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Analysis of Excavator Operators' Situational Awareness in Construction Sites Under Immersive Virtual Environment

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ABSTRACT: In the construction industry, heavy machinery plays a crucial role but is also a significant factor in many accidents. Collisions between machinery and workers account for approximately 30–40% of all heavy machinery-related incidents, according to the Ministry of Land, Infrastructure, and Transport in Korea. To address these issues, various safety technologies, such as alarms, collision avoidance sensors, and red-line lights, have been implemented. However, accidents persist, highlighting the critical role of the operator's attention and focus on people nearby in preventing accidents. situational awareness (SA) refers to the operator's ability to perceive the environment, anticipate risks, and respond effectively. Virtual reality (VR) technology has emerged as a promising tool for measuring and enhancing operators' SA. VR enables operators to safely experience realistic hazardous situations and assess their situational awareness, particularly their ability to detect and respond to workers. For heavy machinery operators, this ability is essential in reducing accidents. This study focuses on excavators, a widely used type of heavy machinery at construction sites, to analyze operators' situational awareness in detail. A high-fidelity immersive virtual environment simulator replicates real construction site conditions, including dynamic risks such as moving vehicles and workers. Participants' SA was evaluated using a combination of subjective assessments, task performance metrics, and the Situation Awareness Global Assessment Technique (SAGAT). By incorporating SAGAT, the study systematically measured SA by intermittently freezing the simulation and prompting operators to recall critical situational information. This approach provided a structured evaluation of SA at different operational phases, allowing for a more comprehensive understanding of operators' awareness levels. Through this approach, the study evaluates excavator operators' situational awareness, gathers relevant data, and proposes measures to reduce heavy machinery-related accidents on construction sites.

1. INTRODUCTION

The construction industry remains one of the most hazardous sectors, with a consistently high accident rate worldwide. According to a 2020 statistical survey on fatal accident rates per 100,000 workers in the construction industry, the United States ranked third, Canada second, and South Korea first (Construction & Economy Research Institute of Korea, 2020)

Among various accident types in construction, the Occupational Safety and Health Administration (OSHA) in the United States has identified "Struck by Object" incidents—often involving heavy machinery—as one of the Fatal Four in construction (OSHA, 2020) Similarly, reports from provincial safety agencies in Canada emphasize that collisions between workers and heavy machinery account for a significant proportion of construction site fatalities.

In South Korea, where this study was conducted, collisions ranked among the most frequent accident types, second only to falls (Korea Occupational Safety and Health Agency, 2020). Notably, between 2019 and

2021, the most common type of collision accident involved excavators(Ministry of Employment and Labor, South Korea, 2022). Despite technological advancements, such as proximity sensors and automated braking systems, these accidents continue to occur at an alarming rate(KOSHA, 2022). Collisions with heavy equipment not only lead to direct fatalities but also contribute to secondary injuries caused by crushing, entrapment, and being caught in/between machinery parts. To this end, understanding the factors influencing an operator's situational awareness is critical, as failures in situational awareness often lead to human errors that directly contribute to workplace accidents. Situation awareness (SA) refers to the ability of workers to perceive, interpret, and respond to environmental hazards in real time. Since SA is continuously updated in response to environmental changes, it can be influenced by various factors, including individual characteristics, job-specific demands, and external environmental conditions (Endsley, 1988). Therefore, a precise understanding of the factors affecting SA and their impact is crucial for accident prevention.

This study analyzes excavator operators' situational awareness (SA) in construction sites under an immersive virtual reality (IVR) environment by experimentally examining how task complexity and various construction noises impact their ability to perceive and respond to situational factors within a safe IVR setting. As shown in Figure 1, excavators were chosen for the experiment as they accounted for the highest number of accidents among heavy equipment (Ministry of Employment and Labor, South Korea, 2020).
This paper is structured as follows: Section 2 reviews prior research on situational awareness and evaluation methods. Section 3 describes the implementation of the VR-based excavator simulator, detailing its key functions and the experimental scenario, along with the evaluation metrics. Section 4 presents the experimental results and their analysis. Finally, Section 5 summarizes the findings of this study and discusses future research directions.

