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Investigating the interplay of bottom-up and top-down attention in hazard recognition: Insights from immersive virtual reality, eye-tracking and electroencephalography☆

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ABSTRACT

The construction industry's high-risk environment demands effective hazard recognition strategies. Attention, a critical cognitive process, plays a crucial role in this task. Previous research focused on individual attention process, such as sustained attention, selective and divided attention. However, no research has been conducted to investigate the effects of the interplay between endogenous and exogenous factors on hazard recognition in construction settings. This paper aims to investigate the effects of the interplay between top-down (T-D) and bottom-up (B-U) attention networks on hazard recognition, using immersive virtual reality (IVR), eye tracking (ET), and electroencephalography (EEG). Two safety interventions—augmented stimuli and toolbox meetings—were tested in a dynamic IVR construction site. The results showed that both augmented stimuli and the safety toolbox meeting significantly affected B-U, T-D, and hazard recognition. This paper provided evidence that the interplay between B-U and T-D can significantly improve workers' hazard recognition performance. The results improved our understanding of the mechanisms that control selective attention and the source of guidance over attention orientation. By demonstrating that T-D and B-U processes can work together rather than in isolation, this research contributes a key theoretical insight: attentional orientation in hazardous construction environments is neither fully determined by external stimuli nor entirely controlled by internal cognitive sets. In addition, this paper highlights and calls for an integrated approach to improving worker's hazard recognition performance, by combining digital-technology-enabled stimuli with safety-goal-oriented training and managerial practices.

1. Introduction

The construction industry is hazardous due to its high-risk nature, with numerous fatalities attributed to the failure to identify potential hazards (Perlman et al., 2014). This is consistent with the dynamic and hazardous nature of construction sites, which are characterized by complex interactions between workers, equipment, and environmental conditions (Guo et al., 2015; Wang et al., 2021; Zhang et al., 2019). Despite efforts to improve safety performance, hazard recognition remains a persistent challenge. Research suggests that over 30 %–50 % of safety hazards on construction sites remain unidentified (Carter and Smith, 2006).

This issue can be partly attributed to workers' limited attentional capacity (Duncan et al., 1997), and it is inherently challenging to maintain full awareness of objects and hazards in a dynamic construction environment (Uddin et al., 2020). In addition, production pressure tends to further undermine the capacity (Haslam et al., 2005; Pooladvand and Hasanzadeh, 2023). Due to its significant role in hazard recognition, the concept of attention has gained increasing interest from researchers to understand better the cognitive processes involved in recognizing hazards in construction settings. For example, research efforts have been made to investigate the effects of safety knowledge on attention (Hasanzadeh et al., 2017a), the impacts of stress on attention (Pooladvand and Hasanzadeh, 2023), the relationship between

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attention and situation awareness (Hasanzadeh et al., 2018), scan patterns of experienced and novice workers (Dzeng et al., 2016). In general, these studies have advanced our understanding of the role of attention in hazard recognition in construction settings. A shared and significant understanding is that workers' attention is selective and subject to the influence of endogenous (e.g., goal, expectation, and safety knowledge) and exogenous (e.g., stimuli and cues) factors.

However, to the authors' best knowledge, no research has been conducted to investigate the effects of the interplay between endogenous and exogenous factors on hazard recognition in construction settings. These factors correspond to two major attention networks proposed by several theorists (Corbetta and Shulman, 2002; Göschl et al., 2014; Navalpakkam and Itti, 2006; Pinto et al., 2013), namely top-down attention (T-D) and bottom-up attention (B-U). T-D refers to a form of attentional control guided by an individual's current objectives, motivations, and expectations, while B-U is involuntarily drawn to external stimuli in the environment that are particularly salient, such as sudden movements, bright colors, loud sounds, or unexpected events. These two major attention networks are useful for understanding the mechanisms that control selective attention and distinguishing the source of guidance over attention orientation (Eysenck and Keane, 2020). In cognitive psychology, Wen et al. (2012) argued that it is important to study interactions between the two visual attention systems. The importance also applies in construction settings. In a relatively early research study, Hasanzadeh et al. (2017a) reviewed the relevance and significance of these two attention networks for hazard recognition. However, the study only focused on top-down influences on attention allocation.

To fill the knowledge gap, this paper aims to investigate the effects of the interplay between T-D and B-U on hazard recognition. To achieve the aim, this paper has three specific objectives: (1) investigate the effects of augmented stimuli on B-U, (2) investigate the effects of safety toolbox meeting on T-D, and (3) investigate the impact of the interactions between augmented stimuli and safety toolbox meeting on hazard recognition.

The research workflow involved setting up the experiment environment and equipment, collecting eye movement, electroencephalography (EEG), and real-time probe answers, followed by three steps of data analysis: attentional density analysis, ERP analysis, and hazard recognition analysis. This paper provided evidence that the interplay between B-U and T-D can significantly improve workers' hazard recognition performance. In addition, this paper highlights and calls for an integrated approach to improving worker's hazard recognition performance, by combining digital-technology-enabled stimuli with safety-goal-oriented training and managerial practices.

2. Literature review

2.1. Attention networks

2.1.1. Bottom-up attention

B-U is an externally induced process that triggers automatic responses to external stimuli without conscious effort (Katsuki and Constantinidis, 2014). This type of attention is characterized by a reflexive reaction to sudden changes or highly noticeable features in the environment, such as loud noises or bright lights, which can capture attention involuntarily (Wickens et al., 2023, p. 26). The neural mechanisms underlying B-U are not only reflected in the activation of specific brain areas, but also shown in distinct patterns of electrical activity in the brain, as measured by event-related potential (ERP) components. Specifically, several ERP components have been identified to be associated with B-U, including P3a, N1 (N100), and N2pc. The P3a component is elicited by unpredictable changes in stimuli and reflects B-U (Gibson et al., 2017; Luck, 2014, p. 95). Additionally, the N1 component is sensitive to attention, with larger amplitudes for valid-cue targets and discrimination responses (Mangun and Hillyard, 1991a; Vogel and Luck, 2000), indicating its association with spatial attention (Hillyard et al., 1998; Mangan, 1995). Furthermore, the N2pc component can be used to determine whether attention is automatically captured by salient but irrelevant objects (Eimer and Kiss, 2008; Lien et al., 2008; Sawaki and Luck, 2010). Its amplitude is influenced by nearby distractors, although it does not reflect the processing of these distractors (Kappenman and Luck, 2012). Research has investigated the brain areas underlying B-U, as shown in Table 1.

