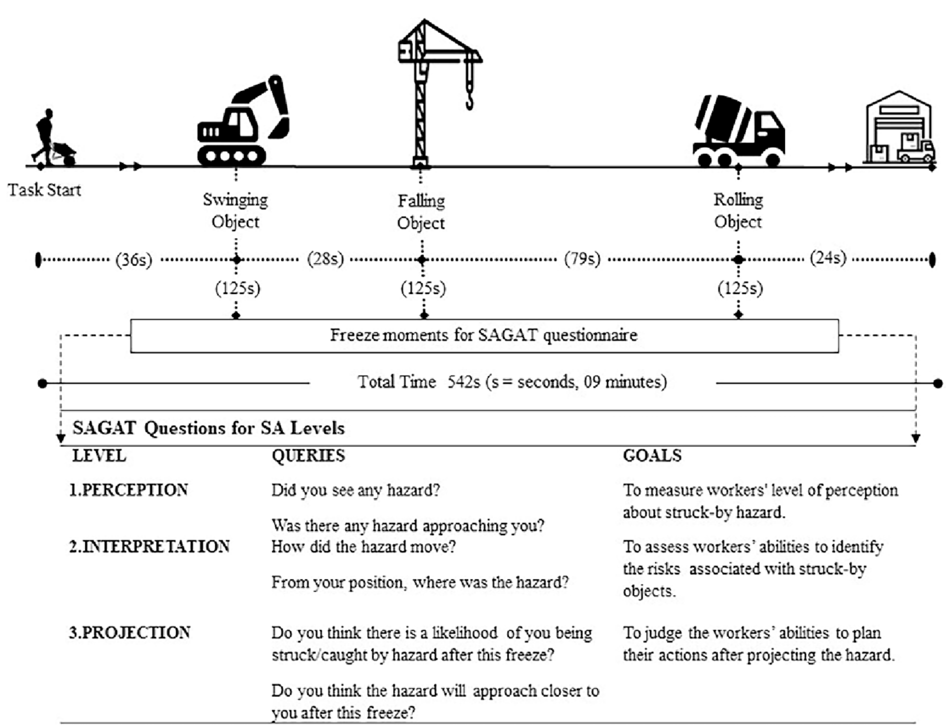

Fig. 5. Example of SAGAT questionnaire with freeze moments and task duration breakdown.

path length and location for this activity differed from the previous module. Workers tend to direct their attentional resources to the activity of shifting material and pay less attention toward construction hazards (Grégoire et al., 2022) while performing such assigned tasks. Therefore, the material shifting path was designed to cross a track twice per cycle, exposing the participants to the random movement of a truck (Fig. 6). Whenever a participant crossed the track, if they looked at the truck to check the proximity or distance from their own position, the system counted the number of sights and recorded the relative distance and time at each sight. Fig. 6 illustrates how the repetitive task was performed and the hazard exposure at the same time, highlighting the possible impact of repetitive tasks on hazard awareness.

To achieve this goal, the Unity ray-cast method was employed to capture data accurately during the simulations. This method operates by inputting an invisible ray and returning information about the collider it hits, including the distance between origin of ray and the collider. The ray-cast method facilitated the experiment by shooting a virtual ray from the participant's gaze direction in the 3D space and detecting if it hit the truck or not. At the same time, the programmed function in the Unity script enabled the system to document the collision time and location in terms of coordinates for both the participant and the truck. The distance between the participant and the object was calculated based on these locations. This data was auto-formatted in an individual comma-separated values file with columns of different fields for each participant. The combined file was further utilized to analyze the trend of visual attention toward the potential hazard over time for the overall population.

The developed system also simulated consequences when a participant was struck by the truck. The experiment was then discontinued instantly, and a new scene highlighting the end of the task was shown. To avoid potential bias, data from the participants who experienced an accident during their attempt was not included for further analysis. This decision was based on evidence from (Grégoire et al., 2022), who demonstrated that a prior accident could impact a participant's attention level. No additional opportunities were provided to these participants in the subsequent sessions. The detailed analysis of the combined effects of the total population in the experiment and its correlation with distinct SA groups is presented in the next section.

4. Data analysis and results

4.1. Level of SA at different struck-by hazards

To assess participants' abilities in maintaining situation awareness across various hazardous scenarios, data collected during Module 1 through the SAGAT was thoroughly examined. Initially, the accurate SAGAT scores for each level of situation awareness - Perception (SA1), Comprehension (SA2), and Projection (SA3) - were recorded and individually presented for each hazardous location, encompassing Swinging Object (Hazard 1), Falling Object (Hazard 2), and Rolling Object (Hazard 3). This breakdown of SAGAT scores at specific hazard locations offers valuable insights into the participants' proficiency in perceiving, comprehending, and projecting their awareness within various hazardous environments. Subsequently, a comprehensive summary was compiled, amalgamating the results of each SA level across all hazardous locations. This aggregated analysis across all hazard locations allows for a broader perspective on participants' overall situation awareness competencies.

The graph in Fig. 7 breakdown of SAGAT scores of each level at specific hazard. Perception level (SA1) shows that the mean score for the flying hazard was higher compared to the other two hazards, indicating that the participants better perceived the situation when facing the crane. The high score for the swinging hazard when measuring the comprehension level (SA2) suggests a better understanding of the situation among the participants compared to the other hazards. The projection level (SA3) had the highest mean score, demonstrating that the participants were better at predicting the outcome of the rolling hazard compared to the other hazards. When comparing the mean scores across the three SA levels, the graph indicates that the scores generally improved with an increase in the SA level.

