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Investigating situation awareness transition in construction hazard recognition: A multimodal study of cognitive and neural mechanisms

Zhe Zhang [a], Brian H.W. Guo [a,*], Zhenan Feng [b], Yang Miang Goh [c]

[a] Department of Civil & Natural Resources Engineering, University of Canterbury, New Zealand
[b] School of Built Environment, Massey University, New Zealand
[c] Department of Built Environment, National University of Singapore, Singapore

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ABSTRACT

Construction sites are dynamic and hazardous environments where workers often struggle to maintain high levels of situation awareness (SA), essential for effective hazard recognition. While technologies exist to aid hazard perception, limited research has explored how external environmental stimuli and internal safety goals jointly influence the SA transition across perception (SA1), comprehension (SA2), and projection (SA3). This study investigates the effects of augmented stimuli and safety goals setting on SA levels, SA transition and hazard recognition. A multimodal experimental approach was employed, integrating virtual reality (VR), eye tracking, modified Situation Awareness Global Assessment Technique (SAGAT) and event-related potentials (ERPs). A novel Temporal Hybrid Situation Awareness Measurement (THSAM) method was introduced to quantify SA by linking eye-tracking data with SAGAT responses. SAGAT data showed that both augmented stimuli and safety goals improved SA across all levels. SAGAT and THSAM indicated that the combination of the two interventions led to the largest improvements across SA1, SA2, and SA3. SA transition analysis revealed that augmented stimuli effectively facilitated the shift from unawareness (SA0) to SA1. THSAM and SA transition analysis confirmed safety goals primarily enhanced SA2. ERPs analyses further indicate distinct brain activity patterns (P2 and N400) associated with each SA level. This study contributes to construction safety research by providing quantitative evidence on the cognitive and neural mechanisms underlying SA transition. It also introduces THSAM as a methodological advancement for capturing real-time SA dynamics and offers practical implications for designing integrated safety interventions that align with workers' goals and environmental demands.

1. Introduction

The construction industry continues to face significant challenges in ensuring safety performance, as evidenced by persistently high rates of workplace fatalities [1]. This problem is exacerbated by the dynamic and hazardous nature of construction sites, where workers must navigate complex interactions between equipment, environmental conditions, and other workers [2,3]. Workers have to continuously adapt to dynamic conditions and manage complex spatiotemporal relationships involving site objects, tasks, and environment. The fact that human cognitive capacity is limited may significantly impair hazard recognition. Research shows that workers frequently overlook up to 50 % of potential hazards [4]. As a result, situation awareness (SA) has emerged as a prominent focus within construction safety research. SA is defined as "the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future" [5]. Numerous studies have been undertaken to explore its role in enhancing hazard recognition, decision-making, and overall site safety performance [6,7].

However, there remains a gap in understanding the role of augmented stimuli and safety goal setting in enhancing situation awareness (SA) and hazard recognition [8–10]. Research efforts have been made to improve our understanding of the role of SA in hazard recognition in the engineering informatics domain. For example, significant research efforts were made to investigate the relationship between attention and situation awareness [8,11,12]. Results of these studies suggest that SA impacts attention allocation, which is in turn influenced by the type of tasks and mental workload [13]. SA was also

* Corresponding author.
E-mail addresses: zhe.zhang@canterbury.ac.nz (Z. Zhang), brian.guo@canterbury.ac.nz (B.H.W. Guo), Z.Feng1@massey.ac.nz (Z. Feng), bdggym@nus.edu.sg (Y.M. Goh).

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investigated in the human–machine collaborative construction operations. For example, the work conducted by Li et al. [14] developed a computational model of construction workers' SA was developed based on the adaptive control of thought-rational (ACT-R) architecture. The authors claimed that the approach can serve as a proactive analysis tool to predict and control risks associated with workers' SA errors. Information inputs from the environment are the prerequisite to SA. As such, there is a wealth of research that focuses on how information assistance or augmentation improves SA [14–17]. In general, results indicated that providing relevant information is beneficial in developing and maintaining a high level of SA. However, researchers Li et al. [14] argued that this might cause information overload and therefore undermine workers' SA. It is clear from Endsley's model of SA that SA encompasses three distinct levels, which are shaped by a combination of external and internal factors, such as information inputs from the environment and goal, respectively [5,18,19]. Previous studies tend to focus on the effects of technological developments (e.g., information assistant systems) on SA, while the joint effects of internal factors (e.g., goals and expectations) are largely ignored. In addition, very limited research was conducted to investigate the cognitive flow, where raw information is processed, interpreted, and projected forward to guide action.

To address these research gaps, the goal of this paper is to investigate the effects of augmented stimuli and safety goals setting on SA level, SA transition (from Level 1 to Level 3 SA) and hazard recognition. This paper contributes to the growing body of research on SA and hazard recognition by providing insights into the cognitive and neural mechanisms that underlying SA transition among construction site workers. By exploring the interactions between augmented stimuli and safety goals, we can identify effective strategies to support workers in transitioning to higher levels of SA and enhance hazard recognition on dynamic construction sites.

2. Literature review

2.1. Impacts of augmented stimuli and goals on SA

SA depends on environmental stimuli, which includes perceptual cues and system displays that operators must detect, integrate, and project into future states. The operator's goals guide attention toward these critical stimulus and shape how information is interpreted to support effective decision making. By selectively tuning into goal-relevant stimuli, operators build a coherent understanding of the current situation and generate accurate projections for dynamic decision making [5]. Despite ongoing debate regarding the various factors that influence SA (such as state of the environment, goals, preconceptions, workload, automation, long term memory stores, and abilities), the study primarily examines two critical elements: states of the environment and goals [5]. The origin of SA has been argued to involve elements and their relationships within environmental settings [20]. Additionally, goals have been considered directly influencing how individuals adapt to changes in these environments [21].

An augmented reality-based warning system was developed to investigate the impacts of stimuli on situational awareness [22]. The study's limitations lay in its use of simplified, less complex tasks and limited hazard simulation, which contrasts with real-world construction environments that involve diverse hazards such as falling objects, fire, and electrocution. Goal selection was used as a parameter to measure SA [18]. However, the computational model based on expert subjective judgment may compromise its reliability.

2.2. SA measurements

SA measurement plays a crucial role in understanding safety performance. Broadly, SA measurements can be categorized into direct and indirect approaches, each with distinct benefits and limitations. Direct SA measurements assess an individual's awareness in a straightforward manner, offering practical advantages such as low cost, minimal training requirements, and time efficiency. A common example is the Situation Awareness Global Assessment Technique (SAGAT), where participants are asked queries about the environment to gauge their awareness [23]. On the other hand, indirect SA measurements infer awareness from cognitive processes, behaviors, or performance outcomes. Techniques such as key performance indexes analysis fall into this category [15]. These methods provide more objective indicators of SA and can help explain underlying cognitive mechanisms. However, their reliability may be compromised by the fact that cognitive behaviors do not always align with actual awareness, potentially leading to inaccurate assessments [24,25].

While traditional SA measurements provide valuable insights into an individual's understanding of their surroundings, they have limitations in capturing the dynamic and real-time aspects of SA that are critical in high-pressure construction sites. Specifically, questionnaires heavily rely on participants' subjective self-assessment rather than objective indicators [11]. Furthermore, a static snapshot of SA at a particular point in time hard to capture the dynamic nature of real-time SA [14]. With the development of neuroscience, electroencephalogram (EEG) [26] as an innovative approach attract more and more attention to measure SA, the effectiveness of psychophysiological metrics needs further investigation.

Eye tracking technology has been increasingly employed to investigate SA in various fields, including construction safety, human factors, aviation, and human-robot interaction. In these domains, researchers have utilized eye tracking to measure SA at specific moments in time, providing valuable real-time insights into individuals' awareness of their surroundings. For example, studies have employed metrics such as first fixation duration, fixation duration, fixation count, and run count in construction safety as a measurement of SA [11]. In human factors, percent fixations, mean fixation duration, and fixation count were employed to quantify SA [15].

In the context of hazard recognition, the concept of area of interest (AOI) has been employed to identify specific physical locations where potential hazards can be found [27]. Moreover, a brief pause in eye movement, lasting approximately 200–300 ms, is considered a fixation [28].

The event-related potentials (ERPs) can be defined as an electrical voltage generated by the brain in response to a specific event [29]. This electrical signal is extracted from continuous EEG recordings into fixed-length segments, or epochs, that are time-locked to stimuli [29]. Within these ERPs epochs, ERPs components emerge, each representing a functionally unique neuronal aggregate characterized by systematic patterns of voltage changes over specific time windows [29,30]. The peak amplitude of these ERPs components serves as an index to measure SA [29].

SA1 is associated with activity in the occipital cortex, specifically at channels Oz, O1, and O2, and is linked to ERPs components P1, P2, and P3. These components are related to visual processing functions such as masking, reduced-contrast stimuli, attentional blink, change blindness, and bistable perception [31]. SA2 and SA3 have been associated with activity in brain regions including the temporal lobe, inferior frontal gyrus, dorsolateral prefrontal cortex, and left inferior prefrontal cortex. These associations correspond to activity at channels T7, T8, F3, F4, F7, F8, and Fz, and involve the ERPs component N400, which is implicated in cognitive processes such as memory formation, language comprehension, working memory, and decision-making [32–34].

2.3. SA transition and hazard recognition

SA transition can be defined as SA transit from SA1 (perceiving stimuli) to SA2 (understanding hazards) and ultimately to SA3 (predicting future status) [5]. Despite its importance, research on temporal SA transition is limited, and there is a lack of comprehensive studies available to inform safety practices. In particular, the process of transitioning from perception to comprehension and projection remains unclear. Specifically, it is not well understood how workers integrate sensory stimuli and safety-relevant data to move from a state of awareness focused on immediate objects (perception) to understanding the hazards associated with those objects (comprehension), and ultimately forecasting potential actions to mitigate these hazards (projection).

SA plays a critical role in hazard recognition on dynamic construction sites, enabling workers to perceive, understand, and predict their surroundings, thereby identifying potential hazards and taking proactive measures to mitigate risks. Previous research on hazard recognition and SA has been limited in its ability to capture the temporal dynamics of SA [15]. The reliance on quantifying SA through performance metrics, such as a 7-point Likert scale with low and high scores, oversimplifies the complex three-level structure of SA [11]. Furthermore, methods that rely on random queries or averaged response time and correctness fail to account for the dynamic nature of SA [14]. These limitations highlight a significant research gap in understanding the underlying cognitive processes driving temporal SA transitions in dynamic construction sites.

3. Methodology

To achieve the research goal, this study adopts a virtual reality (VR) approach to measure participants' SA using multiple devices and tools. Such a triangulation of data sources (e.g., eye-tracking, ERPs, and SAGAT) allows for both subjective and objective measurement of SA during hazard recognition tasks. The VR environment simulates realistic construction site scenarios. This approach enabled us to control manipulation of augmented stimuli and goal-setting conditions. The experiment design is illustrated in Fig. 1, and details are reported in the following subsections.

3.1. Scenarios, tasks and hazards

The VR scenario (Fig. 2) was designed based on accident reports and standards [35]. VR-driven immersive safety training has been shown to surpass traditional methods in both process and outcome-based indicators [36]. In particular, all hazards listed in Table 1 were modeled based on real accidents. The VR scenario also incorporated industry standards, including Fall Protection in Construction (OSHA 3146-05R, 2015) and Warning Line Systems (CFR 1926.502(f)).

To create an interactive virtual construction site, the project utilized Unity version 2021.3.27f1. The VR scenario enabled participants to engage in a virtual environment through locomotion and interaction. Two distinct tasks were designed:

- Task one involved operating a forklift from a start point to a destination point as a forklift driver, where participants utilized a controller while standing within the vehicle.