2.1.2. Top-down attention

T-D is a distinct cognitive process that enables individuals to deliberately direct their attention toward task-relevant stimuli based on voluntarily chosen factors such as goals, knowledge, and intentions (Baluch and Itti, 2011). This internally induced process is characterized by a controlled and selective mechanism that allows individuals to filter out irrelevant information and focus on pertinent details, while also being flexible and adaptable in response to changing priorities or new information (Gazzaley and Nobre, 2012). The neural mechanisms underlying T-D involve both specific brain areas and distinct patterns of electrical activity, as measured by ERP components. Specifically, several ERP components have been associated with T-D, including P1 (P100), P3 (P300), P3b, and N2pc. The P1 component is modulated by selective attention (Hillyard et al., 1998; Luck et al., 2000) and by the subject's state of arousal (Vogel and Luck, 2000). Additionally, the P3 component, which is induced by top-down attention and search, is more distributed in the frontal lobe (Zhang et al., 2022). The parietally maximal P3b component is elicited by unpredictable changes in stimuli that are task-relevant, reflecting T-D attention (Luck, 2014, p. 95). Furthermore, the N2pc component at PO7/PO8 is present only when attention is allocated to an object, suggesting its role in T-D attention (Wascher and Beste, 2010). Studies have investigated the neural mechanisms underlying T-D, as presented in Table 2.

2.2. Attention measurement

Eye-tracking (ET) has been increasingly employed to measure attention in hazard recognition research. ET indicators such as total fixation time (dwell time or fixation duration), total fixation count, time to first fixation, fixation time ratio (dwell percentage, fixation time percentage, or ratio of on-target), and run count have been used in construction safety research (Cheng et al., 2022). The concept of area of interest (AOI) refers to a physical location where specific task-related information can be found (Wickens et al., 2013, p. 62). In the context of hazard recognition, AOI has been utilized to define hazardous areas (Zhang et al., 2023a).

On the other hand, EEG has gained popularity in measuring attention, due to its advantages in real-time monitoring and non-invasive measurement (Hans, 1969). In the context of hazard recognition, EEG has been used to investigate the neural correlates of attention and hazard recognition (Wang et al., 2019, 2017).

ERP has been used to measure attention (Zhang et al., 2023a). ERP

Table 1
Bottom-up attention-related brain areas and electroencephalography channels.

Bottom-up attention-related brain areas	Function	EEG channels
Visual cortex (Treue, 2003)	• Target of attention control signals (Serences and Yantis, 2006) • Consequences of attention shifting (LaBerge, 1995)	• O1 • O2 • Oz
Temporoparietal junction (TPJ)(Corbetta and Shulman, 2002)	• Separate, modality-specific spatial attention mechanisms (Coren et al., 2004)	• P3 • P4
Right ventral frontal cortex (VFC)(Corbetta and Shulman, 2002)	• Detecting targets that appear at unattended and unexpected locations (Arrington et al., 2000)	• F4 • F8

Table 2
Top-down attention-related brain areas and electroencephalography channels.

Top-down attention-related brain areas	Function	EEG channels
Visual cortex (Treue, 2003)	• Target of attention control signals (Serences and Yantis, 2006) • Consequences of attention shifting (Corbetta et al., 2000; LaBerge, 1995)	• O1 • O2 • Oz
Superior parietal lobule (SPL)(Wright and Ward, 2008, p. 179; Yantis et al., 2002)	• Spatial orientation (Posner and Rothbart, 2007)	• Cz • CP1 • CP2
Inferior parietal lobule (IPL)(Wright and Ward, 2008, p. 179)	• Shift and maintain attention (Chambers et al., 2007, 2004)	• CP5 • CP6
Intraparietal sulcus (IPS)(Corbetta and Shulman, 2002)	• Saccades (Andersen, 1989) • Visual spatial attention (Andersen, 1989)	• P3 • P4
Dorsal parietal cortex (Yantis et al., 2002)	• Saccades (Andersen, 1989) • Spatial orientation (Andersen, 1989; Posner and Rothbart, 2007)	• Cz • CP1 • CP2 • P3 • P4
Frontal eye fields (FEF)(Corbetta and Shulman, 2002)	• Saccades (Schiller et al., 1980) • Pursuit and vergence eye movements (Schiller et al., 1980)	• Fz • F3 • F4

component refers to a set of voltage changes in certain time windows that collectively represent a functionally distinct neuronal aggregate (Donchin et al., 1978). Table 3 demonstrates the time windows of ERP components related to B-U and T-D. 50 % area amplitude can be used as a measurement of ERP components, which provides a direct measurement of B-U and T-D (Luck, 2014, p. 239).

Recent studies have observed a significant surge in the integration of ET and EEG/ERP techniques to quantify attention. Notably, research by Zhang et al. (2023a) employed first fixation duration, total gaze duration, average gaze duration, fixation count, and time to first fixation to measure attention. Similarly, Wang et al. (2024) used the attention index calculated from the time–frequency representation of EEG and gaze duration as attention indicators. However, both Zhang et al. (2023a) and Wang et al. (2024) utilized 2D screen-based images as their experiment environment, which may not accurately reflect the dynamic construction sites. One notable advancement is the work by Noghabaei et al. (2021), who conducted an experiment under IVR conditions using a range of metrics, including fixation count, fixation time, mean fixation duration, saccade velocity, pupil diameter, and seven frequency bands of EEG amplitudes (delta, theta, alpha, low beta, beta, high beta, and gamma). Notwithstanding these advancements, Noghabaei et al. (2021) focused primarily on the general attention mechanism, neglecting to explore the intricate relationship between B-U and T-D in hazard recognition.

Table 3
Time windows of event-related potential components.

ERP components	Time windows (milliseconds)	References
P1 (P100)	80–150	(Anllo-Vento, 1995; Eimer, 1994; Harter et al., 1989; Hillyard et al., 1994; Mangun et al., 1993; Mangun and Hillyard, 1991b)
P3 (P300)	300–500	(Zhang et al., 2022)
P3a	220–280	(Squires et al., 1975)
P3b	310–380	(Squires et al., 1975)
N1 (N100)	150–200	(Anllo-Vento, 1995; Eimer, 1994; Harter et al., 1989; Hillyard et al., 1994; Mangun et al., 1993; Mangun and Hillyard, 1991b)
N2pc	170–270	(Matusz et al., 2019)

2.3. The role of attention in construction hazard recognition

Attention plays a crucial role in hazard recognition, as it enables individuals to detect and respond to hazards (Hasanzadeh et al., 2019). A summary of key findings on attention in construction hazard recognition is presented in Table 4.

2.4. A summary of literature review

Previous research on attention in hazard recognition has focused on individual attentional mechanisms like sustained attention (Wang et al., 2019, 2017), visual attention (Cheng et al., 2021; Hasanzadeh et al., 2017a, 2017b; Liao et al., 2021), selective attention (Hasanzadeh et al., 2017a) and divided attention (Hasanzadeh et al., 2017a). While these studies collectively underscore the importance of attention in hazard recognition, their primary focus has been on isolated attentional processes rather than the interplay among them. No known research has directly investigated how these two mechanisms interact to shape hazard recognition outcomes. Understanding this interplay is critical, as real-world hazard recognition rarely involves purely stimulus-driven or goal-directed attention. Instead, it emerges from the dynamic interaction between internal intentions and external cues. Addressing this gap presents an opportunity to deepen our theoretical understanding of attentional processes in hazard recognition and to develop more holistic strategies for improving workers' hazard detection and safety performance.