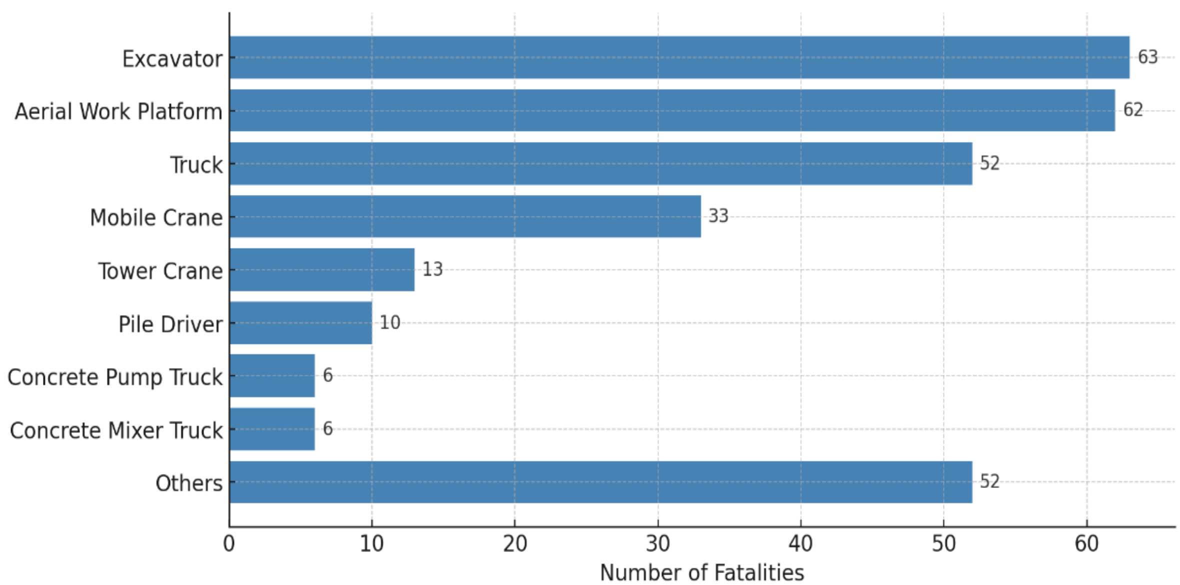

Figure 1: Heavy Equipment Fatalities (2019–2021)

2. LITERATURE REVIEW

2.1 Situational Awareness

Situation awareness (SA) was first conceptually defined by Endsley (1988) and has since been expanded through various studies. Endsley described SA as "the ability of an individual to perceive relevant information in a given environment and use it to predict future states." This concept was later structured into three stages: perception, comprehension, and projection (Endsley, 1995). Researchers have applied

SA across various industries, including aviation, driving, and construction, to analyze its impact on decision-making and accident prevention. Based on Endsley's theory, this study's SA assessment was structured into three levels:

- **Perception (L1):** Identifying moving workers in the environment.
- **Comprehension (L2):** Understanding the movement direction of the identified worker.
- **Projection (L3):** Predicting the likelihood of a collision with nearby workers while performing tasks.