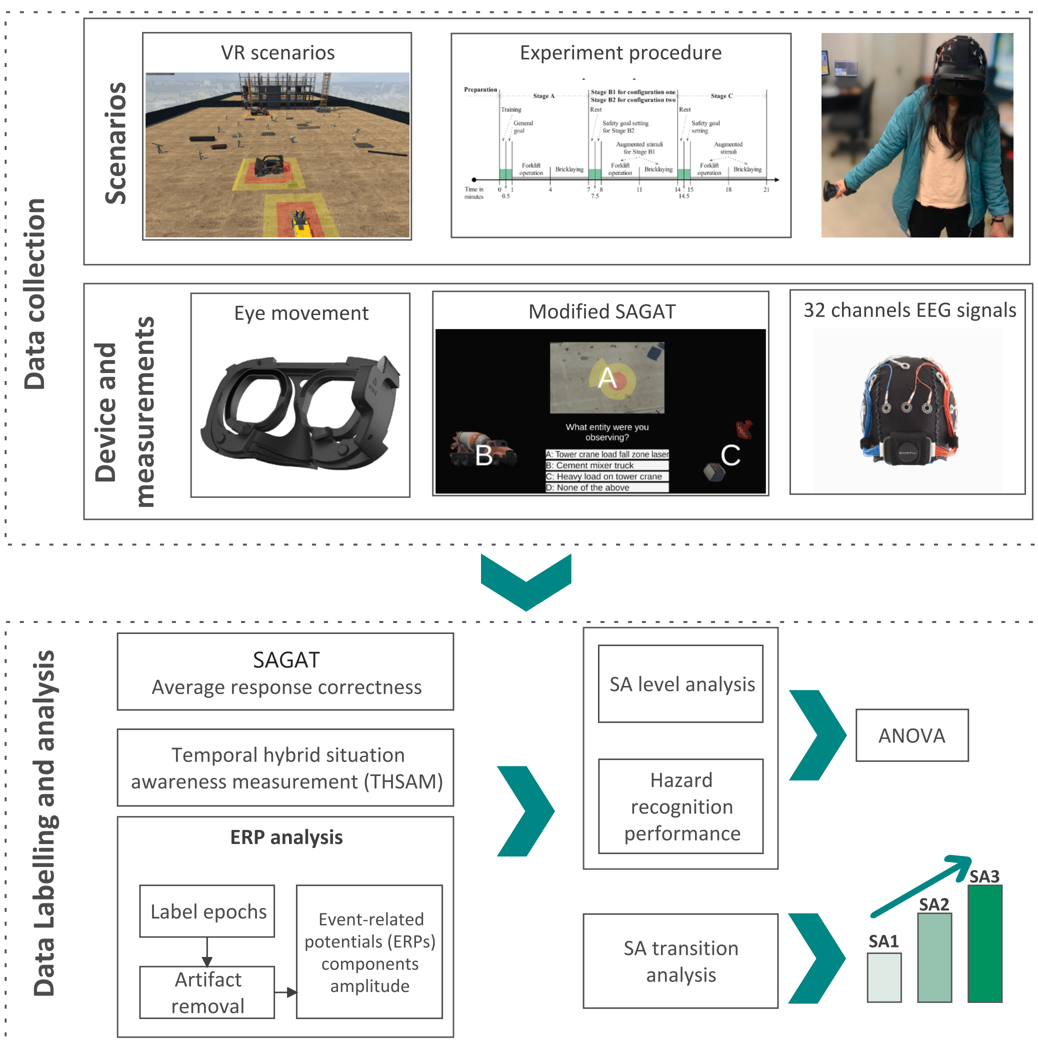

Fig. 1. Experiment design.

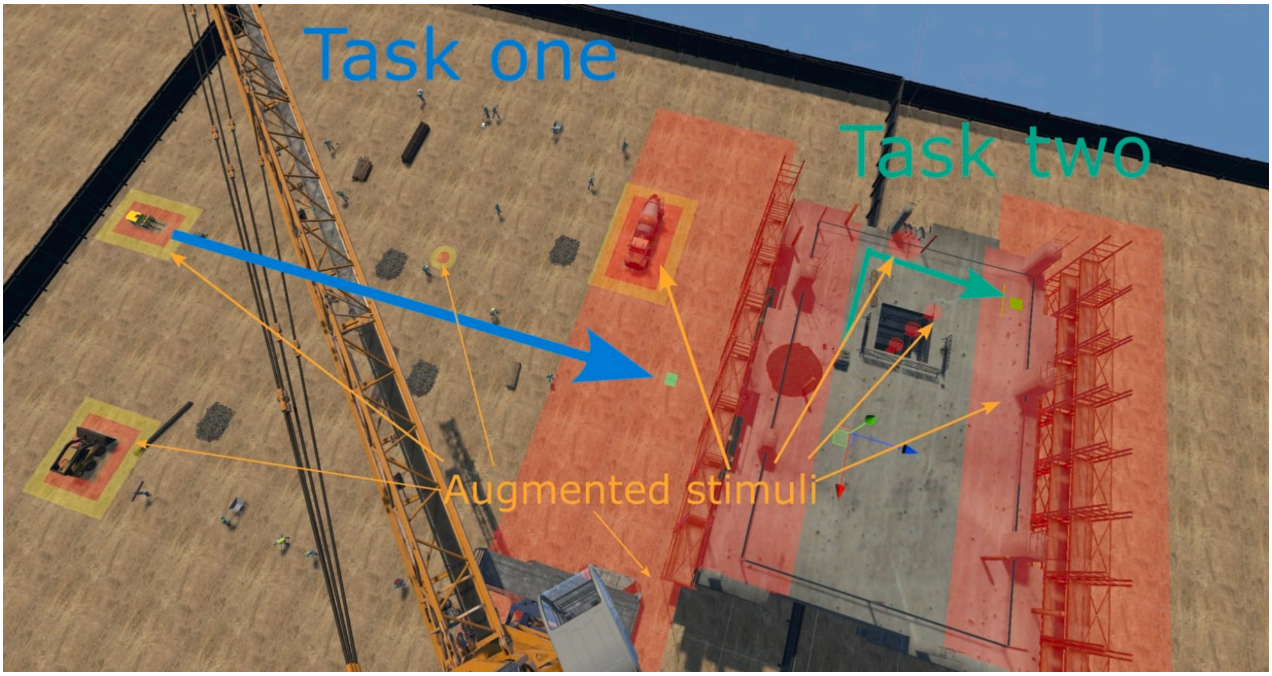

Fig. 2. Overview of the VR scenario and augmented stimuli.

Table 1
Tasks and hazards.

Tasks	Hazards
Task one: Transportation of brick containers via forklift	• H1: Falling object from crane load • H2: Forklift colliding with stationary or moving workers • H3: Forklift colliding with obstacles • H4: Forklift colliding with heavy equipment • H5: The crane load hit the scaffolding, collapsing it
Task two: Bricklaying	• H1: Falling object from crane load • H5: The crane load hit the scaffolding, collapsing it • H6: Contact with live electrical wiring • H7: Trip by obstacles • H8: Fall from opening

- Task two consisted of navigating the virtual environment on foot, where participants performed bricklaying-related activities such as moving containers, laying bricks, applying mortar, and refilling the mortar bucket.

These tasks were specifically designed to encourage participants to cross the danger zone multiple times, thereby exposing them to various hazards. Table 1 summarizes the eight hazards defined in these two tasks.

3.2. Apparatus and measurements

3.2.1. VR headset and eye tracker

The HTC VIVE Focus 3 headset was adopted as the primary apparatus for participant engagement. This advanced VR headset offers exceptional visual fidelity, featuring per-eye resolutions of 2448 x 2448 pixels and a 90 Hz refresh rate, which collectively provide an immersive experience with a 120-degree field of view. In conjunction with the VR headset, an eye-tracking add-on was employed to capture gaze data. This Focus 3 add-on eye tracker recorded gaze origin, gaze direction, pupil position, pupil size, and eye openness at a frequency of 120 Hz, with an accuracy ranging from 0.5° to 1.1°.

3.2.2. EEG recording

The 10–10 system, a modified method of electrode placement on the scalp for recording EEG signals [37], was employed in this study, as shown in Fig. 3. To establish a stable electrical connection between each electrode and the skin, conductive gel (Weaver Nuprep Skin Prep Gel) was injected.

The study utilized the EMOTIV EPOC Flex Gel Sensor Kit for EEG recording. This device utilizes sequential sampling with a single

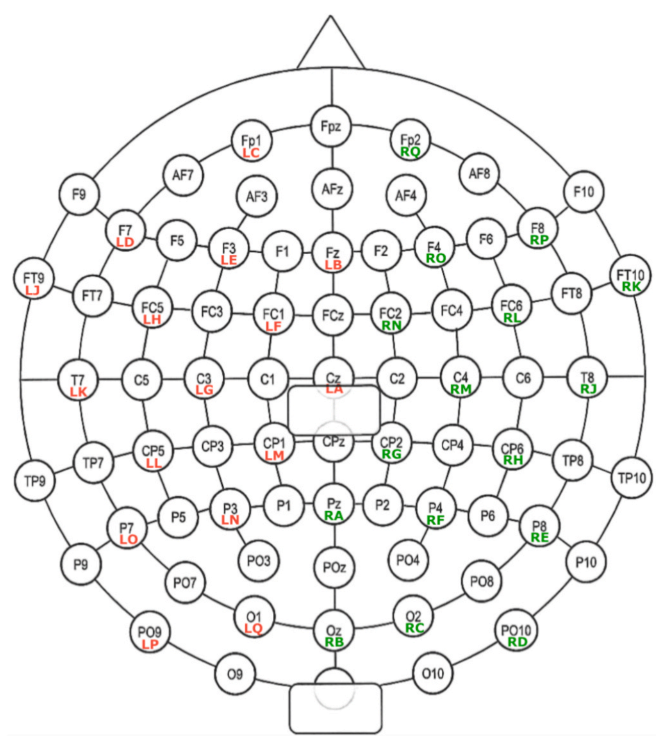

Fig. 3. 10–10 system electrodes placement.

analogue to digital converter (ADC), boasting an internal sampling rate of 1024 Hz and a resolution of 14 bits (where 1 least significant bit (LSB) equals 0.51 μV). The EPOC Flex also features a compressed maximum slew rate of 32 μV per sample, as well as a bandwidth of 0.16–43 Hz with digital notch filters at 50 Hz and 60 Hz, and an AC-coupled dynamic range of 8400 μV (pp).

3.2.3. Modified SAGAT questionnaire

The SAGAT questionnaire comprised three levels of questions, aligned with Endsley's three levels of SA [23]:

- Q1 (SA1-perception): a multiple-choice question identifying the object of focus.
- Q2 (SA2-comprehension): an open-ended question asking what is noteworthy about the object.
- Q3 (SA3-projection): an open-ended question asking what the participant plans to do in response.

As shown in Table 1, each task involved five hazards, with each hazard associated with one set of questions. Thus, each task included a total of five questionnaires. Responses were recorded using a laser pointer for Q1 and voice input for Q2 and Q3. All responses were then assessed manually for correctness.

3.2.4. Triangulation of data sources

The triangulation of data sources (e.g., eye-tracking, ERPs, and SAGAT) were corporate through a custom C# script within Unity. Specifically, the SAGAT questionnaire was triggered when a participant gazed at a hazardous object for more than 0.6 s. This threshold was determined based on the fixation time (0.2 s-0.3 s) [28,38] and maximum ERPs time window (0.5 s) [39,40], with an added buffer to ensure complete ERPs data capture. The hazardous objects associated with the same hazards trigger the questionnaire only once to ensure that participants are not overwhelmed by repeated queries. If a participant answered incorrectly at any level, subsequent questions were skipped to avoid confounding results.

3.3. Demographics of participants

The minimum sample size required for this study was determined through a priori power analysis using G*Power version 3.1.9.7 [41]. Repeated measures ANOVA was employed. To calculate the effect size, we referred to Cohen [98] benchmarks for 'small' (0.2), 'medium' (0.5), and 'large' (0.8) effects. Previous VR research on construction safety has utilized effect sizes of 0.5 [42] and 0.72 [43,44]. For this study, we adopted medium effect size of 0.5. A power analysis revealed that a minimum sample size of 14 would be required for repeated measures ANOVA to achieve sufficient power to detect statistically significant effects. Consequently, we aimed to recruit at least 30 participants for each configuration to ensure that our sample size was well above the minimum required threshold.

Participant recruitment employed post recruitment and snowball sampling [45]. First, post-recruitment involved placing public posters at public locations on university campus and in local construction sites to attract potential participants. Second, snowball sampling was employed to encourage referrals from existing participants, thereby facilitating access to harder-to-reach populations.