In Fig. 8, the box-and-whisker plot visually captures the participants' performance across different Situation Awareness (SA) levels, providing valuable insights into their evolving abilities. Each Situation Awareness level (SA1, SA2, and SA3) represents distinct stages of participants' perceptual, comprehension, and projection skills. Upon meticulous analysis of the provided data, a clear and encouraging trend emerges. The median score for SA3 (0.67) stands notably higher than that of SA1 (0.33) and SA2 (0.50). This substantial difference highlights participants' notable difference in projection abilities, emphasizing their capacity to anticipate and plan for future situations effectively as compared to perception and comprehension. In other words, the box for

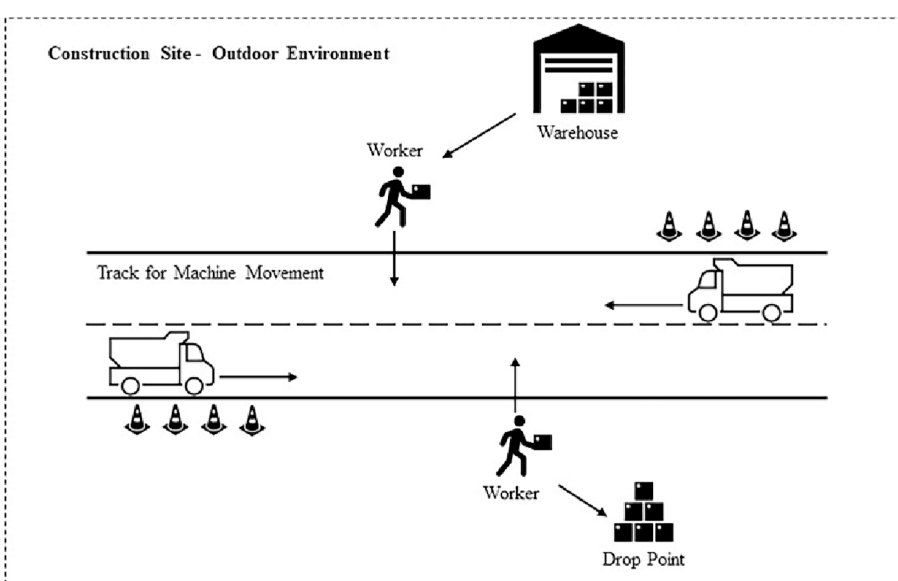

Fig. 6. Concept of repetitive task when exposed to a hazard for module 2.

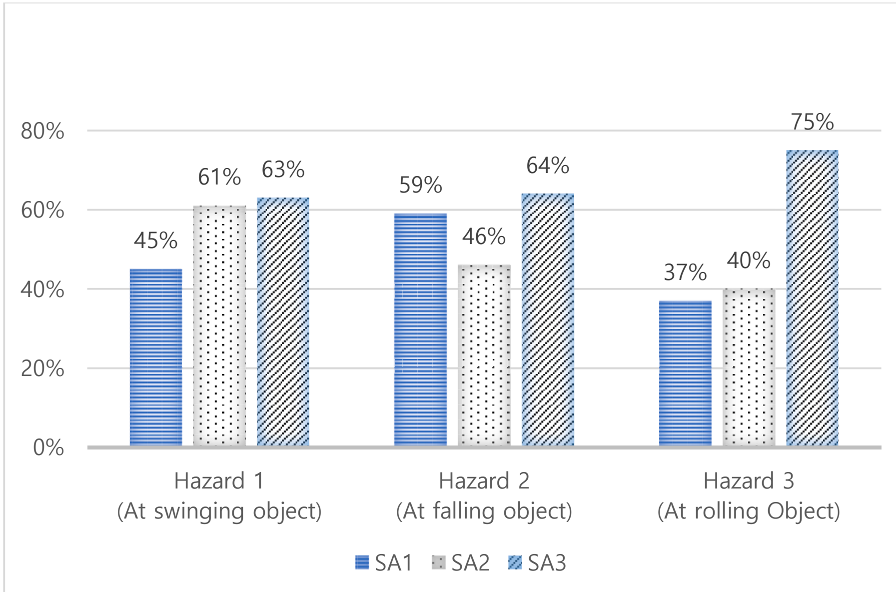

Fig. 7. Percentage of correct answers to queries at each hazardous situation.

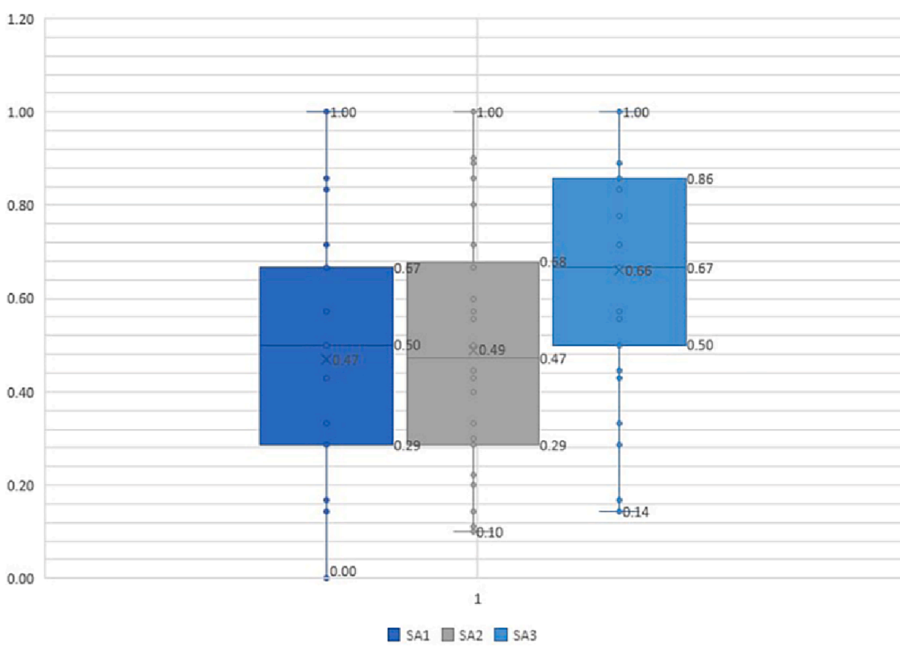

Fig. 8. Combined results at the situation awareness level.