3. Methodology

The experiment employed a within-subject comparison design, where participants were exposed to multiple conditions, and their responses were compared across these stages. The research workflow (Fig. 1) outlines the key steps involved in this study. During the experiment, eye movement, EEG, and real-time probe answers were collected. The subsequent data analysis involved three steps: attentional density analysis, ERP analysis, and hazard recognition analysis.

3.1. Experimental design

The experiment was structured into two configurations, as shown in Fig. 2. Configuration one introduced augmented stimuli at stage B1, followed by a safety toolbox meeting at stage C. Stage A served as the baseline condition for both configurations. Configuration two also featured a two-stage intervention sequence, but with the order reversed: it introduced a safety toolbox meeting and then augmented stimuli. The augmented stimuli were achieved through the implementation of a stimuli warning system, while the augmented T-D was achieved through safety toolbox meetings.

The augmented stimuli visualize hazards through a combination of red and yellow colors, displaying shapes such as circles, cones, or rectangles to alert workers of potential dangers associated with hazardous objects like the load on tower cranes, vehicles, electrical wires, and scaffolding (as shown in Fig. 4). The augmented stimuli design is based on standards: Fall Protection in Construction (Occupational Safety and Health, 2015) and Warning Line Systems (Occupational Safety and Health, 1926).

A real-time probe was designed to directly measure both B-U and T-D by triggering a questionnaire when a participant gazes at a hazardous object for more than 0.6 s. The threshold of 0.6 s was set to match the real-time probe with B-U and T-D attention-related gaze while ensuring the complete collection of ERP components. Specifically, the probe is triggered after verifying that fixation and smooth pursuit movements exist to capture B-U and T-D (0.2 s-0.3 s) (Purves et al., 2018; Rayner, 2009) and the collection of ERP components (0.08 s-0.5 s) has been completed (Anllo-Vento, 1995; Zhang et al., 2022b). Adding a 0.1 s buffer time resulted in the determination of the 0.6 s threshold. The real-

Table 4
Key findings on attention in construction hazard recognition and measurement.

Attention	Study	Key Objective	Brief results
Sustained attention (Vigilance)	(Wang et al., 2017)	Testing participants' vigilance when they faced different obstacles	Overfocusing on a task can compromise a workers' vigilance, reducing their ability to detect potential hazards
	(Chen et al., 2018)	Assessing the impact of safety signs on workers' vigilance	The proper signs can raise worker's vigilance
	(Wang et al., 2019)	Propose vigilance measurement indicators and frameworks	Conducted a pilot study to evaluate the vigilance indicators
Selective attention	(Hasanzadeh et al., 2017a)	Investigating the impacts of safety knowledge on selective attention	• Selective attention patterns are similar across workers. • Injury exposure significantly impacts selective attention
	(Chen et al., 2018)	Assessing the impact of safety signs on workers' selective attention	The proper signs can raise worker's selective attention
	(Hasanzadeh et al., 2019)	Exploring the impacts of personality on the selective attention	Workers' personality significantly relates to selective attention
	(Liu et al., 2021)	Examining the effects of semantic cues on selective attention	Semantic cues drive selective attention toward goal-relevant information more effectively compared with when no such cues are provided.
	(Pooladvand and Hasanzadeh, 2023)	Investigating the effects of stress on selective attention	High-stress levels adversely affect selective attention
Divided attention	(Hasanzadeh et al., 2017a)	Investigating the impacts of safety knowledge on divided attention	Experienced workers need less processing time and deploy more frequent short fixations for divided attention
Visual attention (Attention in general)	(Dzeng et al., 2016)	Comparing search patterns between experienced and novice workers	Experienced workers can quickly assess hazards with equivalent accuracy to novice workers
	(Hasanzadeh et al., 2017c)	Evaluating the impacts of hazard-identification skills on attentional distributions and visual search strategies	Hazard identification skills significantly impact workers' visual search strategies
	(Hasanzadeh et al., 2018)	Examining differences in attentional allocation between workers with low and high situation awareness levels while exposed to tripping hazards	Higher situation awareness leads to higher attention distribution
	(Jeelani et al., 2019)	Examining the relationship between visual search patterns and hazard recognition performance	A higher fixation count and longer fixation duration are associated with superior hazard recognition performance
	(Xu et al., 2019)	Exploring visual searching patterns for construction safety inspection	Successful participants follow similar hazard searching patterns, concentrating on specific hazardous areas, and following a logical and serial search pattern
	(Han et al., 2020)	Investigating the impact of the distinctiveness of hazards, site brightness, and tidiness on attention allocation	Distinct site conditions reduced saccades time
	(Zhang et al., 2023a)	Examining the relationship between visual attention patten and cognitive processing	Workers allocated cognitive resources first to processing targets' visual features and then to discriminating safe or hazardous characteristics

time probe consists of two queries: Q1, "What entity were you observing?" (a single-choice question with four options), and Q2, "Have you noticed anything noteworthy about the entity?" (an open-ended response). If an incorrect answer is provided for Q1, Q2 will be skipped to prevent further interruptions. The real-time probe is triggered only once per hazard, thereby preventing excessive interruptions during experiment procedures. The implementation of the real-time probe was achieved through a customized C# script in Unity that receives eye-tracking data and triggers the real-time probe when it detects a gaze on a hazardous object for more than 0.6 s.

Fig. 3 shows a detailed experiment design. Upon arrival, participants went through a training session to familiarize themselves with the IVR equipment and the designated tasks. This was followed by a hardware setup session, eye-tracking calibration, and baseline EEG recording. Each stage lasted six minutes, with rest periods allotted between stages to ensure participant well-being, minimize EEG artifacts caused by fatigue, and minimize the influence of within-subject comparison.

The design of the virtual scenarios refers to real accidents from reports (Occupational Safety and Health Administration, 2024) and standards (Occupational Safety and Health Administration, 1994). The project employed Unity version 2021.3.27f1 to create an interactive virtual construction site. Fig. 4 presents an overview of the scenario.

The IVR scenario enabled participants to engage in locomotion and interaction with the virtual environment. In this first task, participants navigated a virtual forklift to transport brick containers to designated areas. In this second task, participants used a variety of tools to lay bricks, with the goal of building a wall within a designated area. The purpose of both tasks were to create inducements for participants to cross the danger zone multiple times. Table 5 shows the eight hazards in two tasks.

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 recruited 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. Moreover, given the qualitative nature of AOI identification, statistical significance was not applicable to this analysis. Consequently, based on interviews, AOI were identified and categorized into three categories: workers, equipment, and temporary structures.