A total of 75 healthy individuals with normal or corrected-to-normal vision, without any reported sensory, motor, or cognitive impairments, and no history of substance abuse, participated in this experiment. However, 15 participants were removed from the analysis due to incomplete data collection. Consequently, data from 60 participants (30 workers and 30 postgraduate students) were included in the final analysis. The participants were assigned to two configurations: Configuration One ($n = 30$) and Configuration Two ($n = 30$), each meeting the minimum sample size requirement of 14 to achieve 0.8 power.

3.4. Experiment procedure

To investigate the effects of augmented stimuli and safety goal setting on SA transition and hazard recognition, two experimental configurations were developed. Configuration One examines the impact of augmented stimuli alone and in combination with safety goals. Participants first completed a training session, followed by Stage A, which served as a baseline involving two tasks without any interventions. Next, participants progressed through a two-stage intervention: Stage B1 introduced only augmented stimuli, while Stage C combined augmented stimuli with safety goals.

Configuration Two focuses on assessing the effects of safety goal setting alone and in conjunction with augmented stimuli. After completing the same baseline in Stage A, participants were exposed to Stage B2, which introduced safety goals only, followed by Stage C, where both augmented stimuli and safety goals were applied. The experiment procedure is shown in Fig. 4.

The augmented stimuli were designed to visualize hazards through a combination of red and yellow colors, utilizing shapes such as circles, cones, or rectangles to alert workers of potential dangers associated with hazardous objects. The augmented stimuli design was based on industry standards, including fall protection in construction [46] and warning line systems [47]. In addition, the safety goals emphasized the critical importance of adhering strictly to established safety protocols, prioritizing utmost care and caution over expedited completion, even in situations where time pressures exist.

Several pilot tests were conducted prior to the experiment to identify potential barriers to a positive user experience. To validate the match between AOI and hazards, we conducted interviews with four experts (each with over 20 years of working experience) through snowball sampling. The AOI identified by these experts demonstrated high consistency, particularly between the third and fourth individuals, whose identifications closely matched. This suggests that saturation was reached after four experts. Consequently, based on their input, AOI were identified and categorized into three categories: workers, equipment, and temporary structures.

3.5. Data analysis

To comprehensively evaluate the effects of augmented stimuli and safety goal setting on situation awareness (SA) and hazard recognition, multiple analytical approaches were employed. These include both cognitive-behavioral and neurophysiological assessments. Specifically, three SA measurement methods, including modified SAGAT, Temporal Hybrid Situation Awareness Measurement (THSAM), and event-related potentials (ERPs), were used to capture SA levels. In addition, SA transitions were analyzed to understand shifts in participants' SA levels across experimental stages. Hazard recognition performance was quantified through a hazard recognition index (HRI), and repeated measures ANOVA was conducted to statistically assess the effects of the experimental interventions. The following subsections detail each of these analytical components.

3.5.1. SA levels analysis

SA level analysis aims to investigate the effects of augmented stimuli and safety goal setting on single SA levels (i.e., perception, comprehension, and projection). To measure SA, one subjective and two objective methods were employed: the Modified SAGAT, temporal hybrid situation awareness measurement (THSAM), and ERPs. The following subsections provide a detailed introduction to each of these methods.

A modified version of SAGAT [23] was developed and implemented to capture SA with improved temporal precision and contextual relevance. In this study, the task served as the minimum unit of analysis. Each task included five hazards, and each hazard was associated with one SAGAT questionnaire, resulting in five sets of SAGAT responses per

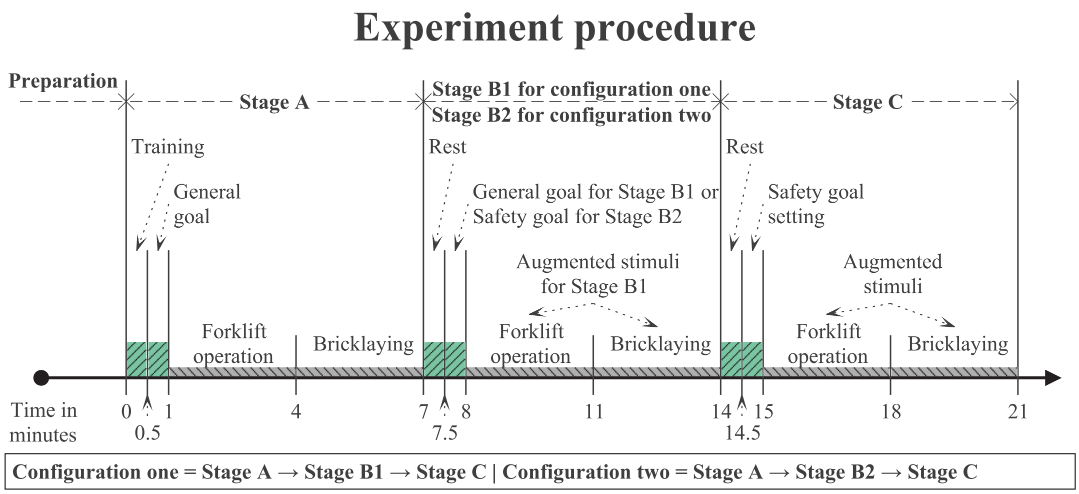

Fig. 4. Experiment procedure.

task. For each SA level (perception, comprehension, and projection), the average response accuracy was calculated as the percentage of correct answers to the corresponding level-specific questions across the five hazards. For example, if a participant correctly answered 4 out of 5 perception-level questions, their perception-level response accuracy for that task would be 80 %. This average response accuracy served as a subjective measure of participants' SA performance within the given task.

The second SA measurement was the THSAM approach, which combines eye-tracking fixation with the SAGAT questionnaire to provide an objective assessment of SA across three levels: perception (SA1), comprehension (SA2), and projection (SA3). Fixations were labeled according to participants' SAGAT responses for each hazard, as follows:

- Perception-labeled fixation: Q1 answered correctly
- Comprehension-labeled fixation: Both Q1 and Q2 answered correctly
- Projection-labeled fixation: Q1, Q2, and Q3 all answered correctly

Fixation count serves as an objective indicator of SA and has been widely used in prior studies, where higher fixation counts are generally associated with higher levels of SA [22,48]. Because SA3 builds upon SA2 and SA1, a fixation labeled as SA3 implies that the participant has also attained SA1 and SA2. Similarly, a fixation labeled as SA2 presumes the achievement of SA1.

The THSAM method extends beyond SAGAT by incorporating eye-tracking data as an objective measure of SA. Whereas SAGAT relies on subjective questionnaire responses collected during manual freeze moments, THSAM complements this with continuous eye movement data that reflect participants' real-time attentional focus. This integration allows for a more temporally sensitive and minimally disruptive assessment of SA, capturing its development throughout the task rather than at isolated points. In contrast to SAGAT's intermittent assessments, THSAM offers a more seamless, temporal continuity, and fine-grained understanding of SA dynamic during task execution.

The third SA measurement was ERPs. The role of ERPs is as objective neural-cognitive complementary evidence of SA levels. SA levels were quantified by the amplitude of key ERPs components: for SA1, P1, P2, and P3 at channels Oz, O1, and O2; and for SA2 and SA3, the N400 at channels T7, T8, F3, F4, F7, F8, and Fz [31–34]. ERPs were analyzed using EEGLAB v2024.0 [49] and ERPLAB v11.03 [50] toolbox in MATLAB R2024b. To identify SA-related epochs, time-marked SA level 1, level 2, and level 3 events were used, which corresponded to correct SA-level SAGAT question times locked with corresponding fixation start times. Independent components analysis (ICA) was employed to decompose the labeled epochs into their statistical abstractions of components. ICA works by generating an unmixing matrix that leads to independent components (ICs), using a neural network and learning algorithm [51].

To mitigate human bias and ensure artifact rejection, ICLabel v1.6 was used to flag ICs as artifacts generated by brain, eye, muscle, heart, line noise, channel noise, or other. ICLabel adopted three artificial neural network architectures: CNN with unweighted cross entropy loss, CNN with weighted cross entropy loss, and semi-supervised learning generative adversarial networks (SSGAN) [52]. ICs with more than 90 % probability labeled as artifacts were rejected. The 0.1–30 Hz band-pass filter is widely used in EEG filtering because it effectively captures the meaningful delta, theta, alpha, beta, and gamma frequency bands of brain activity while removing low-frequency artifacts (e.g., from motion or slow fluctuations) and high-frequency noise (e.g., muscle artifacts or electrical interference), thereby ensuring that the filtered signal reflects accurate and interpretable neural information.

To provide visualization of the effects of the augmented stimuli and safety goals on SA-related brain activity, cross-participants' averaged ERPs waveforms and scalp maps were plotted. This was achieved by first averaging epochs time-locked to events after artifacts removal, which were then used to plot the ERPs waveforms. Subsequently, the specific ERPs components associated with SA were isolated from the waveforms, thereby enabling the quantification of SA. Furthermore, ERPs scalp maps were plotted based on the averaged epochs, in addition to the ERPs waveforms.

3.5.2. SA transition analysis

SA transition analysis was conducted to evaluate the effectiveness of two interventions (i.e., augmented stimuli and safety goal setting) in promoting participants' progression from lower to higher SA levels across distinct stages (i.e., Stage A, B1, B2, and C). Unlike previously modified SAGAT methods that assess SA based on average response accuracy, SA transition analysis evaluates SA by SA-labeled hazard instances.

Each task consists of five hazards and involves 30 participants, resulting in a total of 150 hazard instances per task (30 participants × 5 hazards). These instances are labeled according to SA levels using modified SAGAT questionnaires, where each participant's response to each hazard is assigned a specific SA level. For example, a participant may achieve SA Level 2 (comprehension) for one hazard, but only SA Level 1 (perception) for another. Such variability reflects the inherently dynamic and context-dependent nature of SA, as noted in prior studies.

Each of the 150 hazard instances was classified into one of four SA levels: SA0 (no perception), SA1 (perception), SA2 (comprehension), or SA3 (projection). By analyzing the distribution and transitions of these

SA-labeled hazard instances across stages, this approach provides a detailed view of how each intervention supports the advancement of SA, offering insights into their relative effectiveness in enhancing SA transitions.

3.5.3. Hazard recognition performance

To evaluate participants' hazard recognition abilities, we calculated the hazard recognition index (HRI) using Equation (1) [53]:

$$Hazard\ recognition\ index(HRI) = \frac{H_{Recognized}}{H_{Total}} \tag{1}$$

where $H_{Recognized}$ represents the number of hazards identified by each participant during a stage, and H_{Total} is the total number of recognizable hazards presented in that stage.

The $H_{Recognized}$ was determined by the SAGAT questionnaire. If both Q1 and Q2 were answered correctly, it indicated that the hazard had been successfully recognized. As shown in Table 1, each task presented five hazards, resulting in a constant H_{Total} of 5 for all stages.

3.5.4. Repeated measures ANOVA

Repeated measures ANOVA in MATLAB R2024b was used to statistically analyze SAGAT correctness, SA-labeled fixation count, key ERPs components' peak amplitude, and HRI across different stages: A-B1, A-B2, B1-C, and B2-C. It is worth noting that since SA3 is achieved based on the premise of SA2, SA2-related fixation counts were combined from both SA2- and SA3-labeled fixations. Similarly, as SA2 builds upon SA1, SA1-related fixation counts included all labeled fixations across SA1, SA2, and SA3.

The independent variables were augmented stimuli and safety goals, while the dependent variables comprise the SAGAT correctness, SA-labeled fixation count, key ERPs components' peak amplitude, and HRI. Before performing the repeated measures ANOVA, assumptions of normality and sphericity were evaluated to ensure the validity of the analysis. The normality of each dependent variable within groups was assessed using the Kolmogorov-Smirnov test, which confirmed that all variables followed a normal distribution ($p > 0.05$) [54]. Sphericity was tested using Mauchly's test, and the results indicated that the assumption of sphericity was met ($p > 0.05$) [55]. All degrees of freedom are one.