SA3 is located higher up on the plot than the boxes for SA1 and SA2, suggesting that the participants' performance improved over time. Another interesting observation is the shift in the minimum score line, which suggests that even the lowest-scoring participants improved their abilities to some extent. This improvement in scores indicates that the participants become more familiar with the activity and develop a better understanding of how to identify, understand, and predict situations.

Analysis of Variance (ANOVA) is a statistical method used to compare means among multiple groups. It assesses whether there are any statistically significant differences between the means of three or more independent groups. ANOVA analyzes the variance within different groups to determine if the differences among group means are more than what would be expected by chance. In the context of our study, ANOVA is particularly useful as it allows us to compare the means of SAGAT scores across various hazardous situations. Specifically, a one-way ANOVA is utilized when there is one categorical independent variable with at least three levels and one dependent variable (Abu Aisheh et al., 2022; Gillard, 2020). Therefore, One-way ANOVA was adopted to test for significant differences in mean SAGAT scores between the various struck-by hazard conditions encountered during the experiment. IBM SPSS Statistics program version 26 was used to perform statistical tests, as its reliability has been credited by researchers (Čaplová and Švábová, 2020). The results of the one-way ANOVA (Table 3) indicate a significant difference in the mean values of the subject's SA levels across the three struck-by-hazard groups, meaning that the subjects' SA levels did not remain consistent in all situations. The significance level for all three levels was below the probability value (0.05), indicating that there was a statistically significant difference in the mean values between the groups. Additionally, the F-value for each SA level indicates the relationship between the within-group and between-group variance. The F-

Table 3
One-Way ANOVA.

		Sum of Squares	DF	Mean Square	F	Sig.
SA level 1	Between groups	.825	2	.412	7.085	.001
	Within groups	5.762	99	.058		
	Total	6.586	101			
SA level 2	Between groups	.740	2	.370	5.937	.004
	Within groups	6.167	99	.062		
	Total	6.907	101			
SA level 3	Between groups	510	2	.255	5.155	.007
	Within groups	4.896	99	.049		
	Total	5.406	101			

*Sig = Significant Difference, DF = Degree of freedom.

critical value, calculated using an alpha level of 0.05 with the given degrees of freedom, was 3.14. The F-value being higher than the F-critical value led to the rejection of the null hypothesis for all groups.

For multiple comparisons of data differences among the groups for each SA level, Tukey's honestly significant difference post-hoc test was conducted using the results from the ANOVA test. This method allows the comparison of various pairs of mean values to identify the significant differences within and between the groups (Shafique and Rafiq, 2019). To identify which specific pairs of groups were significantly different from each other, the output from the post-hoc test is illustrated in Table 4.

A detailed examination of the data indicates that based on the subjects' perceptions about the situation (SA level 1), there was a statistically significant mean difference of 0.217 ($p = 0.001 < 0.05$) between the swinging and flying hazard groups. This suggests that the participants perceived the situation well enough when they were exposed to the swinging hazard compared to when they were exposed to the flying hazard. Similarly, for SA level 2, the p-value ($p = 0.003 < 0.05$) between groups experiencing the swinging and rolling hazards implies that the participants were more conscious at the location of the excavator compared to their level of awareness of the truck. Moreover, to predict the future events from the situation, SA level 3, with the mean difference of 0.168 ($p = 0.007 < 0.05$) between the swinging and rolling hazards, indicates that the participants projected the situation more accurately when exposed to the excavator compared to the truck. On the other hand, there was no statistically significant difference in the mean values of the dependent variable between the rolling and flying hazards for all three SA levels ($p > 0.05$). This implies that the type of hazard did not significantly affect the participants' SA when it came to both the rolling and flying struck-by hazard groups.

4.2. Attentiveness during repetitive tasks

Regression analysis was employed in two stages to investigate the deployment of attention over time. First, the overall trend was determined using the bivariate linear regression. This model suggested the best-fit regression line for the relative distance at which the subject looked at the object within the span of exposure time. Second, to test the primary hypothesis, that the subjects' SA level during the first module altered their attentiveness in the second module, multivariate regression models were adopted. Initially, the raw data were preprocessed by normalizing the range of distances for all the participants to eliminate any individual differences using the following equation:

$$x\_normalized = (x - \min(x))/(\max(x) - \min(x))$$

where x is the distance between the participant and the object, at which participants check the proximity of object from their own position, min(x) is the minimum value, and max(x) is the maximum value of the distance. The normalized value x_normalized lies in the range between 0 and 1. Next, the exposure time when the participant looked at the object was used as the second variable for data processing. The fixation duration was marked as 200 ms (Kim et al., 2022), and only those readings when the participants gazed at the object for more than 200 ms were incorporated into the data to gather precise results. For the first stage, the regression model was constructed as follows:

$$\hat{y}_{ij} = \beta_0 + \beta_1 T_{ij} + \varepsilon_{ij}$$

where $\hat{y}_{ij}$ is the predicted value for the jth observation of the normalized distance (dependent variable) of the ith participant, β_0 is the intercept or first value when time = 0, β_1 is the slope of the regression line showing the change in $\hat{y}_{ij}$ for each increment in time unit, T_{ij} is the value of the independent variable (time) for participant i at observation j, and ε_{ij} is the error representing the difference between the observed and predicted values.