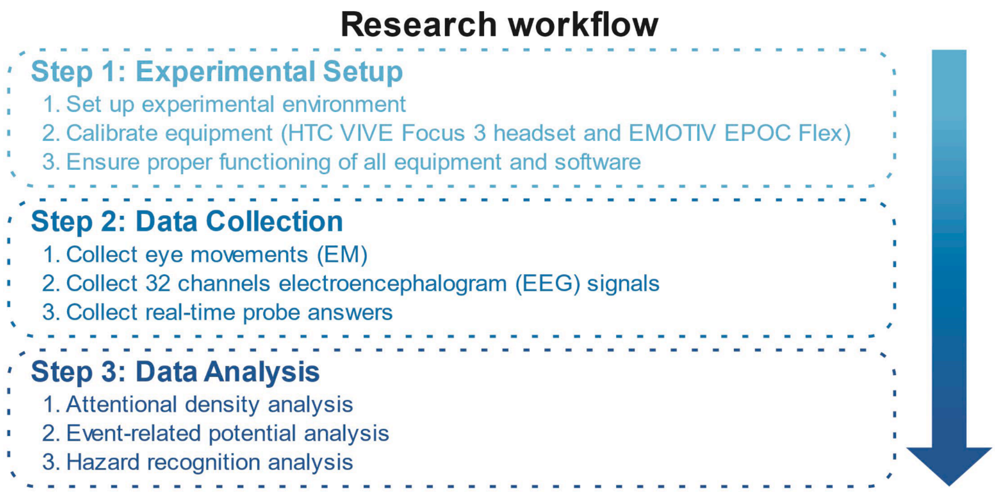


Fig. 1. Research workflow.

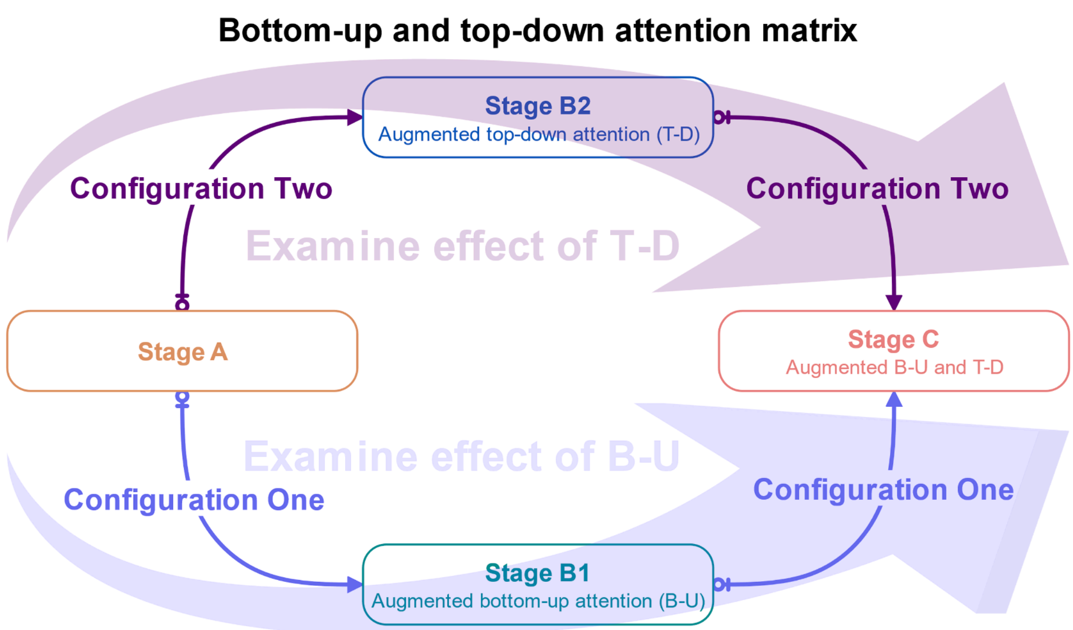


Fig. 2. Bottom-up and top-down attention matrix.

3.2. Demographics of participants

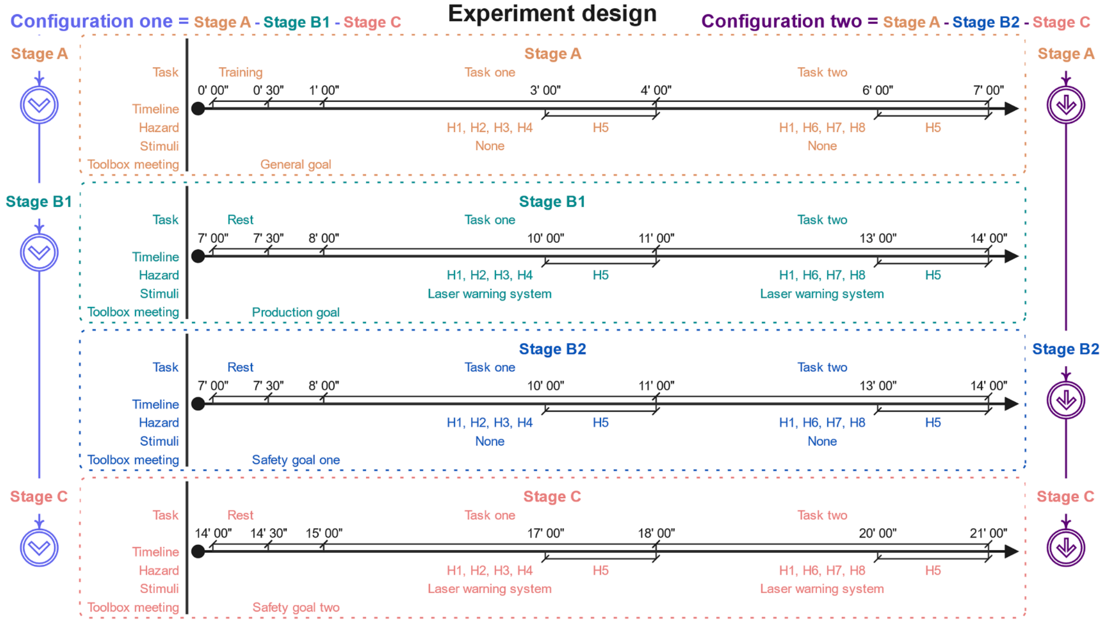
The determination of the minimum sample size was achieved through a priori power analysis using G*Power version 3.1.9.7 (Faul et al., 2009). This study employed repeated measures ANOVA, focusing on within-subject factors. The variables incorporated into this calculation are delineated in Table 6. (Cohen, 1988) has proposed 'conventional' effect size as benchmarks with 'small' (0.2), 'medium' (0.5), and 'large' (0.8). In previous IVR research on construction safety, effect sizes of 0.5 (Adami et al., 2023) and 0.72 (Joshi et al., 2021; Wang et al., 2020) have been employed. This study adopted an effect size of 0.4. As a result, the requisite sample size for this investigation was calculated to be 21, resulting in 0.8 power.

Participant recruitment employed a combination of strategies, including post recruitment and snowball sampling (Zhang et al., 2022). Post recruitment involved placing public posters at the university and construction sites to attract potential participants. Snowball sampling was used to encourage referrals from existing participants, effectively reaching harder-to-access populations. These combined methods ensured a diverse and representative participant pool.