In the repeated measures ANOVA, the effect size was estimated via eta squared (η^2). This measure, widely utilized in statistical analyses [56], is defined as the ratio of the between-group sum of squares for factor A (SS_A) to the total sum of squares (SS_T). Eta squared reflects the proportion of variance in the dependent variable explained by factor A relative to the total observed variance. Here, SS_A captures systematic differences between groups associated with factor A, while SS_T accounts for all variability in the dataset.

$$\eta^2 = \frac{SS_A}{SS_T} \tag{2}$$

4. Results

4.1. Effects of interventions on SA levels

This subsection reports how each intervention impacts SA levels. Fig. 5 and Fig. 6 show the average response correctness in the modified SAGAT for each SA level across various stages in two tasks. In specific, as shown in Fig. 5, for SA level 1 (perception) in Task 1, average response correctness improved from 47 % (Stage A) to 75 % (Stage B1) and 81 % (Stage C). This indicates that both augmented stimuli alone and combined with safety goals significantly enhanced participants' ability to perceive hazards. Such a SA enhancement suggests that interventions are effective to help participants perceive more hazards. Similar upward trends were observed for SA2 and SA3, and this suggests that these interventions also improved participants' comprehension of hazard meaning and ability to project future risks. Similar results and trends were observed in Configuration Two, as shown in Fig. 6.

Fig. 5 demonstrates that, when comparing Stage A with Stage B1, all average response correctness values increased. This indicates that augmented stimuli enhanced all three SA levels, with the enhancement being particularly pronounced for SA1 in Task 2 (increasing from 34 % to 65 %, a 31 % gain). Conversely, Fig. 6 reveals minimal improvement in average response correctness across SA levels when comparing Stage A with Stage B2. This suggests that safety goal settings alone do not significantly increase SA performance. This is most notable for SA3 in Task 1, where average response correctness remained unchanged at 39 % between stages. Collectively, these results indicate that safety goals alone are less effective than augmented stimuli for improving SA levels.

Within-subject repeated measures ANOVA were conducted to statistically evaluate the effects of the interventions on within-subject SAGAT correctness. The results between Stages A and Stage B1 revealed that employing augmented stimuli resulted in statistically significant improvements in all three levels of SA (perception, comprehension, and projection), as indicated by P-values < 0.001 (Table 2). Similarly, when safety goals were introduced at Stage B2, repeated measures ANOVA showed that they also significantly improved all three levels of SA, with P-values <0.01 (Table 2). Furthermore, the combination of augmented stimuli and safety goals demonstrated even greater enhancements, with statistically significant improvements in all three levels of SA ($P < 0.05$) as shown in Table 2. These findings collectively suggest that implementing both augmented stimuli and safety goals can

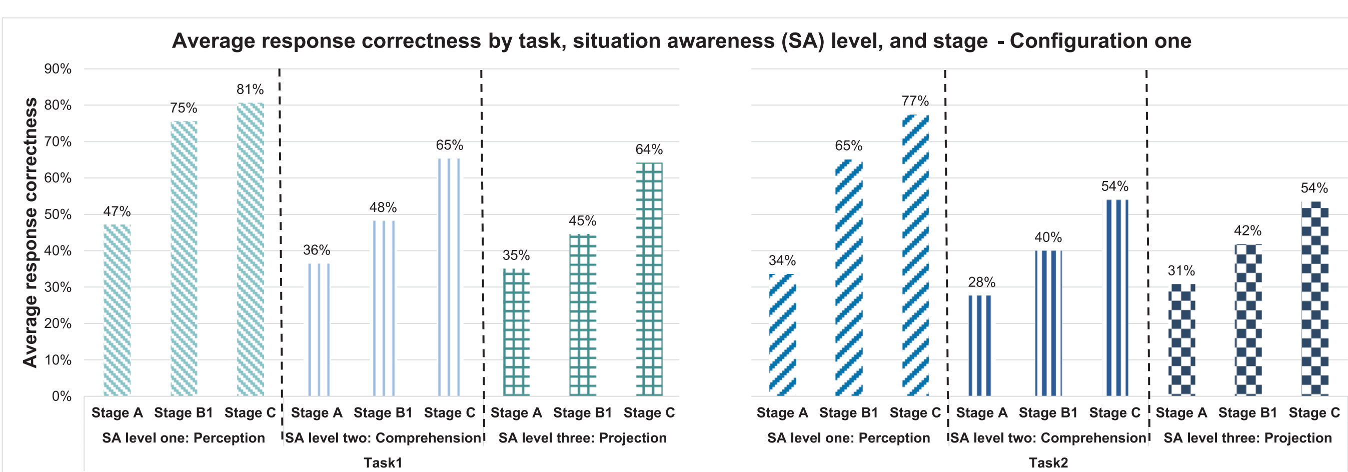

Fig. 5. Average response correctness – Configuration one.

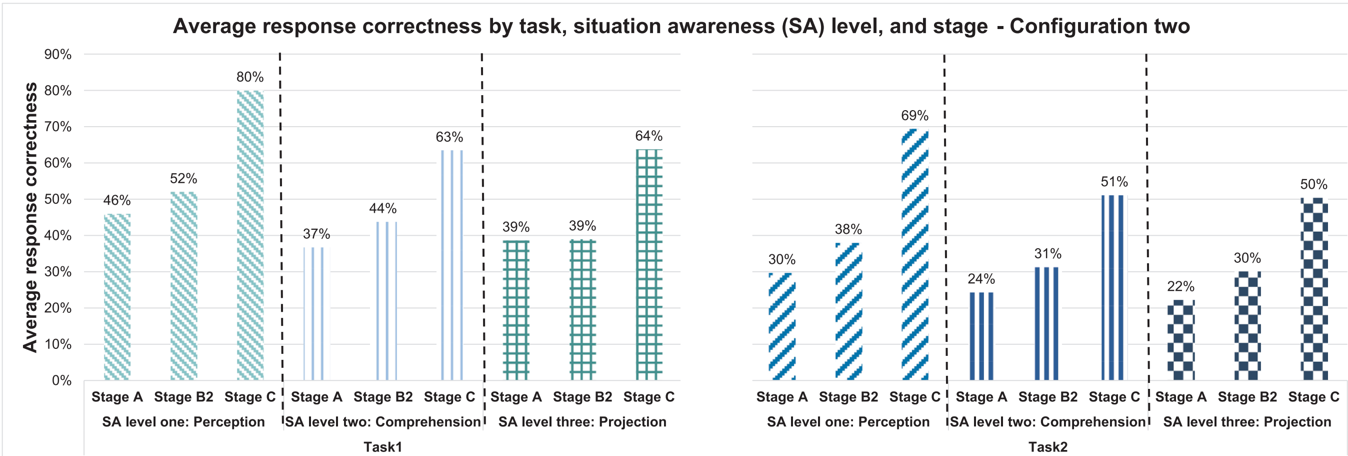

Fig. 6. Average response correctness – Configuration two.

Table 2
Repeated measures ANOVA results for the effects of interventions on SAGAT correctness.

Stages	SA level	Task	P value	F-statistic	Effect size
A-B1	SA1	One	<0.0001	33.846	0.70
		Two	<0.0001	42.058	0.79
	SA2	One	<0.0001	21.434	0.73
		Two	<0.0001	20.458	0.74
	SA3	One	<0.001	15.690	0.76
		Two	<0.0001	22.993	0.77
A-B2	SA1	One	<0.01	10.412	0.56
		Two	<0.001	16.698	0.64
	SA2	One	<0.001	16.319	0.67
		Two	<0.0001	19.886	0.76
	SA3	One	<0.01	7.973	0.58
		Two	<0.01	11.518	0.77
B1-C	SA1	One	<0.05	5.749	0.53
		Two	<0.01	10.121	0.57
	SA2	One	<0.0001	20.942	0.65
		Two	<0.0001	21.380	0.64
	SA3	One	<0.0001	28.738	0.71
		Two	<0.0001	26.634	0.67
B2-C	SA1	One	<0.0001	37.223	0.69
		Two	<0.0001	38.715	0.76
	SA2	One	<0.0001	20.262	0.68
		Two	<0.0001	22.692	0.73
	SA3	One	<0.0001	27.143	0.78
		Two	<0.0001	25.944	0.83

lead to a comprehensive enhancement of within-subject SAGAT correctness across all three levels.

The results presented above were complemented by the THSAM analysis results, where fixation counts and duration were coded by SA level. As shown in Fig. 7 and Fig. 8, fixations on hazards that are labelled in a green cross represent perception-fixations, those in purple triangle represent comprehension-fixations, and those in red circle represent projection-fixation. In specific, as shown in in subfigure (a) "SA-labeled fixation count – Configuration one" of Fig. 7 and Fig. 8, it is clear that participant's aggregated perception level significantly enhanced from Stage A (baseline) to Stage B1 (augmented stimuli intervention). This provides objective evidence that augmented stimuli could effectively enhance participants' perception of hazards. In task one, there is no increase in perception from Stage B1 to Stage C. This suggests that participants' perception at SA1 reached a ceiling, even with the addition of safety goals, fixation counts did not rise further. In contrast, comprehension- (SA2) and projection-fixation (SA3) counts continue to climb steadily from Stage A to Stage B1 to Stage C.

Subfigure (c) of Fig. 7 and Fig. 8, titled "SA-labeled fixation count – Configuration Two," presents the THSAM results for Configuration Two. Comparing participants' fixations between Stage A (baseline) and Stage B2 (safety goal only), there was a noticeable increase in fixations at the comprehension (SA2) and projection (SA3) levels. This suggests improved understanding and anticipation of hazards. Interestingly, perception-level fixations (SA1) decreased at Stage B2 compared to Stage A, indicating that a global focus on safety goals may divert attention away from basic perceptual processing of hazards. However, in Stage C, where both augmented stimuli and safety goals were combined, fixation counts increased across all three SA levels—perception, comprehension, and projection. This demonstrates that the combined approach results in the most comprehensive enhancement across all levels of SA. In contrast, subfigures (b) and (d) in Fig. 7 and Fig. 8, which report "SA-labeled fixation duration," show that fixation duration remains largely unaffected by either intervention, suggesting that duration is less sensitive to changes in stimuli or goal framing.

A within-subjects repeated-measures ANOVA was conducted to examine the effects of augmented stimuli and safety goals on SA1–SA3 labeled fixation counts across different stages (Table 3). For Task 1, the difference in SA1 between Stage B1 (augmented stimuli only) and Stage C (augmented stimuli + Safety Goals) did not reach statistical significance ($p = 0.789$), indicating no appreciable enhancement in Level-1 awareness due to the addition of Safety Goals. Similarly, the comparisons between Stage A (baseline) and Stage B2 (safety goals only) shown non-significant effects for SA1 ($p = 0.748$), SA2 ($p = 0.090$), and SA3 ($p = 0.851$), suggesting that safety goals alone did not significantly alter fixation behavior at any SA level. In contrast, all other stage contrasts produced significant differences in fixation counts ($p < 0.05$), confirming that either augmented stimuli alone or the synergy of augmentation with safety goals substantially improved situation awareness at the corresponding levels.

Cross-participants averaged ERPs waveforms and scalp maps were used to visualize the effects of augmented stimuli and safety goals on brain activity in three SA levels. For Task 1 under SA1 (H5, Configuration 1) at channel O1 (Fig. 9), the ERPs waveforms for Stages A, B1, and C reveal a clear P2-component modulation. Specifically, P2 amplitude increases from Stage A to B1 to C, suggesting that the augmented stimuli elicit progressively stronger neural engagement in later stages. This progression is further supported by the scalp maps in Fig. 10: activation at O1 is lowest in Stage A and increases through B1 to peak in Stage C.