The standard libraries of Python programming language were

Table 4
Multiple Comparisons- Tukey Honestly Significant Difference.

Multiple Comparisons- Tukey Honestly Significant Difference Dependent variable	(i) Hazard type	(j) Hazard type	Mean difference (i-j)	Std. error	Sig.	% confidence interval Lower bound	Upper bound
SA level 1	A	B	-.13647	.05851	.056	-.2757	.0028
		C	.08147	.05851	.349	-.0578	.2207
	B	A	.13647	.05851	.056	-.0028	.2757
		C	.21794*	.05851	.001	.0787	.3572
	C	A	-.08147	.05851	.349	-.2207	.0578
		B	-.21794*	.05851	.001	-.3572	-.0787
SA level 2	A	B	.14412*	.06053	.050	.0001	.2882
		C	.20265*	.06053	.003	.0586	.3467
	B	A	-.14412*	.06053	.050	-.2882	-.0001
		C	.05853	.06053	.599	-.0855	.2026
	C	A	-.20265*	.06053	.003	-.3467	-.0586
		B	-.05853	.06053	.599	-.2026	.0855
SA level 3	A	B	-.04971	.05394	.628	-.1780	.0786
		C	-.16853*	.05394	.007	-.2969	-.0402
	B	A	.04971	.05394	.628	-.0786	.1780
		C	-.11882	.05394	.076	-.2472	.0095
	C	A	.16853*	.05394	.007	.0402	.2969
		B	.11882	.05394	.076	-.0095	.2472

A = Rolling Hazard, B = Flying Hazard, C = Swinging Hazard.
* . The mean difference is significant at the 0.05 level.

utilized to perform regression analysis based on the equations and to visualize the outcomes. The trend of being attentive toward hazard over time for all participants was analyzed as shown in Fig. 9, and the results indicate that the models were significant for the first stage with R-square (R^2) = 0.096, mean squared error (MSE) = 0.06, and $p < 0.001$. It's worth noting that, in the context of our study, the R^2 value of 0.096, though seemingly modest, can be meaningful. As highlighted by (Sapra, 2014) and (HU, 2018), a model with a R^2 value closer to one may not always reflect a true relationship, emphasizing the importance of interpreting R^2 values with caution. The value of β_1 was below zero (negative), which suggests that the trend of the participants' attention toward hazardous objects declined during the short span of the experiment. This result indicates that the tendency to check the proximity of the hazard was high at the start of the experiment. However, the gaze count relative to the distance was found to be low at the end of the session, which means that the participants showed a decrease in their state of vigilance with the passage of time.

In order to examine the potential impact of participants' SAGAT scores on their level of attentiveness, we implemented a categorization approach for the total participants. This involved segregating participants into two distinct groups (low and high) based on whether their SAGAT score fell below or above the average. The decision to categorize participants using a mean split is supported by established academic research. For instance, Jiang et al. (2021) in their evaluation of pilots' situation awareness, categorized pilots into high and low situation awareness groups based on subjective score division to facilitate the analysis. Similarly, (Hasanzadeh et al., 2018) employed this technique to examine the relationship between workers' visual activities and situation awareness, to delineate their sample into comparable groups. Furthermore, Grégoire et al. (2022) utilized a similar division to introduce an independent variable in their virtual reality-based experiments, differentiating participants based on their experience of virtual accidents. This categorization was deemed essential for our analysis of attentiveness levels in relation to their comprehension, as assessed in module 1. Consequently, the SAGAT score was introduced as a categorical variable (Si) and dummy coded as 0 for low situation awareness and 1 for high situation awareness, using the following multivariate regression equation:

$$\hat{y}_i = \beta_0 + \beta_1 T_i + \beta_2 S_i + \beta_3 T_i S_i + \varepsilon_i$$

where $\hat{y}_i$ is the estimated value of the normalized distance at time T_i for participant i, β_0 is the intercept, and the coefficients β_1 and β_2 represent changes in the expected value of $\hat{y}$ for a unit increase in T_i and S_i, respectively. β_3 is the coefficient for the interaction of T_iS_i in comparison with the high SA group (S = 1) and low SA group (S = 0). From the results of the regression analysis, hypothesis **H1** was rejected, indicating that the model was significant between the high (R^2 = 0.075, MSE = 0.06, β_0 = 0.41, and $p < 0.001$) and low (R^2 = 0.12, MSE = 0.06, β_0 = 0.45, and $p < 0.001$) SA groups, although the trend of the line for both groups was declining. However, the high SA group maintained the level of attentiveness over a prolonged period of time, while the performance of the low SA group continuously decreased during the experiment. The graph comparing the trends of both groups is shown in Fig. 10.