A systematic review on driving performance measurement based on situation awareness (Park & Jung, 2015) analyzed various methods for assessing drivers' cognitive abilities and situational awareness. The study reviewed previous research on driving performance assessment and identified key techniques, including the freeze method, verbal probe technique, and driving error analysis, which are widely used to measure situational awareness in driving. Results indicated that driving simulators were the most commonly employed tools, followed by on-road driving tests and computer-based programs (Park & Jung, 2015). These findings highlight the importance of assessing situational awareness in driving rehabilitation and safety training, as it plays a crucial role in preventing accidents and improving driving performance (Park & Jung, 2015). A previous study conducted by the author assessed the situational awareness (SA) of heavy equipment operators in construction sites using an immersive virtual reality (IVR) environment (Choi et al., 2020). This study focused on how different operational tasks influence forklift operators' SA and identified key factors affecting collision risk. The researchers found that SA levels significantly dropped when performing tasks that required higher cognitive loads, such as lifting a load or driving in reverse with a load, compared to straightforward driving or turning maneuvers(Choi et al., 2020).
Additionally, a systematic review on SA-based driving performance evaluation (Park & Jung, 2015)categorized different SA assessment methods and analyzed their advantages and limitations. The most commonly used method was the Freeze Method, where the simulation pauses at specific moments to assess the driver's awareness. However, this method has limitations as it fails to reflect the continuous changes in real-world environments. Alternatively, Driving Error Measurement and Driving Behavior Checklists provide more realistic assessments but may introduce subjective errors from participants(Park & Jung, 2015).
Despite the various SA assessment methods, a standardized evaluation framework is lacking, making comparisons across studies challenging. Furthermore, most studies focus on **road driving environments**, with limited research extending to construction sites or heavy equipment operations. Given the similarities between road driving and heavy machinery operation in assessing cognitive ability and response time, findings from road driving research could serve as a foundation for SA evaluation in construction safety. However, **there is a significant gap in understanding how factors such as task complexity, noise levels, and other environmental conditions in construction sites influence SA, as existing studies have not sufficiently addressed these aspects.**

2.2 VR-Based Construction Safety Research

The effectiveness of VR-based training in construction sector has been empirically validated in multiple studies. (Sacks et al.,2013) found that VR-based construction safety training improved hazard recognition by 15–20% compared to traditional lecture-based training. Moreover, trainees who underwent VR training retained safety knowledge better even one month after the session, indicating improved learning retention. Yoo et al. (2023) identified vividness and interactivity as key factors influencing VR training effectiveness. Their study revealed that the more immersive and interactive the VR environment, the greater the trainees' engagement and likelihood of applying safety measures in real-world scenarios.
When VR-based immersive training is applied, these benefits become even more pronounced. VR training significantly improved hazard recognition accuracy (78.3%) and reduced false hazard identification by 50% compared to 2D training (Jung et al., 2022). Unlike conventional VR, which may still rely on screen-based or semi-immersive experiences, VR-based immersive training fully immerses the user, making hazard recognition and risk assessment more intuitive.

3. METHODS

3.1 IVR-Based Experimental Environment

The IVR-based excavator simulation was developed using Unity 2022.3.31f, and the experimental environment was implemented utilizing the HTC Vive Focus 3 standalone VR headset. By integrating an IVR system that realistically simulates real-world construction sites, this study ensures a controlled and measurable environment for assessing situational awareness in heavy equipment operations. Unlike conventional VR, the IVR system was designed to maximize realism by closely replicating real-world construction sites, incorporating detailed terrain, dynamic obstacles, and realistic lighting conditions. Furthermore, ambient construction site noise was integrated to enhance immersion and facilitate the evaluation of situational awareness (SA).

The experiment was conducted in a VR environment that closely mimicked real-world construction site conditions. Participants were required to perform a series of tasks while detecting and responding to sudden worker appearances and environmental hazards. A total of 20 participants, all in their 20s and 30s, were recruited for this study. Regardless of prior experience, all participants underwent the same experimental conditions. Before the main experiment, each participant completed a ten-minute familiarization session in an open area, where they practiced basic excavator controls. To support participants in task execution, a real-time task prompt was displayed in the upper-left corner of the IVR display. This feature allowed participants to clearly understand and follow their assigned tasks throughout the simulation.

3.2 Experimental Scenario

The experiment was designed to assess the situational awareness (SA) of excavator operators under realistic construction site conditions. The task sequence involved driving straight, making a left turn, lifting a designated rock with the excavator bucket, and placing it at a marked drop-off point. This process was repeated twice to evaluate SA under different environmental conditions with and without loud construction noise.

The tasks were divided into two phases: the first half (Tasks 1-4) was conducted in a low-noise environment with only the engine noise of the machinery and ambient sounds. The second half (Tasks 5-8) introduced additional construction noise, such as workers' voices, piledriver noise, metal clanging sounds, small bulldozer leveling noise, and drilling sounds, to simulate a more complex and distracting worksite.

During each phase, workers unexpectedly appeared at specific moments, requiring participants to detect their presence (SA level 1), comprehend potential risks (SA level 2), and anticipate how the workers' movements might impact the operation (SA level 3).