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 had to be excluded from the analysis due to incomplete data collection caused by reported dizziness. As a result, data from 60 participants were included in the final analysis. 30 participants were assigned to Configuration One, while the other 30 participants were assigned to Configuration Two. Each configuration has reached the minimum sample size of 21 to achieve 0.8 power. Ethical approval was granted by the Human Research Ethics Committee (Ref: HREC 2023/73/LR-PS).

3.3. Apparatus

Participants engaged with the experiment using an HTC VIVE Focus 3 headset. This advanced IVR headset offers per-eye resolutions of 2448 × 2448 pixels, a 90 Hz refresh rate, and a 120-degree field of view, utilizing Dual 2.88″ LCD panels. Additionally, eye movement was



Legend

Category	Abbreviation	Expanded form
Task	Task one	Transportation of brick containers via forklift
Task	Task two	Bricklaying
Hazard	H1	Falling object from crane load
Hazard	H2	Forklift collide with stationary or moving workers
Hazard	H3	Forklift collide with obstacles
Hazard	H4	Forklift collide with heavy equipment
Hazard	H5	The crane load hit the scaffolding, collapsing it
Hazard	H6	Contact with live electrical wiring
Hazard	H7	Trip by obstacles
Hazard	H8	Fall from opening
Toolbox meeting	General goal	Complete two tasks: driving a forklift to move brick boxes and laying bricks
Toolbox meeting	Production goal	Improve production efficiency
Toolbox meeting	Safety goal one	Prioritize personal safety
Toolbox meeting	Safety goal two	Stay alert to potential dangers indicated by red and yellow lasers and prioritize personal safety
Toolbox meeting	Safety goal two	Stay alert to potential dangers indicated by red and yellow lasers and prioritize personal safety

Fig. 3. Experiment design.

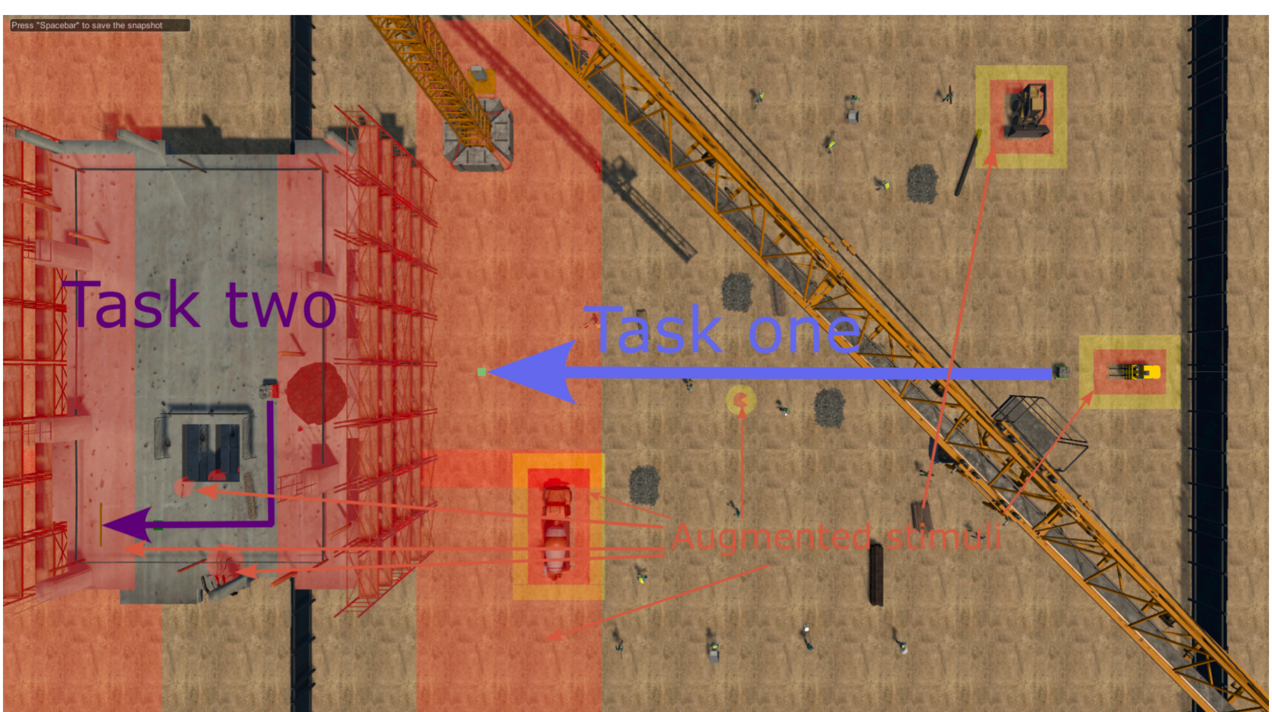


Fig. 4. Overview of the immersive virtual reality scenario.

Table 5
Tasks and hazards.

Task	Hazard
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

Table 6
Variables used in G*Power.

Variable name	Variable value
Test family	F tests
Statistical test	ANOVA: Repeated measures, within factors
Type of power analysis	A priori: Compute required sample size – given α, power, and effect size
Effect size f	0.4
α error probability	0.017
Power (1 − β error probability)	0.80
Number of groups	3
Number of measurements	2
Corr among rep measures	0.5
Nonsphericity correction	1

tracked using an eye-tracking add-on for the VIVE Focus 3. This device captured gaze data at a frequency of 120 Hz with an accuracy ranging from 0.5° to 1.1°. The study also employed the EMOTIV EPOC Flex Gel Sensor Kit, which features sequential sampling with a single analogue to digital converter (ADC), an internal sampling rate of 1024, and a resolution of 14 bits where 1 least significant bit (LSB) equals 0.51 μV, with a compressed maximum slew rate of 32uV per sample. It boasts a bandwidth of 0.16–43 Hz with digital notch filters at 50 Hz and 60 Hz, a dynamic range of 8400 μV(pp), and is AC coupled. As shown in Fig. 5, the participant is shown wearing the EMOTIV EPOC Flex EEG headset alongside the HTC VIVE Focus 3 headset, illustrating the integrated setup used for data collection in this study.

triggered, with a gaze duration on hazardous objects exceeding 300 ms, and both Q1 and Q2 correctly identified the hazard, the gaze had been labeled as T-D-related fixation (Purves et al., 2018, p. 451). Notably, only hazardous objects were included in labeling; objects unrelated to hazards, such as sky and ground, were not considered.

Developed by Ester et al. (1996), DBSCAN is renowned for its high efficiency and ability to discover clusters with arbitrary shapes. DBSCAN was employed for a more accurate representation of customers' visual attention patterns during car-interior inspections in a VR showroom (Li, 2021). DBSCAN is particularly suitable for this analysis due to its robustness in handling noise in eye-tracking data, allowing it to filter out isolated or irrelevant fixation effectively. Its ability to detect clusters of any shape also aligns well with the irregular gaze patterns observed in real-world tasks.