To compare workers' attention in accordance with the SA levels defined in Endsley's theory (Table 1), as measured by the SAGAT, the variable Si was dummy coded with level 1 representing perception (SA1), level 2 representing comprehension (SA2), and level 3 representing projection (SA3). Within each SA level, participants were further categorized based on their scores in module 1. This decision of splitting the population by their subsequent SA levels and module 1 performance is aligned with the approach used by (Choi et al., 2020). Regression lines were established for each case using the following equation:

$$\hat{y}_i = \beta_0 + \beta_1 T_i + \beta_2 SA1_i + \beta_3 SA2_i + \beta_4 SA3_i + \varepsilon_i$$

Here, $\hat{y}_i$ the normalized distance at a specific time T_i. The term β_0 denotes the intercept of the regression equation, representing the value of $\hat{y_i}$ when all predictor variables are zero. β_1 represents the coefficient associated with the continuous variable T_i, indicating the change in $\hat{y_i}$ for a unit change in time. Additionally, β_2, β_3 and β_4 are coefficients corresponding to the binary variables $SA1_i$, $SA2_i$, and $SA3_i$ respectively. These coefficients signify the change in $\hat{y_i}$ when the corresponding categorical variable changes from 0 to 1, assuming all other variables remain constant.

The graph comparing the trends of these three distinct levels is shown in Fig. 11. The variations in regression lines for the distinct SA level were not aligned with the research hypothesis **H2**, which posits that there is no significant difference in attention allocation over time between participants exhibiting high levels of perception, comprehension, and projection. Overall, each group exhibited the same declining trend of inspecting the hazard distance throughout the experiment. However, a sharp decline in the regression line of the SA1 group was observed, indicating that although the group perceived the hazards accurately, they became acclimatized to it over time. In contrast, the intercept value for the group that scored high in SA2 and SA3 was similar (β_0 = 0.41), meaning that both groups paid similar attention toward hazards at the start, with the SA3 group showing more attentive behavior at the end. The SA2 group showed a slight decline compared to SA1, which reveals that the participants who fully comprehended their immediate environment were more conscious of the hazards than those who only perceived the situation. Overall, the SA3 group, with a high ability to project the situation, performed well compared to the other groups.

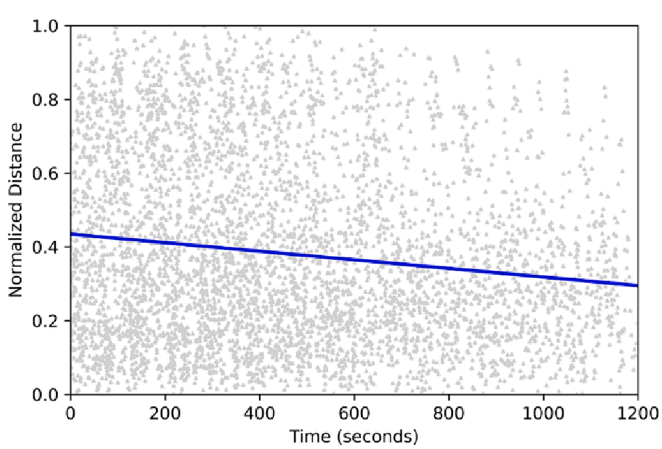

Fig. 9. Trend of being attentive toward hazard over time for all participants.

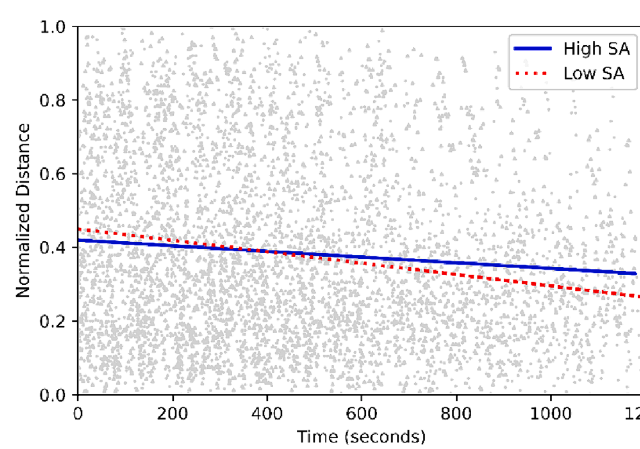

Fig. 10. Comparing trends between high/low SA groups.

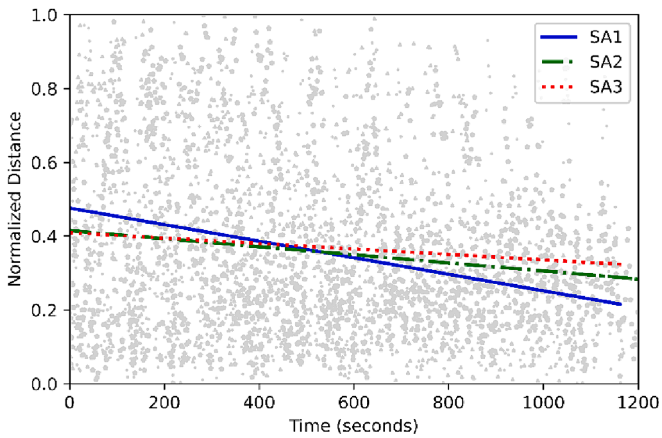

Fig. 11. Comparing trends among groups who secured a high score in each SA Level.

5. Discussion

This study aimed to explore the relationship between workers' situation awareness (SA), attentiveness, and the impact of struck-by hazardous situations on their levels of attentiveness. The findings showed that workers' attentiveness varied depending on their SA levels and the type of hazardous condition they were exposed to. This analysis shows that workers with high SA levels were more attentive to hazards, while workers with low SA levels were at risk when performing repetitive activities under struck-by hazards. Although good hazard perception is typically considered an important indicator of attentiveness, the study found that this was not always the case due to the repetitive nature of the task being performed. This attention narrowing phenomenon, which can result in a reduction of SA, has been documented in various aspects of construction tasks (Choi et al., 2020). The workers who accurately predicted situations were able to use their maximum attentional resources towards specific hazards. The analysis results emphasize the importance of considering specific workers' SA levels to maximize attention towards hazards. Understanding the relationship between SA and attentiveness can provide valuable insights into improving safety in different struck-by hazardous situations.