Analogous effects on the N400 component were observed for SA2 and SA3. Fig. 11 and Fig. 13 display the averaged N400 waveforms for SA2 and SA3, while Fig. 12 and Fig. 14 present the corresponding scalp maps. In each case, later stages exhibit stronger N400 amplitudes, mirroring the pattern seen in SA1. Collectively, these findings indicate that the inclusion of augmented stimuli and safety goals elicits significantly larger P2 and N400 amplitudes, reflecting an overall

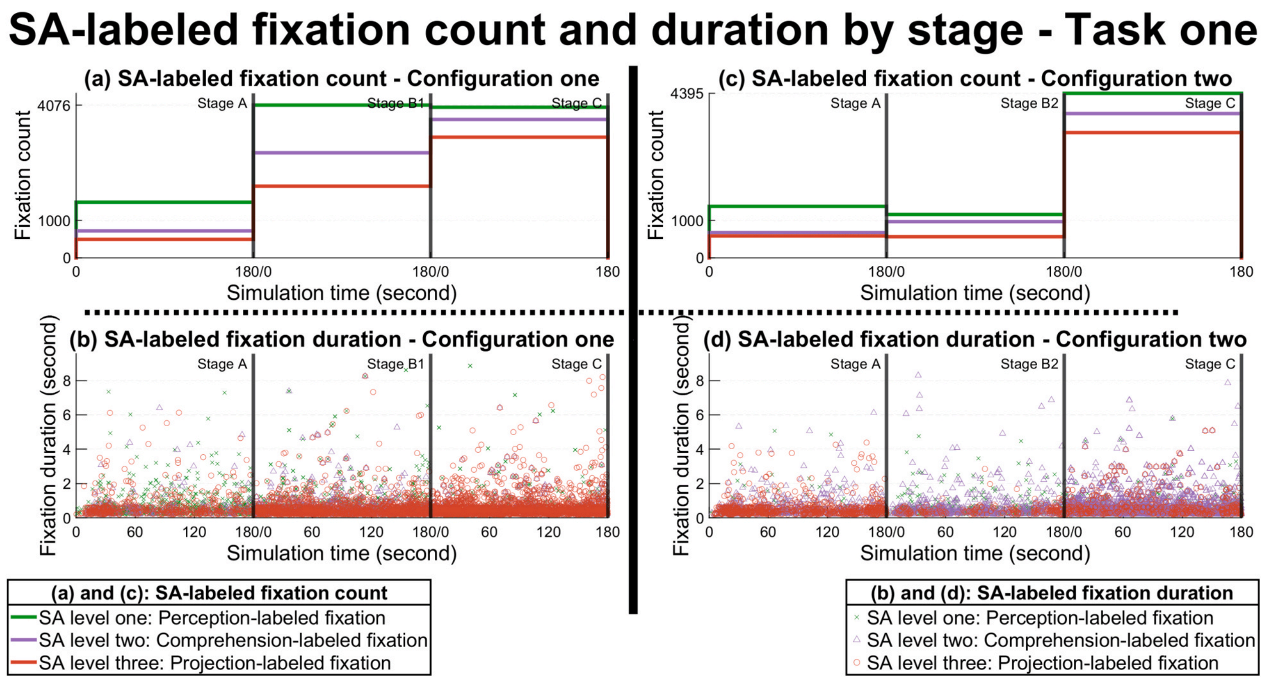

Fig. 7. SA-labeled fixation count and duration by stage – Task one.

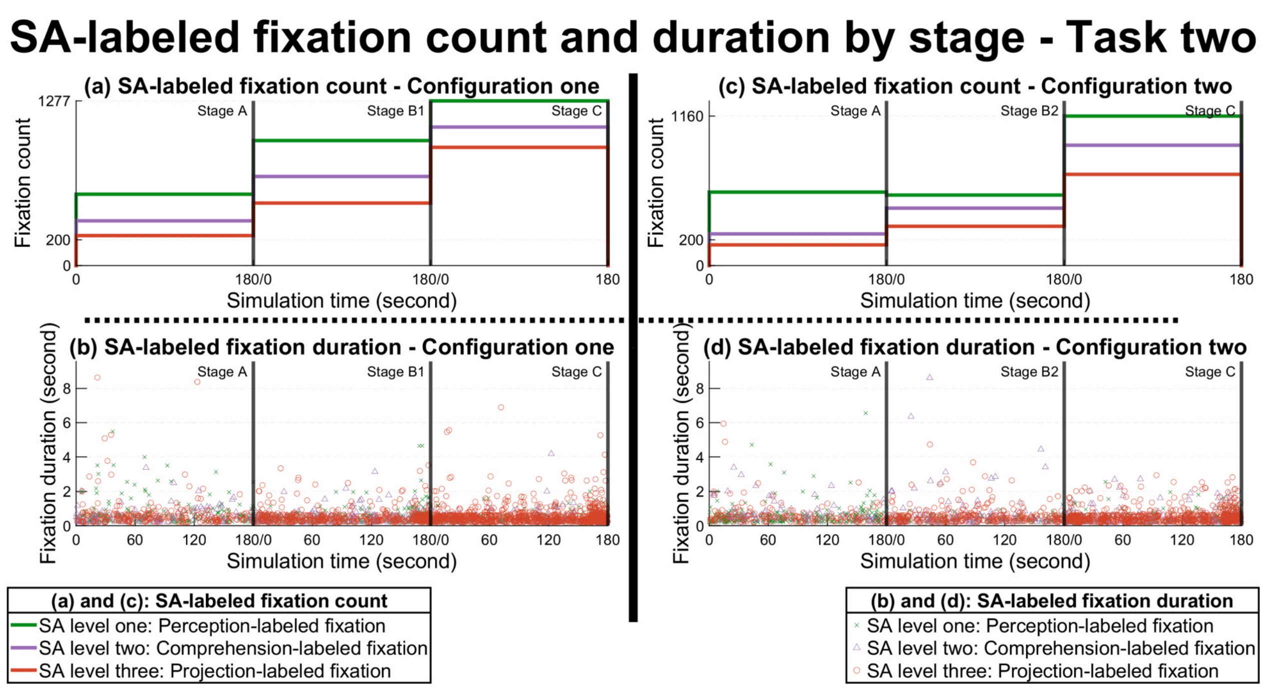

Fig. 8. SA-labeled fixation count and duration by stage – Task two.

enhancement in SA1, SA2, and SA3.

4.2. SA transition

To assess transitions between SA levels, Fig. 15 and Fig. 16 present aggregated results from five hazards across all participants (N = 30), resulting 150 SA-labeled hazard instances per task per stage.

In Task 1 of Configuration One (augmented stimuli first, followed by safety goal setting), Fig. 15 shows that the baseline Stage A was characterized by a high number of unperceived hazards (SA0 = 79) and relatively few at the perception level (SA1 = 38). Introducing augmented stimuli in Stage B1 significantly reduced SA0 (down to 36) and more than doubled the number of SA1 instances (rising to 76), indicating a strong impact on initial hazard detection. Although comprehension-level awareness (SA2) saw a modest increase, from 10 to 17, the effect on projection-level awareness (SA3) was limited. This suggests that augmented stimuli alone are more effective in fostering transitions from no awareness to perception (SA0–SA1) than in supporting higher-level understanding (SA2) and projection (SA3). Similar patterns emerged in Task 2.

In Stage C of Task 1, the combination of augmented stimuli with safety goal setting resulted in a pronounced increase in projection-level

Table 3
Repeated measures ANOVA results for the effects of interventions on SA1–SA3 labelled fixation counts.

Configuration	Task	Cognitive process	Stages	pValue	F	Effect size
One	Task1	SA1	A-B1	<0.0001	36.368	0.885
			B1-C	0.789	0.072	0.502
	Task2	SA1	A-B1	<0.0001	23.289	0.711
			B1-C	<0.001	13.071	0.635
	Task1	SA2	A-B1	<0.0001	31.059	0.910
			B1-C	<0.01	7.187	0.597
	Task2	SA2	A-B1	<0.001	15.327	0.759
			B1-C	<0.0001	17.704	0.668
	Task1	SA3	A-B1	<0.0001	19.640	0.906
			B1-C	<0.001	14.338	0.665
	Task2	SA3	A-B1	<0.001	13.154	0.762
			B1-C	<0.0001	22.312	0.695
Two	Task1	SA1	A-B2	<0.05	4.221	0.433
			B2-C	<0.0001	40.588	0.924
	Task2	SA1	A-B2	0.748	0.104	0.463
			B2-C	<0.0001	35.586	0.794
	Task1	SA2	A-B2	0.090	2.962	0.570
			B2-C	<0.0001	38.875	0.929
	Task2	SA2	A-B2	<0.01	9.893	0.650
			B2-C	<0.0001	26.497	0.784
	Task1	SA3	A-B2	0.851	0.036	0.408
			B2-C	<0.0001	33.440	0.960
	Task2	SA3	A-B2	<0.01	9.001	0.658
			B2-C	<0.0001	19.675	0.795

awareness. SA3 rose sharply from 23 to 66, reflecting a significant improvement in participants' ability to anticipate potential hazards. This synergistic effect was evident across both tasks.

In Configuration Two (safety goal setting followed by augmented stimuli), baseline Stage A in Task 1 (Fig. 16) mirrored those of Configuration One, with high SA0 counts (81) and moderate SA3 levels (34). When safety goals were introduced in Stage B2, the number of SA0 instances decreased slightly to 72. However, a marked shift occurred in comprehension-level awareness: SA2 more than tripled, reaching 20. This suggests that safety goals primarily support deeper understanding rather than initial perception. Interestingly, both SA1 and SA3 decreased slightly, implying that participants may have focused more cognitive effort on understanding hazards than on perceiving or projecting their outcomes. Task 2 followed a similar trajectory.

With the addition of augmented stimuli in Stage C of Configuration Two, improvements became more widespread. SA0 dropped to 30, while SA1, SA2, and SA3 rose to 35, 23, and 62, respectively. These results underscore the broad efficacy of the combined interventions. Importantly, the sequence of interventions influenced the nature of the gains: initiating with augmented stimuli tended to optimize early-stage perception (SA1), whereas starting with goal setting better supported mid-level comprehension (SA2). Regardless of sequence, the combination of both methods consistently produced the strongest outcomes across all awareness levels (SA1–SA3). These effects were consistently replicated in Task 2.

4.3. Effects on hazard recognition

A repeated measures ANOVA was employed to investigate the effects

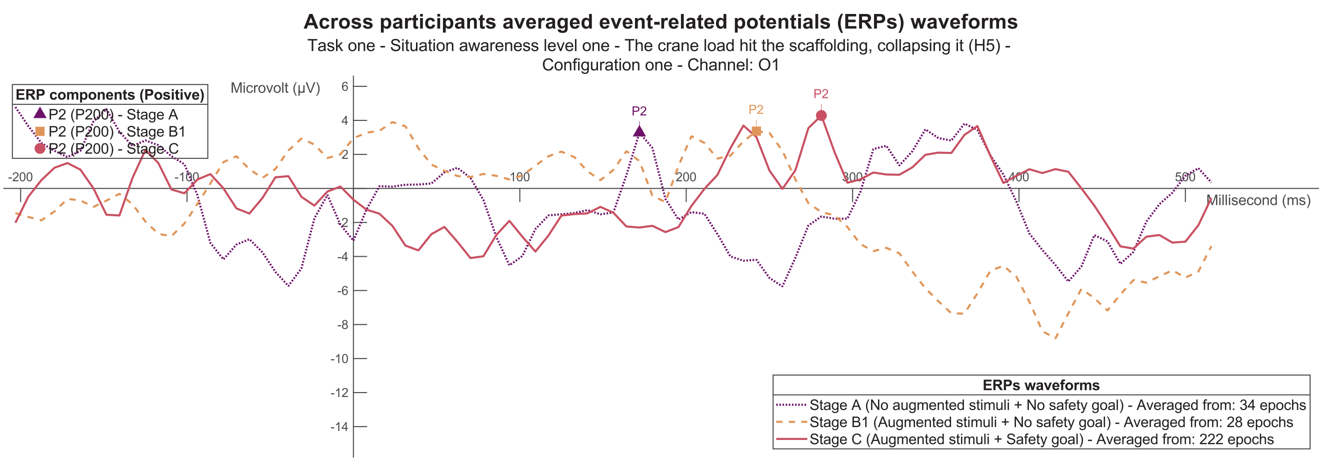

Fig. 9. SA1 ERPs waveforms.