To analyze fixation in relation to hazardous objects, we employed the DBSCAN algorithm to group fixations into clusters based on their density. DBSCAN analysis was performed using Python 3.12.4 and Visual Studio Code 1.92.2 on B-U-related and T-D-related fixations within the AOI. Subsequently, fixation durations within each cluster were summed up to facilitate further analysis. The next step involved grouping the clusters and summed fixation durations within the same hazardous object into a single cluster, thereby generating object-based clusters and summed fixation durations. Finally, these object-based clusters and summed fixation durations were grouped together to produce hazard-based total fixation count and total fixation duration.

Attentional density index (ADI) is a novel metric proposed in this study. ADI combines two fundamental measures of B-U and T-D: fixation count and fixation duration. Fixation count has been widely used in previous studies to measure B-U and T-D, where higher fixation counts indicate increased allocation of attentional resources (Han et al., 2020; Hasanzadeh et al., 2017; Jeelani et al., 2019; Liu et al., 2021). Similarly, fixation duration has been employed in various research to assess B-U and T-D, where longer fixation durations suggest greater engagement with task-relevant stimuli (Hasanzade et al., 2017; Jeelani et al., 2019). Combining fixation count and duration into an attentional density index allows for a more comprehensive measurement of B-U and T-D attention, integrating both the spatial frequency and temporal persistence of attention.

The computation of the ADI followed Equation (1). Two different approaches were employed to calculate the hazard-based ADI: one involved summing the values across all participants to obtain the cross-participants' hazard-based ADI; the other involved summing the corresponding values within each participant to derive the within-participant hazard-based ADI. The results cross-participants' hazard-based ADI and within-participant hazard-based ADI serve as a measure of both B-U and T-D.

$$Attentionaldensityindex(ADI) = Totalfixationscount + Totalfixationsduration\# \tag{1}$$

3.4. Data analysis

Fig. 6 provides an overview of the data sources and measurements used in this study. Details of data analysis are presented as follows.

3.4.1. Attentional density analysis

The study utilizes eye-tracking technology to quantify both B-U and T-D. An overview of the attentional density analysis method is shown in Fig. 7. The B-U-related and T-D-related gaze points and durations were labeled by the real-time probe. Specifically, if a fixation or saccade was triggered, where the gaze duration on hazardous objects exceeded 200 ms, and Q1 was correct, the gaze had been labeled as B-U-related fixation (Purves et al., 2018, p. 451). If smooth pursuit movements were

The cross-participants hazard-based ADI enabled the assessment of cross-participants' attention distribution towards hazards, which was visualized through hazard-based attentional density maps in Unity version 2021.3.27f1. Furthermore, the cross-participants hazard-based ADI was processed using MATLAB R2024b (24.2.0.2712019) to plot cross-participants hazard-based attentional density lines.

3.4.2. Electroencephalogram acquisition and event-related potential analysis

The 10–10 system is a modified method for placing electrodes on the scalp to record EEG signals (American Clinical Neurophysiology Society,

Fig. 5. EMOTIV EPOC Flex and HTC VIVE Focus 3.

2006). Fig. 8 depicts the placement of 32 electrodes in the experiment. To establish a stable electrical connection between each electrode and the skin, conductive gel (Weaver Nuprep Skin Prep Gel) was injected.

Fig. 9 is an overview of ERP analysis method. EEG data were analyzed employing EEGLAB v2024.0 (Delorme and Makeig, 2004) and ERPLAB v11.03 (Lopez-Calderon and Luck, 2014) toolbox in MATLAB R2024b (24.2.0.2712019) 64-bit. The B-U and T-D epochs were labeled by eye movement and real-time probe. When a fixation or saccade occurred in response to a hazardous object, lasting more than 200 ms on stimuli, the gaze was then labeled as B-U-related eye movement (Purves et al., 2018, p. 451). On the other hand, when smooth pursuit movements were triggered, with a gaze duration on hazardous objects exceeding 300 ms, and both Q1 and Q2 correctly identified and comprehended the hazard, the gaze was subsequently labeled as T-D-related eye movement (Purves et al., 2018, p. 451). The timestamps from these B-U-related and T-D-related eye movements were used to match EEG signals to their corresponding epochs' start times. Independent components analysis (ICA) was employed to decompose the labeled epochs into their statistical abstractions of components. ICA works by using a neural network and learning algorithm to generate an unmixing matrix that leads to independent components (ICs) (Tharwat, 2018).

ICLabel v1.6, developed by (Pion-Tonachini et al., 2019), was utilized to identify ICs as artifacts generated by the brain, eye, muscle, heart, line noise, channel noise, and other sources. ICs with more than 90 % probability labeled as artifacts were rejected. ICLabel leverages three artificial neural network architectures: convolutional neural networks with unweighted cross-entropy loss, CNNs with weighted cross-entropy loss, and semi-supervised learning generative adversarial networks (SSGAN) (Pion-Tonachini et al., 2019). Notably, ICLabel has been employed by numerous research studies across various disciplines, underscoring its utility as a valuable tool for EEG data processing (Chen et al., 2024; Li et al., 2024; Weber et al., 2024).

ICLabel is a robust choice for EEG artifact removal because it combines precision, reliability, and efficiency through its advanced design. By utilizing multi-class categorization, it can accurately classify EEG components into various categories, such as brain activity, muscle artifacts, and eye movements, enabling targeted removal of artifacts. Its machine learning-based approach, trained on extensive labeled datasets, ensures high accuracy. Moreover, ICLabel reduces subjectivity by providing standardized and automated classifications, eliminating inconsistencies introduced by manual artifact identification. This contributes to its reliability, as it delivers consistent performance across diverse datasets and research settings. Additionally, ICLabel minimizes data loss by selectively removing artifact components rather than discarding entire channels or epochs, preserving the integrity of the data and retaining valuable neural signals. Together, these features make ICLabel a trustworthy tool for EEG artifacts removal.

The epochs were filtered using a band-pass filter of 0.1–30 Hz (Luck, 2014, p. 510). The 0.1–30 Hz band-pass filter is commonly employed 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), ensuring that the filtered signal reflects meaningful neural information. Baseline correction was performed on the epochs to remove voltage offsets and drifts by using a prestimulus period of −200 ms to 0 ms.