Measuring SA by Endsley's theory in levels and comparing the levels of SA across different hazards can provide valuable insights for the development of targeted interventions to improve safety. Specifically, by measuring SA at different hazards, it is possible to identify the specific SA level that is most important for individual workers in different hazardous situations. The results of the experiment indicate that the type of struck-by hazard can impact a worker's SA. For instance, the multiple comparison in this study indicates that the hazards involving falling objects require greater perception skills, while hazards involving swinging objects may require more advanced SA level 3-Projection. Thus, by comparing SA levels across different hazards, it is possible to identify the hazards that pose the greatest risk to worker safety in a particular environment. This information can be used to prioritize safety interventions and allocate resources more effectively.

Consequently, this approach will help to identify areas where additional training may be needed to improve specific SA levels after evaluating workers' abilities in the specific context of hazardous situations. For instance, the findings recommend that workers with good SA for levels 1 and 2 should engage in special training sessions for level, as they showed less attentiveness compared to the SA 3 group. Although perception (SA 1) of a situation is essential, a wrong interpretation of the current situation (SA 2) or projection (SA3) of a situation can result in a serious accident if the worker does not pay full attention to the situation. This information can ultimately help practitioners enhance safety, efficiency, and effectiveness in a variety of contexts by identifying targeted interventions that can be developed to enhance worker safety in specific hazardous situations.

This research has the potential to drive progress and improve outcomes in both academic and practical domains. Academically, it offers a novel addition to the body of construction knowledge by providing valuable insights into the relationship between SA and attentiveness, which has not been widely explored. The combination of contextual data and physical actions with the incorporation of advance tools provides a unique data analysis practice for researchers (Wolf et al., 2022). For instance, the use of a questionnaire (context-based) and eye-tracking (physical patterns) data using VR tools supports the current study to acquire its research objectives. These methods can be applied in future studies related to cognitive ergonomics, helping us better understand the root causes of construction accidents.

From a practical perspective, the insights gained from this study can be applied to improve the safety of workers in the construction industry. Gaining a holistic understanding of the comprehensive link between SA and different constructs (e.g., attentiveness) can help safety practitioners classify workers who are at high risk. It can also enable them to develop targeted safety interventions for at-risk workers, thus helping mitigate the risk of accidents at job sites and enhance overall safety in the construction industry. The presented experiment modules can offer direct aid for workers to overcome the limitations of their attention span and maintain their vigilance toward hazards. For example, the rehearsal of selecting safe training methods and utilizing maximum attentional resources to perform an activity can make workers more vigilant toward hazards (Grégoire et al., 2022). Moreover, occupational health and safety organizations can use the visions of current research to design training scenarios and develop robust tools and techniques to address noteworthy issues associated with workers' behavior.

There are a few limitations associated with this study, which can be addressed by future research. The Unity engine's ray-cast method was employed to trigger objects for the experiments. This might have resulted in reduced precision and accuracy compared to a dedicated eye-tracking system. This limitation can be addressed through further in-depth programming and development in C-sharp to accurately interpret and track participants' gaze direction. Furthermore, it should be noted that the eye-tracking system adopted in this research only measured the participants' visual attention by monitoring the movement of their foveal (central) vision. Consequently, behaviors involving the examination of exposed hazards using peripheral vision were not captured in this study. Regression techniques can be used for both trend and prediction analysis (Fox, 2015). The Results of this study were used for computing only the trends of inspecting the hazard distance over time, which was the primary objective of this analysis. As (Sapra, 2014), mentioned in their study that the R-squared value near zero does not indicate that variables are not related. It only means that the linear relationship between the two variables is modest. Therefore, inferring the relationship between a significant independent variable and the dependent variable is still possible. In contrast, predictive analysis needs goodness-to-fit models with a high value of coefficient of determination (close to 1). Despite the low R-squared value in the regression model, the results suggest a significant proportion of variance ($p < 0.001$) in the dependent variable (normalized distance) is explained by the predictor variable (time) (HU, 2018; Kutner et al., 2005). Attentiveness was computed based on the number of observations to inspect the distance from the hazard. As a result, the R-square and adjusted R-square values are equivalent in this context. Other relevant variables that may influence the targeted construct can be added in future studies to generate more accurate regression models for predictions.

An alternative way of approaching the issue of reduced attentiveness and SA under varying hazardous conditions is to explore additional safety interventions aimed at reducing the safety risks that result from diminished attention and SA. One potential intervention is the use of automation and monitoring technologies to supplement worker safety performance. For example, (Anjum et al., 2022; Khan et al., 2022a) utilized automated computer vision-based techniques to prevent falls from heights. In the context of enhancing workers' attentiveness and situation awareness, different alert systems and intrusion areas could be introduced at each hazardous object and location (Khan et al., 2022b). However, real-time monitoring via live cameras may require more precision and technological measures that are not easily accessible in all hazardous situations. A further investigation would be needed to determine cost-effective and easy-to-use solutions that help workers to maintain their attentiveness and SA in dynamic hazardous situations at construction jobsites.