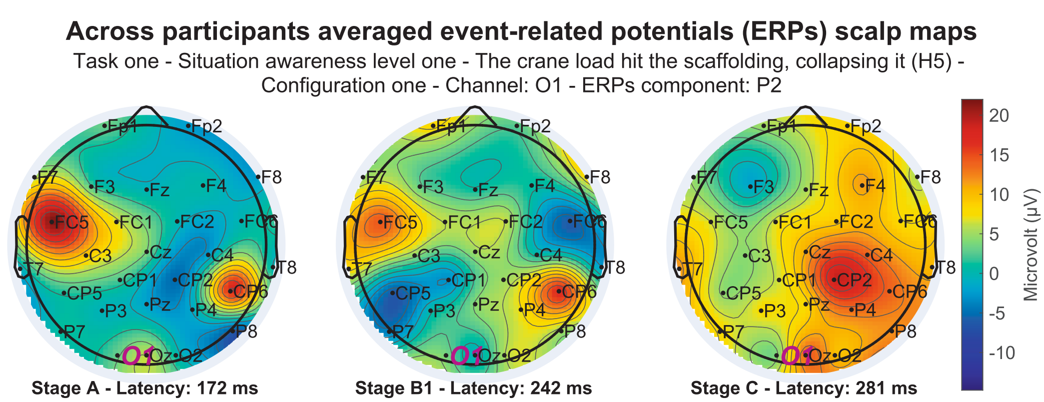

Fig. 10. SA1 ERPs scalp maps.

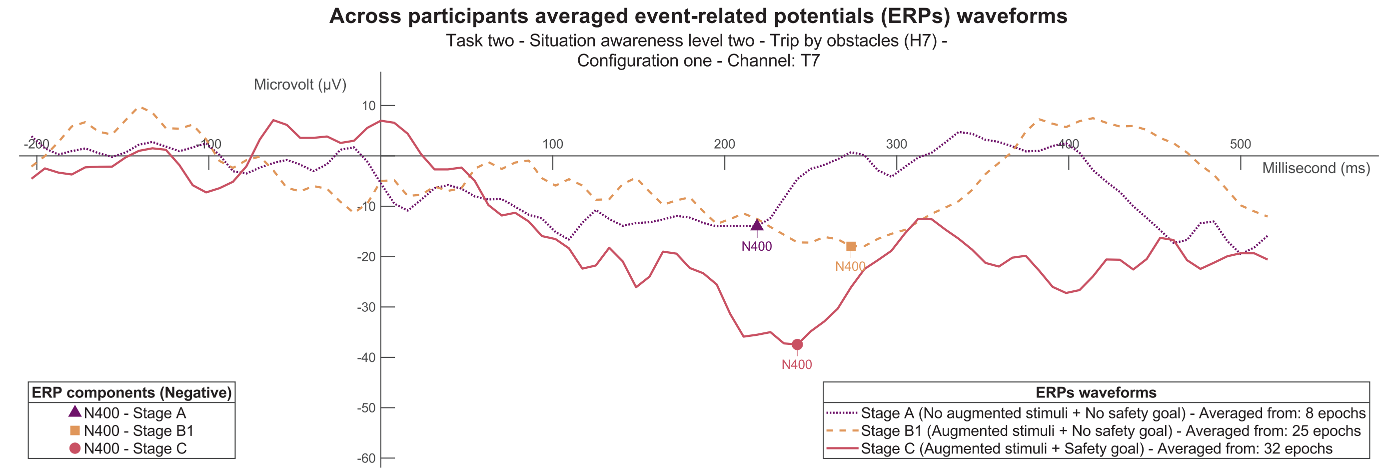

Fig. 11. SA2 ERPs waveforms.

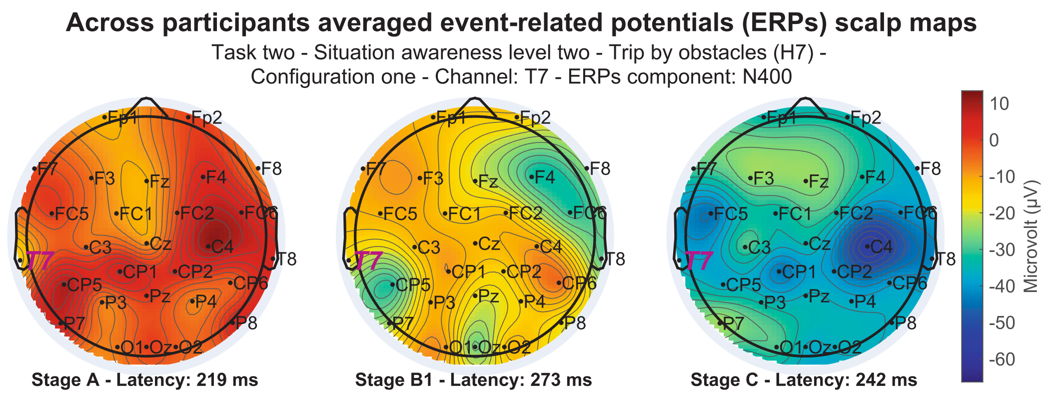

Fig. 12. SA2 ERPs scalp maps.

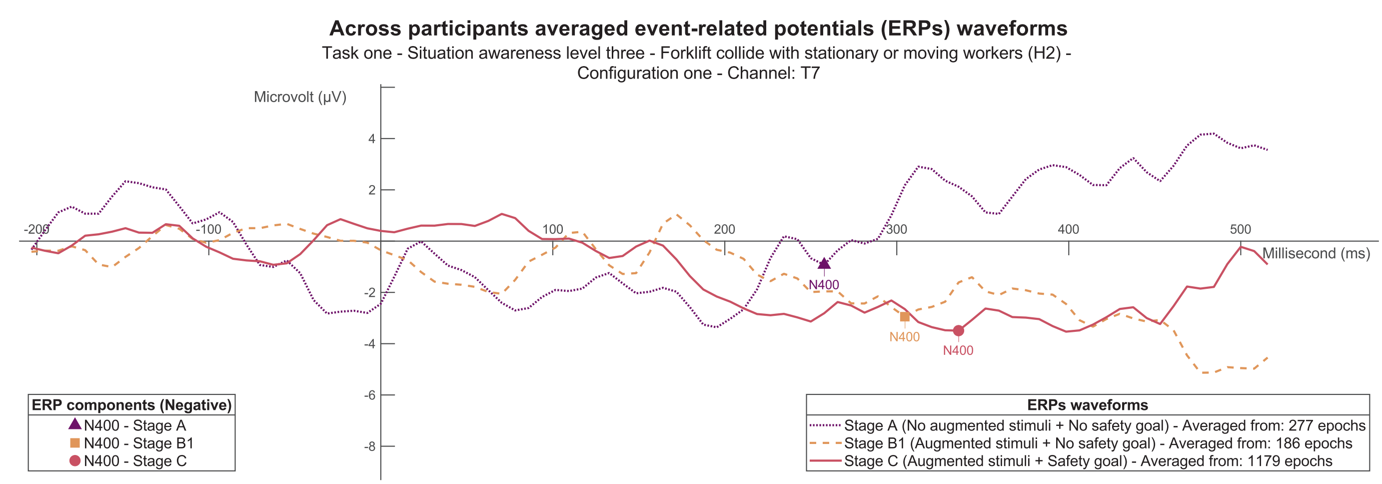

Fig. 13. SA3 ERPs waveforms.

of augmented stimuli and safety goals on HRI within-subject. The results, as presented in Table 4, demonstrate a significant influence of augmented stimuli on HRI between stages A and B1 ($P < 0.0001$). Furthermore, the analysis indicates a significant main effect of safety goals on HRI between stages A and B2 ($P < 0.0001$). An interaction effect was observed with both augmented stimuli and safety goals on HRI between stages B1/B2 and C ($P < 0.0001$).

5. Discussion

This study investigated the effects of augmented stimuli and safety goal setting on SA levels, SA transition and hazard recognition in dynamic construction environments. SA was assessed using a multimodal approach that combined modified SAGAT, THSAM, and ERPs. Together, these methods enabled a robust investigation of the temporal and cognitive dynamics underlying SA development and transition.

The modified SAGAT revealed that both augmented stimuli and

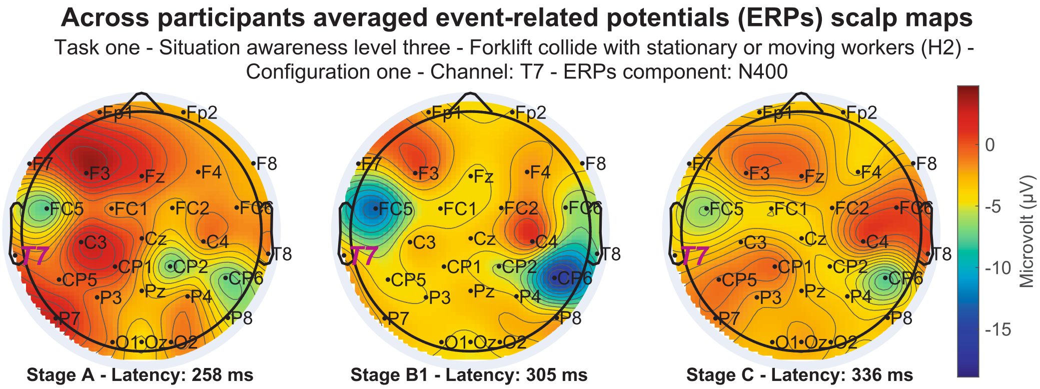

Fig. 14. SA3 ERPs scalp maps.

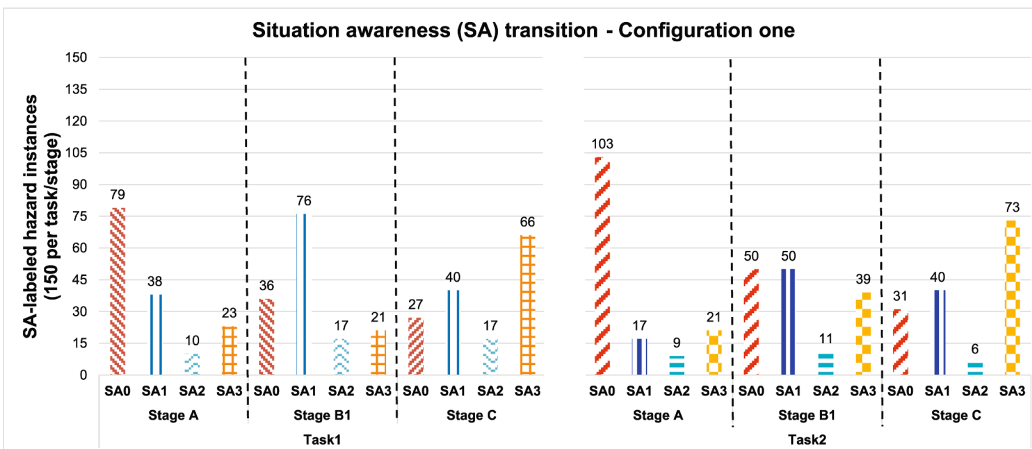

Fig. 15. Configuration one SA transition map between levels.

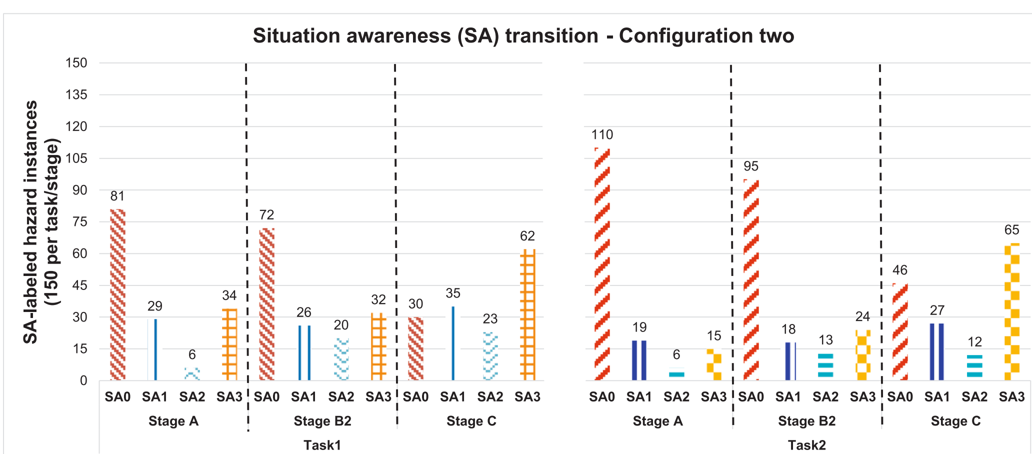

Fig. 16. Configuration two SA transition map between levels.

safety goals significantly improved average response correctness for all three SA levels. It should be noted that the combination of both interventions in Stage C produced the highest gains: perception accuracy increased from 47 % (baseline) to 81 %, while comprehension and projection levels also improved. By leveraging fixation count data labeled by SAGAT correctness, THSAM proved effective in quantifying SA transitions across perception (SA1), comprehension (SA2), and projection (SA3). These results suggest that augmented stimuli enhance attention allocation and sensory input processing, while safety goals promote deeper cognitive processing necessary for higher-level SA.