Through this experimental setup, the study aimed to analyze how different types of task complexity and environmental factors, such as construction noise, influence the situational awareness of operators.

3.3 Experiment Design

This study evaluates participants' Situational Awareness (SA)based on Endsley's (1995) three-level model, which has been widely applied in aviation, driving, and construction industries for accident prevention and decision-making analysis. SA refers to an operator's ability to perceive the environment, understand its significance, and anticipate future events, which is crucial for reducing accidents in high-risk workplaces.

Various methods have been developed to assess SA, including the Situation Awareness Global Assessment Technique (SAGAT)(Endsley, 1995), Driving Error Measurement(Gugerty, 1997), and the Behavior Checklist(Patrick & Morgan, 2010). This study adopts a hybrid approach, using SAGAT as the primary SA evaluation method, while Driving Error Measurement is subjectively assessed by experimenters based on the severity of speeding and collision incident observed during the VR simulation.

SAGAT involves pausing the simulation at predefined moments to assess participants' awareness of the situation. At each freeze point, participants are prompted with questions designed to evaluate their perception (detecting hazards), comprehension (understanding risks), and projection (anticipating future movements)(Endsley, 1995). This structured approach enables an objective assessment of SA throughout the simulation.

3.4 Experimental Preparation and procedure

The experiment consisted of three phases.

- **Experimental Preparation** : Before starting the experiment, participants were assessed for their prior experience with VR environments and their physical condition using immersive tendencies questionnaires. The experiment accounted for differences between participants with extensive VR experience and those with minimal exposure to ensure a proper interpretation of results. Additionally, potential symptoms of motion sickness, fatigue, or other physical conditions that could affect focus and performance were checked prior to the VR session. After the assessment, participants practiced excavator operations in an open area, allowing them to familiarize themselves with the VR interface and simulation controls.
- **VR task execution and SA assessment**: Participants performed eight tasks, each designed to assess SA in a specific scenario. The simulation was paused at predefined moments (Freeze Method) to evaluate the participant's SA.
- **Post-experiment interviews**: Participants provided feedback regarding their experience in the VR environment by completing the Presence and Immersion Questionnaire and offering additional verbal feedback.

To analyze the effect of noise on SA, the simulation included two experimental conditions with structurally similar tasks:

- Tasks 1–4 (Low-Noise Condition): Only background sounds, such as light excavator engine noise and ambient site noise, were present.
- Tasks 5–8 (High-Noise Condition): Additional loud construction noise was introduced to simulate a more distracting work environment.

Table 1 : Task Description and Environmental Setting

Task 1 / Task 5	Driving forward
Task 2 / Task 6	Turning left
Task 3 / Task 7	Loading a rock
Task 4 / Task 8	Unload a rock

*Corresponding task steps are labeled with numbers in Figure 2(B) for reference.

By maintaining consistent task structures across both conditions, this design aimed to isolate the effect of noise on SA and analyze its impact on perception, comprehension, and projection within a controlled VR environment. The participant sat upright in the excavator seat and performed the role of operating the excavator. Inside the excavator, a rearview camera display was installed to assist with reversing (Figure 3(A)). In addition to this setup, the participant's screen display provided a first-person perspective of the excavator's operation, including the surrounding environment and task instructions (Figure 3(B)).

The participant operated the excavator using a keyboard, with the designated control keys being WASD, arrow keys, and the spacebar. For example, the experiment primarily started in driving mode. Pressing the up arrow key moved the excavator forward. Pressing the spacebar switched the control to excavation mode, in which pressing the up arrow key extended the excavator arm. Through this flexible mode switching and control mechanism, participants performed the assigned tasks.