To provide an overview of the effects of the augmented stimuli and

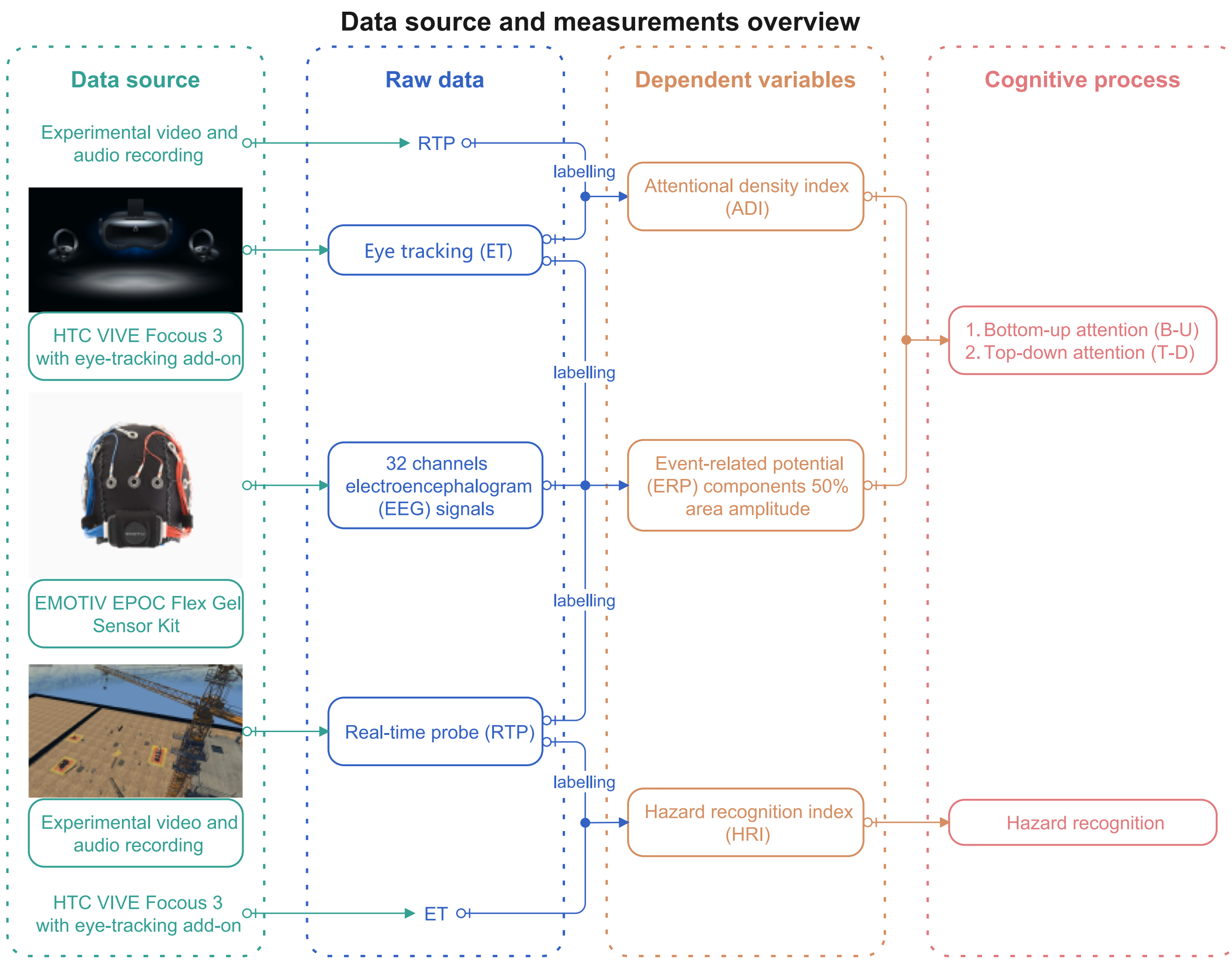


Fig. 6. Data source and measurements overview.

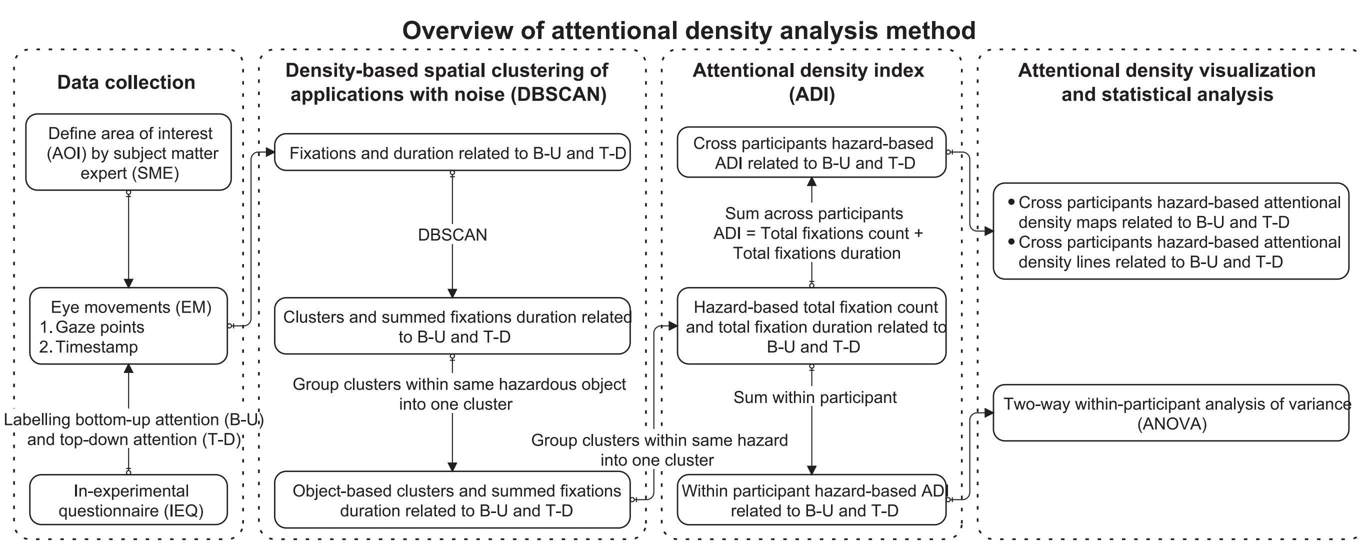


Fig. 7. Overview of attentional density analysis method.

toolbox meeting on brain activity in both B-U and T-D, we plotted the cross participants averaged ERP waveforms and scalp maps. To achieve this, baseline-corrected epochs were averaged cross participants based on the task type, attentional process, hazard, configuration, stage, and channel. Moreover, ERP components associated with B-U (P3a, N1, and N2pc) and T-D (P1, P3, P3b, and N2pc) were isolated from the ERP waveforms within predetermined time windows (Table 3), allowing for the quantification of B-U and T-D.

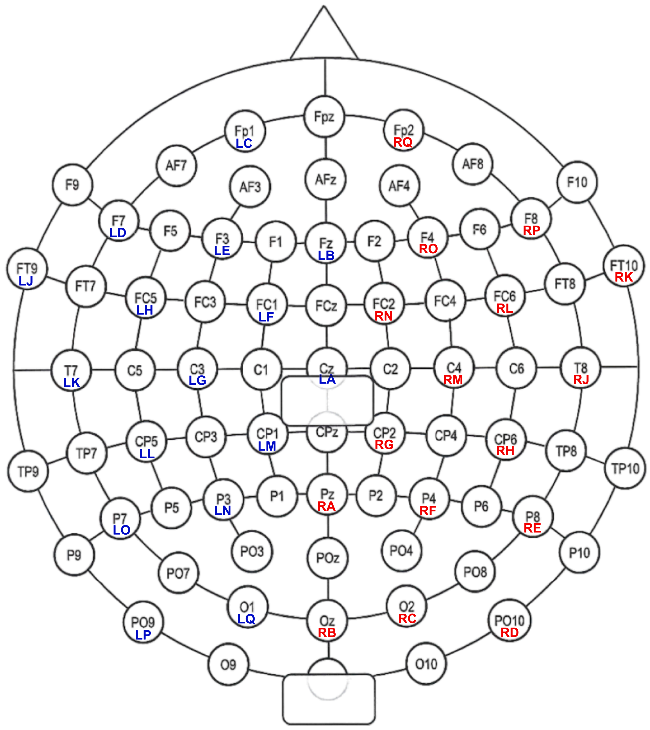


Fig. 8. 10–10 system electrodes placement.