In contrast, the SA transition analysis offered a complementary perspective by tracking the distribution of SA-labeled hazard instances across SA levels. Results showed that in the baseline stage (Stage A), more than half of the hazard instances (79 out of 150) were not even perceived (SA0). In Stage B1 (augmented stimuli), SA0 cases dropped to 36, and SA1 increased substantially, which shows improved hazard detection. In Stage C (combined interventions), 66 out of 150 hazard instances reached SA3, which indicates a significant shift toward

Table 4
Repeated measures ANOVA results for the effects of interventions on HRI.

Stages	Task	P value	F-statistic	Effect size
A-B1	Task1	<0.0001	28.835	0.67
A-B1	Task2	<0.0001	40.078	0.80
A-B2	Task1	<0.0001	23.768	0.68
A-B2	Task2	<0.0001	22.277	0.80
B1-C	Task1	<0.0001	23.094	0.63
B1-C	Task2	<0.0001	27.242	0.69
B2-C	Task1	<0.0001	32.491	0.65
B2-C	Task2	<0.0001	34.683	0.70

proactive hazard anticipation. These findings reinforce that augmented stimuli primarily support early SA (perception), while safety goals contribute more to comprehension and projection, and their combination yields a synergistic effect.

ERPs results further validate these findings by showing that augmented stimuli and safety goals elicited increased neural activity across key components (P2 and N400), associated with attention, working memory, and decision-making. These neural patterns align with increased SA levels measured behaviorally, which shed light on the cognitive mechanisms driving SA transition.

Our findings are consistent with prior research demonstrating that hazard visualization, exposure estimation, and real-time alerts enhance workers' hazard recognition [14,57] The results expand upon existing literature by showing that cognitive transitions between SA levels are not automatic. Instead, they require both external sensory cues and internal motivational structures, such as safety-oriented goals.

Our results suggest that the mechanism underlying SA enhancement can be attributed to the complementary roles of augmented stimuli and safety goals. Augmented stimuli improve the acquisition of environmental cues through bottom-up attention, while safety goals activate top-down cognitive processes, such as schema-guided comprehension and goal-directed decision-making. Together, they enable more complete SA transitions and more effective hazard recognition. It should be noted that SA is inherently dynamic and iterative. Workers must continuously update their mental models as site conditions evolve. These findings highlight the need for ongoing support to maintain high SA levels over time and suggest that future safety interventions should integrate both real-time visual assistance and motivational framing to sustain SA in complex, changing environments.

One potential concern is the inclusion of both workers and postgraduate students in the participant pool, as previous research suggests that experienced workers may exhibit different task performances and neural responses to hazards across SA1 to SA3. However, in our study, ANOVA results revealed no significant differences between the two groups on key outcome measures, including SAGAT scores, THSAM ratings, and hazard recognition performance. These findings indicate that, within the context of our experimental design, participant experience level did not have a substantial impact on performance. It is also important to note that most of the workers in our sample had less than five years of practical experience, which may account for the absence of significant differences. Therefore, we deemed it appropriate to include both groups in the final analysis without compromising the validity of the results.

5.1. Theoretical contribution

This paper makes the following key theoretical contributions in the field of engineering informatics and construction safety. First, this paper extends Endsley's SA framework [5] by empirically validating how bottom-up (stimuli-driven) and top-down (goal-driven) processes interact to shape SA transitions and hazard recognition outcomes in the construction context. It conceptualizes SA not as a static state for the whole site scene, but as a dynamic and transitional process involving four levels (i.e., no perception, perception, comprehension, and projection) at each hazard level. This highlights that higher SA level for a hazard does not guarantee the same SA level for another hazard. This paper advances the theoretical understanding of SA by framing it as dynamic cognitive flow.

Second, this paper introduces the Temporal Hybrid Situation Awareness Measurement (THSAM) approach, which combines real-time eye tracking with the Situation Awareness Global Assessment Technique (SAGAT). This innovative method enables detailed temporal mapping of SA transitions and captures the dynamic evolution of SA across three levels. By labeling gaze data based on SAGAT correctness, THSAM bridges the gap between objective sensor-based inputs and subjective cognitive processes.

Third, the study applies ERPs derived from EEG signals to quantify the neural underpinnings of SA transition. ERPs components such as P1, P2, and N2pc provide robust neural evidence of the effects of augmented stimuli and safety goals on cognitive processing, adding a neuroscientific layer to hazard recognition research in construction.

Last but not least, results suggest that augmented stimuli significantly enhance perception and comprehension, while safety goals more effectively support comprehension and projection. When combined, these interventions produce a synergistic effect, facilitating smoother and more complete transitions to higher SA levels and improving hazard recognition performance. Results also show that SA development is not only goal- and environment-dependent but also highly influenced by task type and hazard characteristics.

5.2. Managerial implication

This paper provides several practical implications for construction safety management, particularly in the context of ongoing digital transformation and the evolving role of cognitive safety support. As the construction industry undergoes a wave of digitalization and automation, there is increasing interest in deploying advanced technologies to enhance workers' hazard recognition and situational awareness (SA). Our research findings suggest that both technology-enabled interventions and traditional safety management practices play distinct yet complementary roles in supporting SA transitions across different cognitive levels. First, augmented stimuli significantly enhance hazard perception and comprehension. Managers should adopt smart technologies (e.g., AR alerts, wearables) to direct workers' attention to immediate dangers in real time. There has been a wealth of research in this area. This study provides another piece of evidence. Second, the combined use of digital stimuli and safety goals yields the greatest improvement in situational awareness. Managers should design safety interventions that synchronize technology with cognitive safety framing. Third, tools like eye tracking and EEG can identify SA gaps during training. Managers can use these insights to provide targeted feedback and develop personalized safety coaching. Training programs should support transitions from perception (SA1) to projection (SA3), using realistic simulations and guided reflection to develop proactive hazard recognition.

5.3. Limitations and future research

While this study makes several contributions to the literature on SA and hazard recognition, there are some limitations that should be noted. To mitigate carry-over effects and learning effects, a 10-minute break was incorporated between each stage, during which participants were guided to refocus their attention. Additionally, safety goals were introduced in later stages (B2 and C), and unique differences existed among the three stages presented. Moreover, the Hawthorne effect was addressed by creating non-intrusive environments where participants remained unaware of the experiment facilitator's presence throughout the experiments. Despite technical limitations, we were unable to completely eliminate artifacts caused by motion and interference between the HTC VIVE and EMOTIV devices. However, these issues were effectively mitigated using ICA and filtering techniques, significantly reducing artifact-related noise in EEG data. The primary focus of this study was on eye movement data collected via HTC VIVE, with EEG serving as supplementary evidence to support the findings.

While the proposed multimodal SA measurement model, which integrates self-report (Modified SAGAT), behavioral (eye tracking), and physiological (ERPs) data, provides a comprehensive framework for understanding SA dynamics, several limitations should be acknowledged. The current implementation was tested in relatively simple task environments, specifically forklift operation and bricklaying. In more complex and high-stakes scenarios, SA dynamics are likely to involve non-linear transitions and higher inter-individual variability. Therefore, future studies should assess the adaptability of the model under varying levels of task complexity, cognitive load, time pressure, and uncertainty. Although post hoc analysis enabled alignment of behavioral and physiological markers, achieving real-time synchronization and effective integration of multimodal data streams remains a significant challenge. This limitation currently restricts the model's application for real-time SA monitoring and decision support. Future research should investigate computational frameworks capable of fusing multimodal inputs in real time, with adaptive temporal resolution based on task demands. Additionally, while the THSAM method demonstrated promise in capturing dynamic SA transitions, its sensitivity parameters (e.g., SA label alignment window, AOI, and fixation calibration) were defined heuristically. These parameters require further empirical validation. Establishing normative baselines across different populations and task contexts will improve the interpretability, reliability, and generalizability of the THSAM approach.

Several future research directions can be identified based on the findings from this study. Firstly, further research is needed to investigate the optimal deployment of augmented stimuli and safety goals in different contextual conditions, potentially across various industries or work environments. Secondly, neuroimage technology such as functional magnetic resonance imaging (fMRI) can provide subcortical brain activity where EEG cannot measure, warranting future research exploration. Thirdly, real-time monitoring systems using wearable EEG devices have the potential to detect SA failure and provide alerts during high-risk tasks. Moreover, safety training programs can integrate neurofeedback tools, enabling individuals to enhance SA through personalized, measurable regimens, potentially augmented by VR or augmented reality simulations. Furthermore, work schedules and environments can be optimized based on ERPs metrics of low SA levels, improving task allocation and rest cycles. Finally, ERPs metrics can also serve as standardized assessment tools for SA readiness during recruitment and performance evaluations.

6. Conclusion

This study has significantly contributed to understanding SA transition and hazard recognition among construction site workers. By integrating VR, eye tracking, EEG, and ERPs with tools like SAGAT and THSAM, the research offered valuable insights into the cognitive and neural mechanisms underlying SA. The findings demonstrated that augmented stimuli combined with safety goals effectively enhance SA, though their effectiveness varies based on contextual conditions. While the study's virtual environment may not fully mirror real-world settings, its immersive nature provided valuable insights. Future research should explore optimal deployment of these interventions across industries, utilize advanced neuroimaging techniques like fMRI for deeper brain activity analysis, and develop tailored training programs. These efforts aim to enhance safety protocols and workplace training strategies, emphasizing the need for continued exploration in this critical area of construction safety.

CRediT authorship contribution statement

Zhe Zhang: Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Brian H.W. Guo:** Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **Zhenan Feng:** Writing – review & editing, Supervision, Methodology. **Yang Miang Goh:** Writing – review & editing, Supervision, Methodology, Funding acquisition, 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.

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Data availability

Data will be made available on request.

References

[1] S.M. Jamil, A. Uddin, A. Albert, B. Alsharef, Y. Pandit, C.N. Patil, Hazard recognition patterns demonstrated by construction workers, Int. J. Environ. Res. Public Health 17 (2020), https://doi.org/10.3390/ijerph17217788.

[2] Z. Zhang, B.H.W. Guo, A. Chang-Richards, Z. Feng, R. Jin, Y. Zou, Y.M. Goh, Digital technology enhanced situation awareness for construction safety: systematic review and future research directions, Saf. Sci. 167 (2023) 106280, https://doi.org/10.1016/J.SSCI.2023.106280.

[3] B.H.W. Guo, Q. Li, W. Yi, B. Ma, Z. Zhang, Y. Zuo, Network analysis and graph neural network (GNN)-based link prediction of construction hazards, Autom. Constr. 176 (2025) 106302, https://doi.org/10.1016/J.AUTCON.2025.106302.

[4] G. Carter, S.D. Smith, Safety hazard identification on construction projects, J. Constr. Eng. Manag. 132 (2006) 197–205, https://doi.org/10.1061/(ASCE)0733-9364(2006)132:2(197).

[5] M.R. Endsley, Toward a theory of situation awareness in dynamic systems, Hum. Factors 37 (1995) 32–64, https://doi.org/10.1518/001872095779049543.

[6] S. Hasanzadeh, B. Esmaeili, M.D. Dodd, Impact of construction workers' hazard identification skills on their visual attention, J. Constr. Eng. Manag. 143 (2017), https://doi.org/10.1061/(ASCE)CO.1943-7862.0001373.

[7] A. Albert, M.R. Hallowell, M. Skaggs, B. Kleiner, Empirical measurement and improvement of hazard recognition skill, Saf. Sci. 93 (2017) 1–8, https://doi.org/10.1016/j.ssci.2016.11.007.

[8] M. Choi, S. Ahn, J.O. Seo, VR-Based investigation of forklift operator situation awareness for preventing collision accidents, Accid. Anal. Prev. 136 (2020), https://doi.org/10.1016/j.aap.2019.105404.