(A) Overall Model View

(B) Task Execution Order

(C) Model Close up View (D) Indication of Rock Loc

Figure 2: Simulation Environment and Task Flow

(A) Built-in Rear Camera (B) VR display

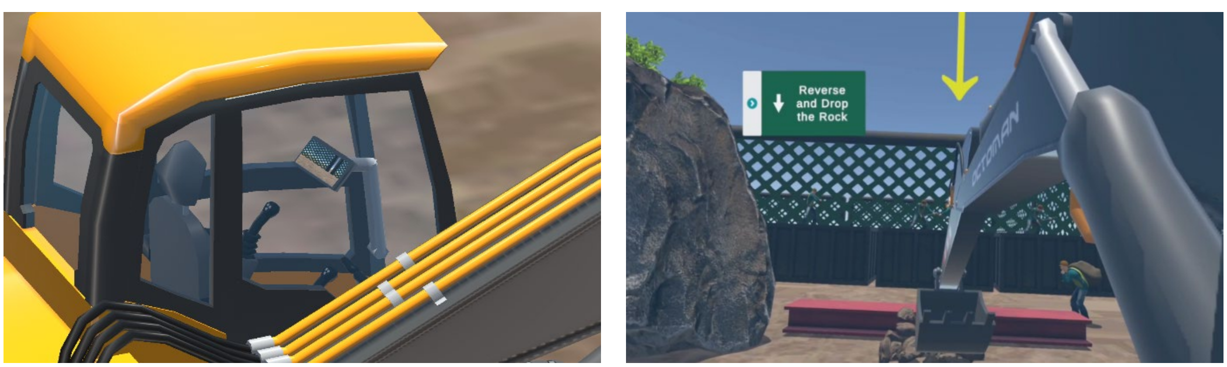

Figure 4: Internal Perspective and Assistive Device

3.5 SA Assessment Framework

The Situational Awareness (SA) assessment consisted of three levels:

- Perception (L1): Identifying moving workers in the environment.
- Comprehension (L2): Understanding the movement direction of the identified worker.
- Projection (L3): Predicting the likelihood of a collision with nearby workers while performing tasks.

Participants were asked specific SA-related questions after encountering workers in the simulation. The questions were designed to evaluate their ability to detect, understand, and anticipate environmental hazards:

- Perception (L1): "Did you see the worker moving in your vicinity?
- Comprehension (L2): "Did you recognize the direction in which the moving worker was heading?
- Projection (L3): "Do you think there is a high possibility of colliding with a nearby worker while performing the task?

This structured SA evaluation method allowed for an objective assessment of situational awareness throughout the simulation, providing insights into how participants perceive and react to dynamic hazards, particularly moving workers, in a construction site environment.
Each question was scored as either 1 point for a correct answer or 0 points for an incorrect answer. Additionally, a hierarchical scoring method was applied: if a participant answered incorrectly at a lower level (e.g., Perception), their responses to higher levels (e.g., Comprehension and Projection) within the same task were also considered incorrect due to reduced reliability.

Table 2: SA Task and Assessment Points

	SA Object	SA Freeze
Task 1	Drive straight until instruction changes	While driving straight
Task 2	Turn left	After left turn
Task 3	Load the rock on the left	After loading a rock
Task 4	Load the rock on the left	After unloading a rock
Task 5	Turn left	While driving straight
Task 6	Drive straight along the left-side path	After left turn
Task 7	Load the rock in front	After loading a rock
Task 8	Reverse using the rear camera and **unload** the rock at the marked spot	After unloading a rock

4. RESULT

Both quantitative and qualitative methods were used for data analysis. Situational awareness (SA) scores were quantitatively evaluated based on predefined questions assessing Perception, Comprehension, and Projection. Even if a participant reported detecting a worker, a score of 0 was assigned if the experimenter subjectively determined that the collision risk was significantly high due to inappropriate situational awareness. Qualitative data were collected through post-experiment interviews to analyze participants' perceptions of the realism and effectiveness of VR-based training.
The experiment initially hypothesized that SA performance would decline in the latter phase of the session due to increased noise. However, contrary to expectations, participants demonstrated higher accuracy rates in noisy conditions. This suggests that rather than acting solely as a distraction, noise may have served as a stimulus for heightened focus and situational awareness.
The task with the highest accuracy rate was Task 7, achieving an overall correct response rate of 83.3%. Notably, Level 1 (Perception) and Level 2 (Comprehension) recorded a 90% accuracy rate, indicating that participants were able to effectively perceive moving workers and predict their movement direction. This

was because the worker in Task 7 passed directly in front of the participants, allowing them to recognize the movement more easily.