6. Conclusion

Construction workers' repetitive tasks can decrease attentiveness towards potential hazards, and their level of situation awareness (SA) can also affect this decline as SA involves perceiving, comprehending, and projecting future events in the environment. Despite its crucial significance in construction safety, the relationship between SA and attentiveness is often understudied. This research offers novel insights into the relationship between SA and attentiveness in the construction industry, using a unique combination of contextual data and physical actions. To achieve the research objectives, VR based eye-tracking technology with a blend of objective and subjective evaluation methods were utilized. It was discovered that as workers progressed in performing their tasks, their capacity to identify, understand, and predict hazardous situations improved. Workers with higher SA levels tended to exhibit greater attention toward hazards over prolonged periods while performing repetitive tasks when randomly exposed to struck-by hazards. The findings also indicate that a good identification of hazards does not necessarily equate to a high level of attentiveness. SA levels can play a significant role in shaping attentiveness and, thus, significantly enhance workers' safety behavior, resulting in reduced risks of struck-by accidents.

Future studies can deal with further perspectives of this study by utilizing dedicated eye-tracking systems for precise measurement of visual attention and incorporating additional variables into regression models to improve predictive ability. Additionally, researchers can further utilize deep computer programs to enable more accurate interpretation and tracking of participants' gaze direction, contributing to a more comprehensive understanding of eye movements during hazard inspection. Nonetheless, the study contributes to the body of construction knowledge and provides data analysis practices that can be used in future studies related to cognitive ergonomics. Furthermore, the study's insights can be applied to improve the safety of workers in the construction industry by identifying at-risk workers, developing targeted safety interventions, and enhancing overall safety outcomes.

The outcomes of this study open a vast realm of possibilities for further research in this area. For instance, the proposed approach can be extended to other high-risk construction trades to assess workers' safety behavior and determine different angles through which SA can be analyzed, including its relationship with other variables. For example, scaffolders are constantly exposed to fall hazards when undertaking repetitive tasks. The impact of individual differences, such as prior experience, age, gender, site conditions, and cognitive abilities, on workers' attentional behavior at the workplace can be examined. Moreover, the integration of physiological responses with physical responses in VR environments presents a promising avenue for advanced research, which could provide a comprehensive understanding of workers' attentional behavior in high-risk construction environments and inform the development of effective safety management strategies. Furthermore, it would be beneficial to investigate the long-term effects of training and exposure to hazards on workers' SA and attentiveness to hazards in construction environments. These future research avenues could greatly enhance the understanding of the relationship between SA and attention in construction work and apprise the development of effective safety management strategies.

CRediT authorship contribution statement

Rahat Hussain: Writing – original draft, Software, Methodology, Conceptualization. **Syed Farhan Alam Zaidi:** Visualization, Validation, Software, Formal analysis, Data curation. **Akeem Pedro:** Writing – review & editing, Investigation, Conceptualization. **Heejae Lee:** Visualization, Software, Resources. **Chansik Park:** Writing – review & editing, Supervision, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

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Appendix A

Hazard 1: Excavator Scenario		
Level 1: Perception		
1.1	Where are you currently located in relation to the excavator?	a. In front of excavator***b. Behind excavator***c. To the right of excavator***d. To the left of excavator
1.2	Can you see the excavator from your current location?	a. Digging a trench.***b. Laying pipes.***c. lifting a load.***d. Other
1.3	What task the excavator is currently doing?	a. Yes***b. No
1.4	Is the excavator's movement impacting your task?	a. Yes***b. No***c. Not sure
1.5	What is the excavator's current activity?	a. Digging***b. Moving dirt.***c. Lifting a load.***d. Other
1.6	Are there any other workers in the vicinity of the excavator?	a. Yes***b. No***c. Not sure
Level 2: Comprehension		
1.1	Are you aware of the excavator's proximity to your task area?	a. Yes***b. No***c. Not sure
1.2	Are you aware of the excavator's movement and direction?	a. Yes***b. No***c. Not sure

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(*continued*)