[9] Z. Zhang, B.H.W. Guo, Z. Feng, Y.M. Goh, Exploring the interplay of bottom-up and top-down attention in hazard perception: Insights from electroencephalogram and eye-tracking methods, in: 10th International Conference on Innovative Production and Construction (IPC2024), Perth, Australia, 2024: pp. 195–201. https://www.researchgate.net/publication/382462076 (accessed September 4, 2024).

[10] E.Y.T. Chian, Y.M. Goh, J. Tian, B.H.W. Guo, Dynamic identification of crane load fall zone: a computer vision approach, Saf. Sci. 156 (2022) 105904, https://doi.org/10.1016/j.ssci.2022.105904.

[11] S. Hasanzadeh, B. Esmaeili, M.D. Dodd, Examining the relationship between construction workers' visual attention and situation awareness under fall and tripping hazard conditions: using mobile eye tracking, J. Constr. Eng. Manag. 144 (2018) 4018060, https://doi.org/10.1061/(ASCE)CO.1943-7862.0001516.

[12] S. Kim, H. Lee, S. Hwang, J.-S. Yi, J.W. Son, Construction workers' awareness of safety information depending on physical and mental load, J. Asian Archit. Build. Eng. 21 (2022) 1067–1077, https://doi.org/10.1080/13467581.2021.1908899.

[13] A. Ibrahim, C. Nnaji, M. Namian, A. Koh, U. Techera, Investigating the impact of physical fatigue on construction workers' situational awareness, Saf. Sci. 163 (2023) 106103, https://doi.org/10.1016/J.SSCI.2023.106103.

[14] Y. Fang, Y.K. Cho, F. Durso, J. Seo, Assessment of operator's situation awareness for smart operation of mobile cranes, Autom. Constr. 85 (2018) 65–75, https://doi.org/10.1016/j.autcon.2017.10.007.

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

[16] T.A. Sitompul, S. Roysson, J. Rosa, Developing a windshield display for mobile cranes, Proceedings of the 37th International Symposium on Automation and Robotics in Construction, ISARC 2020: From Demonstration to Practical Use - To New Stage of Construction Robot (2020) 1444–1451. Doi: 10.22260/ISARC2020/0200.
[17] T. Cheng, J. Teizer, Modeling tower crane operator visibility to minimize the risk of limited situational awareness, J. Comput. Civ. Eng. 28 (2014), https://doi.org/10.1061/(ASCE)CP.1943-5487.0000282.
[18] J. Li, S. He, H. Lu, G. Xu, H. Wang, Modeling and risk assessment of workers' situation awareness in human-machine collaborative construction operations: a computational cognitive modeling and simulation approach, Adv. Eng. Inf. 63 (2025) 102951, https://doi.org/10.1016/J.AEI.2024.102951.
[19] L. Melloni, S. Van Leeuwen, A. Alink, N.G. Müller, Interaction between bottom-up saliency and top-down control: how saliency maps are created in the human brain, Cereb. Cortex 22 (2012) 2943–2952, https://doi.org/10.1093/CERCOR/BHR384.
[20] K. Smith, P.A. Hancock, Situation awareness is adaptive, externally directed consciousness, Hum. Factors 37 (1995) 137–148, https://doi.org/10.1518/001872095779049444.
[21] G. Bedny, D. Meister, Theory of activity and situation awareness, Int. J. Cogn. Ergon. 3 (1999) 63–72, https://doi.org/10.1207/s15327566ijce0301_5.
[22] S. Wu, H. Chen, L. Hou, G. (Kevin) Zhang, C.Q. Li, Using eye-tracking to measure worker situation awareness in augmented reality, Autom. Constr. 165 (2024) 105582, https://doi.org/10.1016/J.AUTCON.2024.105582.
[23] M.R. Endsley, Situation awareness global assessment technique (SAGAT), 1988. Doi: 10.1109/NAECON.1988.195097.
[24] B.H.W. Guo, Y.M. Goh, K. Le Xin Wong, A system dynamics view of a behavior-based safety program in the construction industry, Saf. Sci. 104 (2018) 202–215, https://doi.org/10.1016/J.SSCI.2018.01.014.
[25] Y.M. Goh, C.U. Ubeynarayana, K.L.X. Wong, B.H.W. Guo, Factors influencing unsafe behaviors: a supervised learning approach, Accid. Anal. Prev. 118 (2018) 77–85, https://doi.org/10.1016/J.AAP.2018.06.002.
[26] J.L. Kästle, B. Anvari, J. Krol, H.A. Wurdemann, Correlation between situational awareness and EEG signals, Neurocomputing (Amsterdam) 432 (2021) 70–79, https://doi.org/10.1016/j.neucom.2020.12.026.
[27] S. Comu, G. Kazar, Z. Marwa, Evaluating the attitudes of different trainee groups towards eye tracking enhanced safety training methods, Adv. Eng. Inf. 49 (2021) 101353, https://doi.org/10.1016/J.AEI.2021.101353.
[28] K. Rayner, Eye movements and attention in reading, scene perception, and visual search, Q. J. Exp. Psychol. (Hove) 62 (2009) 1457–1506, https://doi.org/10.1080/17470210902816461.
[29] S.J. Luck, An introduction to the event-related potential technique, Second, The MIT Press, 2014. https://go.exlibris.link/KmQMyMNC.
[30] E. Donchin, W. Ritter, W.C. McCallum, COGNITIVE PSYCHOPHYSIOLOGY: THE ENDOGENOUS COMPONENTS OF THE ERP, in: E. Callaway, P. Tueting, S.H. Koslow (Eds.), Event-Related Brain Potentials in Man, Academic Press, 1978: pp. 349–411. Doi: Doi: 10.1016/B978-0-12-155150-6.50019-5.
[31] M. Koivisto, A. Revonsuo, Event-related brain potential correlates of visual awareness, Neurosci. Biobehav. Rev. 34 (2010) 922–934, https://doi.org/10.1016/J.NEUBIOREV.2009.12.002.
[32] K.D. Federmeier, Connecting and considering: electrophysiology provides insights into comprehension, Psychophysiology 59 (2022) e13940, https://doi.org/10.1111/PSYP.13940.
[33] M. Xiang, G. Kuperberg, Reversing expectations during discourse comprehension, Lang Cogn. Neurosci. 30 (2015) 648–672, https://doi.org/10.1080/23273798.2014.995679;JOURNAL:JOURNAL:PLCP20;WGROUP:STRING:PUBLICATION.
[34] G.R. Kuperberg, Separate streams or probabilistic inference? What the N400 can tell us about the comprehension of events, Lang Cogn. Neurosci. 31 (2016) 602–616, https://doi.org/10.1080/23273798.2015.1130233.
[35] Occupational Safety and Health Administration, Integrated Management Information System (IMIS), 2024 (2024). https://www.osha.gov/ords/imis/accidentsearch.html.
[36] Y. Han, J. Yang, Y. Diao, R. Jin, B. Guo, Z. Adamu, Process and outcome-based evaluation between virtual reality-driven and traditional construction safety training, Adv. Eng. Inf. 52 (2022) 101634, https://doi.org/10.1016/J.AEI.2022.101634.
[37] American Clinical Neurophysiology Society, Guideline 5: Guidelines for standard electrode position nomenclature, J Clin Neurophysiol 23 (2006) 107–110. Doi: 10.1097/00004691-200604000-00006.
[38] Dale. Purves, G.J.. Augustine, David. Fitzpatrick, W.C.. Hall, A.-Samuel. LaMantia, R.D.. Mooney, M.L.. Platt, L.E.. White, Neuroscience, 6th ed., Oxford University Press, 2018.
[39] Q. Zhang, C. Luo, R. Ngetich, J. Zhang, Z. Jin, L. Li, Visual selective attention P300 source in frontal-parietal lobe: ERP and fMRI study, Brain Topogr. 35 (2022) 636–650, https://doi.org/10.1007/S10548-022-00916-X.
[40] L. Anllo-Vento, Shifting attention in visual space: the effects of peripheral cueing on brain cortical potentials, Int. J. Neurosci. 80 (1995) 353–370, https://doi.org/10.3109/00207459508986109.
[41] F. Faul, E. Erdfelder, A. Buchner, A.G. Lang, Statistical power analyses using G*Power 3.1: tests for correlation and regression analyses, Behav. Res. Methods 41 (2009) 1149–1160, https://doi.org/10.3758/brm.41.4.1149.
[42] P. Adami, R. Singh, P. Borges Rodrigues, B. Becerik-Gerber, L. Soibelman, Y. Copur-Gencturk, G. Lucas, Participants matter: effectiveness of VR-based training on the knowledge, trust in the robot, and self-efficacy of construction workers and university students, Adv. Eng. Inf. 55 (2023) 101837, https://doi.org/10.1016/J.AEI.2022.101837.
[43] S. Joshi, M. Hamilton, R. Warren, D. Faucett, W. Tian, Y. Wang, J. Ma, Implementing virtual reality technology for safety training in the precast/prestressed concrete industry, Appl. Ergon. 90 (2021) 103286, https://doi.org/10.1016/J.APERGO.2020.103286.
[44] P. Wang, P. Wu, H.L. Chi, X. Li, Adopting lean thinking in virtual reality-based personalized operation training using value stream mapping, Autom. Constr. 119 (2020) 103355, https://doi.org/10.1016/J.AUTCON.2020.103355.
[45] M. Zhang, L. Shu, X. Luo, M. Yuan, X. Zheng, Virtual reality technology in construction safety training: Extended technology acceptance model, Autom. Constr. 135 (2022) 104113, https://doi.org/10.1016/J.AUTCON.2021.104113.
[46] Occupational Safety and Health, Fall Protection in Construction (3146-05R 2015), Occupational Safety and Health, 2015. https://www.amazon.com/Fall-Protection-Construction-3146-05R-2015/dp/1514177617 (accessed September 9, 2024).
[47] Occupational Safety and Health, Warning Line Systems 1926.502(f), (1926). https://www.traffixdevices.com/standards/osha-1926-502f (accessed September 9, 2024).
[48] E.M. Argyle, J.J. Gourley, Z. Kang, R.L. Shehab, Investigating the relationship between eye movements and situation awareness in weather forecasting, Appl. Ergon. 85 (2020) 103071, https://doi.org/10.1016/J.APERGO.2020.103071.
[49] A. Delorme, S. Makeig, EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis, J. Neurosci. Methods 134 (2004) 9–21, https://doi.org/10.1016/j.jneumeth.2003.10.009.
[50] J. Lopez-Calderon, S.J. Luck, ERPLAB: an open-source toolbox for the analysis of event-related potentials, Front. Hum. Neurosci. 8 (2014), https://doi.org/10.3389/fnhum.2014.00213.
[51] A. Tharwat, Independent component analysis: an introduction, Appl. Comput. Inf. 17 (2018) 222–249, https://doi.org/10.1016/J.ACI.2018.08.006/FULL/PDF.
[52] L. Pion-Tonachini, K. Kreutz-Delgado, S. Makeig, ICLabel: an automated electroencephalographic independent component classifier, dataset, and website, Neuroimage 198 (2019) 181, https://doi.org/10.1016/J.NEUROIMAGE.2019.05.026.
[53] D. Hardison, D. Gray, Improving firefighters hazard recognition with energy based hazard recognition training, Saf. Sci. 136 (2021) 105128, https://doi.org/10.1016/J.SSCI.2020.105128.
[54] F.J. Massey Jr., The Kolmogorov-Smirnov test for goodness of fit, J. Am. Stat. Assoc. 46 (1951) 68–78, https://doi.org/10.1080/01621459.1951.10500769.
[55] J.W. Mauchly, Significance test for sphericity of a normal N-variate distribution, Ann. Math. Stat. 11 (1940) 204–209. https://api.semanticscholar.org/CorpusID:119821954.
[56] D.M. Medley, F.N. Kerlinger, Foundations of behavioral research, Am. Educ. Res. J. 2 (1965) 121, https://doi.org/10.2307/1161926.
[57] S. Hasanzadeh, B. Esmaeili, M.D. Dodd, Measuring the Impacts of safety knowledge on construction workers' attentional allocation and hazard detection using remote eye-tracking technology, J. Manag. Eng. 33 (2017) 04017024, https://doi.org/10.1061/(ASCE)ME.1943-5479.0000526.