Conversely, Task 4 had the lowest accuracy rate of 41.7%. This may be because participants were highly focused on the process of unloading the rock, which resulted in lower situational awareness (SA) performance. In particular, the most challenging item was Level 1 (Perception) in Task 1, where participants struggled to detect workers due to obstructed visibility caused by the excavator's bucket. This finding suggests that visual obstructions significantly impact participants' SA performance.

In the first half of the experiment, background noise levels were relatively low, whereas in the second half, various loud construction noises were introduced. According to previous research, external environmental factors such as noise can negatively impact SA performance (Endsley et al., 2003). Based on this, the present study also incorporated noise effects and hypothesized that SA performance would decline in the latter half of the experiment.

However, contrary to this theoretical expectation, the average SA score in the second half was slightly higher than in the first half. This result deviates from conventional findings and suggests that factors beyond auditory distractions influenced participants' SA performance.

Possible explanations for this result include the fact that the experiment was conducted with reduced noise intensity compared to an actual construction site, considering potential hearing protection concerns for participants. As a result, the noise levels may not have been sufficiently disruptive to impair SA. Additionally, despite the similarity in task structures, participants were more likely to detect workers when their position was closer to the central field of view. This finding reinforces the idea that visual factors play a more significant role in SA performance than auditory distractions.

Table3: Situation Awareness Experiment Data Summary

	Average	Task Accuracy(%)	Level 1 Accuracy(%)	Level 2 Accuracy(%)	Level 3 Accuracy(%)
Task 1	4.3	21.7	25	20	20
Task 2	11	55	65	65	15
Task 3	10.7	53.3	55	50	40
Task 4	8.3	41.7	35	35	25
Task 5	14.7	73.3	90	60	40
Task 6	11	55	55	55	25
Task 7	16.7	83.3	90	90	70
Task 8	13	65	75	60	40

5. DISCUSSIONS AND CONCLUSIONS

This study evaluated the Situational Awareness (SA) of excavator operators using a VR-based simulation and analyzed its impact on worksite safety and operational efficiency. A VR environment modeled after real construction sites was utilized to simulate realistic working conditions. Participants completed eight tasks while responding to the sudden appearance of workers.

SA was assessed through three levels of questioning during the experiment, where the simulation was paused at specific moments to collect real-time awareness data. The results indicated that auditory factors must be significantly pronounced to influence SA. Additionally, while SA was relatively high for objects in front of the excavator, it was markedly lower for the right-side bucket and arm areas.

The results showed that participants exhibited varying levels of Situational Awareness (SA), with an average score of 12 out of 24. Additionally, Level 3 (Projection) scores exhibited the greatest variability among participants, indicating significant individual differences in recognizing potential collision risks.

This study has several limitations. First, while the SAGAT method used for SA assessment is effective in collecting real-time data, it does not fully replicate the dynamic nature of real-world construction environments, where continuous SA adjustments are required. Second, although the VR environment was designed to simulate real construction sites, it may not fully capture all sensory and environmental factors present in actual fieldwork. Third, to accurately assess the impact of auditory factors on SA, sound levels should have been set to match the decibel levels of real construction sites. Differences in auditory stimuli between virtual and real environments could influence SA differently.

Future research should focus on refining SA assessment methods by developing a more detailed and quantitative evaluation framework that goes beyond binary scoring. Expanding the sample size would also enhance the reliability and generalizability of the findings.

To create a more immersive and realistic construction environment, auditory and visual safety features should be integrated based on participant feedback. For instance, visual emphasis when workers appear or an audio-based warning system could enhance the effectiveness of SA assessment and training.

Additionally, the IVR-based SA assessment model developed in this study should be explored for application to other types of construction equipment, such as cranes or forklifts. Expanding this methodology could contribute to broader safety improvements across the construction industry.

This study highlights the potential of IVR-based simulations for SA assessment and training, demonstrating their value in improving excavator operator safety. Furthermore, by utilizing SA evaluation data to develop tailored training programs and on-site feedback systems, this research could contribute to the advancement of safety management strategies in construction environments.

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