Hazard 1: Excavator Scenario		
1.3	Are you aware of any potential hazards related to the excavator's proximity?	a. Yes***b. No***c. Not sure
1.4	Have you assessed the impact of the excavator's movement on your task?	a. Yes***b. No***c. Not sure
1.5	Are you aware of the excavator operator's signals or communication?	a. Yes***b. No***c. Not sure
1.6	Are you aware of any posted safety guidelines related to the excavator?	a. Yes***b. No***c. Not sure
1.7	Are you aware of any safety equipment or devices that are being used in relation to the excavator?	a. Yes***b. No***c. Not sure
Level 3: Projection		
1.1	Are you able to predict the excavator's future location and movement?	a. Yes***b. No***c. Not sure
1.2	Are you able to anticipate any potential hazards related to the excavator's proximity?	a. Yes***b. No***c. Not sure
1.3	Have you planned for contingencies related to the excavator's movement?	a. Yes***b. No***c. Not sure
1.4	Are you able to predict the excavator operator's next move?	a. Yes***b. No***c. Not sure
1.5	Have you identified any potential hazards related to the excavator's activity?	a. Yes***b. No***c. Not sure
1.6	Can you tackle the potential hazards with the excavator?	a. Yes***b. No***c. Not sure
Hazard 2: Crane Scenario		
Level 1: Perception		
1.1	Where are you currently located in relation to the crane?	a. In front of crane***b. Behind crane***c. To the right of crane***d. To the left of crane
1.2	What task are you currently completing?	a. Lifting a load***b. Building a wall***c. Welding***d. Other (please specify)
1.3	Can you see the crane from your current location?	a. Yes***b. No
1.4	Is the crane's movement impacting your task?	a. Yes***b. No***c. Not sure
1.5	What is the crane's current activity?	a. Lifting a load***b. Moving horizontally***c. Lowering a load***d. Other (please specify)
1.6	Are there any other workers in the vicinity of the crane?	a. Yes***b. No***c. Not sure
Level 2: Comprehension		
1.1	Have you identified the crane's proximity to your task area?	a. Yes***b. No***c. Not sure***d. N/A
1.2	How close is the crane to your task area?	a. Within 5 feet***b. Within 10 feet***c. More than 10 feet***d. Not sure
1.3	Have you determined the crane's movement and direction?	a. Yes***b. No***c. Not sure***d. N/A
1.4	Have you recognized any potential hazards related to the crane's proximity?	a. Yes***b. No***c. Not sure***d. N/A
1.5	Have you evaluated the impact of the crane's movement on your task?	a. Yes***b. No***c. Not sure***d. N/A
1.6	Have you been informed of the crane operator's signals or communication?	a. Yes***b. No***c. Not sure***d. N/A
1.7	Have you been familiarized with any posted safety guidelines related to the crane?	a. Yes***b. No***c. Not sure***d. N/A
1.8	Have you been briefed about any safety equipment or devices that are being used in relation to the crane?	a. Yes***b. No***c. Not sure***d. N/A
Level 3: Projection		
1.1	How confident are you in predicting the crane's future location and movement?	a. Very confident***b. Somewhat confident***c. Not confident***d. Not sure
1.2	How familiar are you with any potential hazards related to the crane's proximity?	a. Very familiar***b. Somewhat familiar***c. Not familiar***d. Not sure
1.3	Have you taken any steps to plan for contingencies related to the crane's movement?	a. Yes, I have taken steps.***b. No, I haven't taken steps.***c. Not sure
1.4	How able are you to adjust your task to accommodate the crane's movement?	a. Very able***b. Somewhat able***c. Not able***d. Not sure
1.5	How confident are you in predicting the crane operator's next move?	a. Very confident***b. Somewhat confident***c. Not confident***d. Not sure
1.6	How familiar are you with any potential hazards related to the crane's activity?	a. Very familiar***b. Somewhat familiar***c. Not familiar***d. Not sure
1.7	Can you tackle the potential hazards with the crane?	a. Yes***b. No***c. Not sure***d. N/A
Hazard 3: Truck Scenario		
Level 1: Perception		
1.1	What is the current location of the truck in relation to your Location?	a. In front of truck***b. Behind truck***c. To the right of truck***d. To the left of truck
1.2	What is the truck's current activity?	a. Loading***b. Moving***c. Unloading***d. Other (please specify)
1.3	Are there any other workers in the vicinity of the truck?	a. Yes***b. No***c. Not sure
1.4	Are there any blind spots on the truck that could impact your task?	a. Yes***b. No***c. Not sure
1.5	Are there any warning lights or signals on the truck that you should be aware of?	a. Yes***b. No***c. Not sure
1.6	Are there other potential hazards in surrounding related to truck movement?	a. Yes***b. No***c. Not sure
1.7	Is the truck's load properly secured?	a. Yes***b. No***c. Not sure
Level 2: Comprehension		
1.1	How close is the truck to your task area?	a. Within 5 feet***b. Within 10 feet***c. More than 10 feet***d. Not sure
1.2	How familiar are you with the truck's movement and direction?	a. Very familiar***b. Somewhat familiar***c. Not familiar***d. Not sure
1.3	Have you recognized any potential hazards related to the truck's proximity?	a. Yes***b. No***c. Not sure
1.4	Have you been informed of the truck driver's signals?	a. Yes***b. No***c. Not sure
1.5	How familiar are you with any posted safety guidelines related to the truck	a. Very familiar***b. Somewhat familiar***c. Not familiar***d. Not sure
1.6	How familiar are you with any safety equipment or devices that are being used in relation to the truck?	a. Very familiar***b. Somewhat familiar***c. Not familiar***d. Not sure
1.7	Are you aware of the truck's maximum speed and weight capacity?	a. Yes***b. No***c. Not sure
1.8	Are you aware of the truck's braking distance and turn radius?	a. Yes***b. No***c. Not sure
1.9	Are you aware of any specific safety procedures related to the truck, such as loading and unloading procedures?	a. Yes***b. No***c. Not sure

(*continued on next page*)

(*continued*)

Hazard 1: Excavator Scenario		
1.10	Are you aware of the emergency situations while crossing the track?	a. Yes***b. No***c. Not sure
	Level 3: Projection	
1.1	Are you able to predict the truck's future location and movement?	a. Yes***b. No***c. Not sure
1.2	Are you able to anticipate any potential hazards related to the truck's proximity?	a. Yes***b. No***c. Not sure
1.3	Have you planned for contingencies related to the truck's movement?	a. Yes***b. No***c. Not sure
1.4	Are you able to adjust your task to accommodate the truck's movement?	a. Yes***b. No***c. Not sure
1.5	Are you able to predict the truck driver's next move?	a. Yes***b. No***c. Not sure
1.6	Are you able to anticipate any potential hazards related to the truck's load?	a. Yes***b. No***c. Not sure
1.7	Have you planned for contingencies related to the truck's load shifting or falling?	a. Yes***b. No***c. Not sure
1.8	Are you able to identify the truck's blind spots and adjust your task accordingly?	a. Yes***b. No***c. Not sure
1.9	Are you able to anticipate the truck driver's next move based on their signals and communication?	a. Yes***b. No

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