Using a within-participant design, this study employed repeated measures ANOVA. First, baseline-corrected epochs were averaged based on task type, attentional process, hazard, configuration, stage, channel, and participant. The single participant-averaged epochs were utilized to generate single participant-averaged ERP waveforms that facilitated the identification of specific ERP components. Specifically, B-U ERP components (P3a, N1, and N2pc) and T-D ERP components (P1, P3, P3b, and N2pc) were isolated from ERP waveforms within predetermined time windows (Table 3). To quantify the ERP components, we employed 50 % area amplitude as an indicator. This approach involves computing the 50 % rectified area under the ERP waveform over a given range. The 50 % rectified area is calculated using geometric regions defined by the ERP waveform, baseline, and edges of the measurement window as boundaries. The reason for using 50 % area amplitude as a measure in EEG studies is that it allows for a wide range of measurement windows without cancellation from preceding or subsequent waves, making it a flexible and reliable approach to capturing brain activity (Luck, 2014, p. 295).

3.4.3. *Hazard recognition performance analysis*

To assess participants' hazard recognition performance, the hazard recognition index (HRI) was calculated by Equation (2) (Albert et al., 2017, 2014; Hardison and Gray, 2021):

$$Hazardrecognitionindex(HRI) = \frac{H_{Recognized}}{H_{Total}}\# \tag{2}$$

where $H_{Recognized}$ = number of hazards recognized by participant during the task for each stage and H_{Total} = total number of recognizable hazards the participant was exposed to during the task for each stage.

To calculate the $H_{Recognized}$, the Q1 and Q2 from the real-time probe were utilized. When both Q1 and Q2 are correct, the hazard was identified as recognized by the participant. The hazards recognized within each task of each stage were then summed to calculate the $H_{Recognized}$. As shown in Table 5, each task contains five hazards, resulting in $H_{Total} = 5$ for each task of each stage.

3.4.4. *Repeated measures ANOVA*

Repeated measures ANOVA in MATLAB R2024b (24.2.0.2712019) was used to statistically analyze within-participant hazard-based ADI, key ERP components' 50 % area amplitude, and HRI across different stages: A-B1, A-B2, B1-C, and B2-C.

The independent variables are augmented stimuli and safety toolbox meetings, while the dependent variables comprise the attentional density index (ADI), ERP components 50 % area amplitude, and hazard recognition index (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 ($p > 0.05$) (Massey Jr., 1951). Sphericity was tested using Mauchly's test, and the results indicated that the assumption of sphericity was met ($p > 0.05$) (Mauchly, 1940). Comprehensive details regarding the data collection procedures and analytical methods are outlined in subsequent

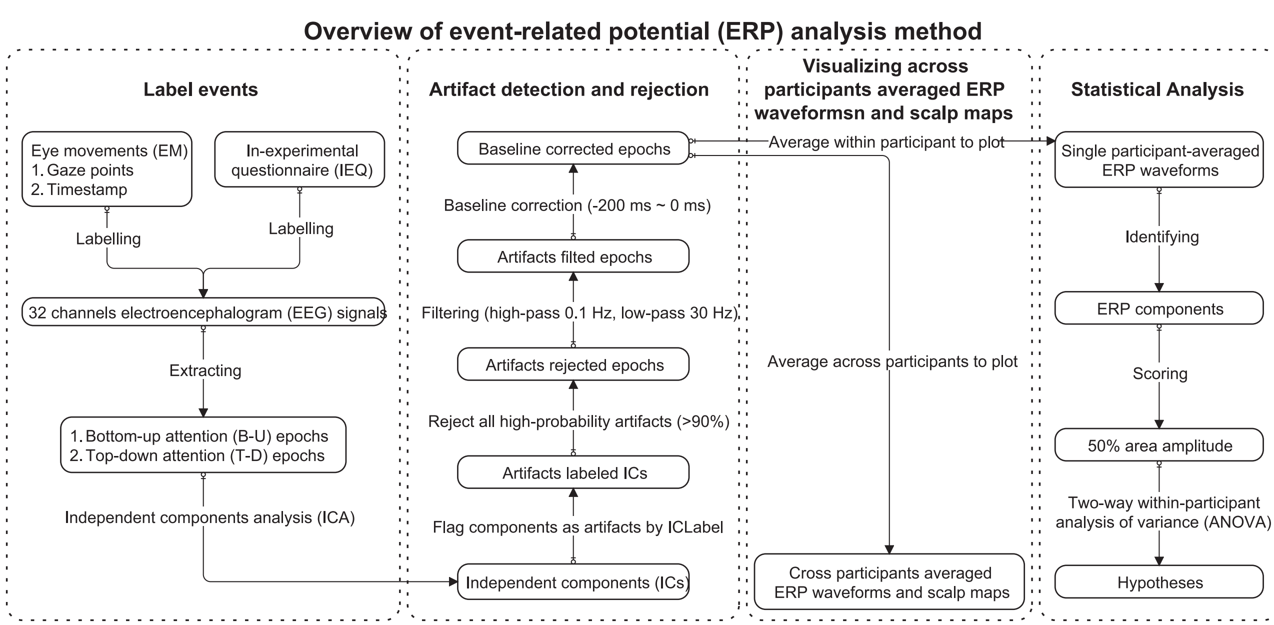


Fig. 9. Overview of event-related potential analysis method.

sections. All degrees of freedom are one.

In repeated measures ANOVA, the effect size eta squared (η^2) was calculated using the formula (1) proposed by Kerlinger (Cohen, 1973; Lakens, 2013; Medley and Kerlinger, 1965):

$$\eta^2 = \frac{SS_A}{SS_T} \tag{1}$$

where SS_A represents the between-group sum of squares for factor A, and SS_T denotes the total sum of squares. Eta squared (η^2) quantifies the proportion of the total variance in the data attributable to factor A.

4. Results

4.1. Effects of augmented stimuli on bottom-up attention

4.1.1. Eye tracking evidence

The cross-participants hazard-based attentional density maps facilitate visualization of participants' attention distribution on hazards. The ADI was visualized through Unity, yielding 24 groups (2 tasks × 2 attentional processes × 2 configurations × 3 stages) of attentional density maps. Fig. 10 showed the attentional density map for task one, B-U, configuration two, Stage B1. Each sphere in these figures represented an ADI, with its size indicating the number of ADI within that hazard. The color bar served as a visual reference, ranging from blue (smallest clusters) to red (largest clusters), with cyan and yellow representing intermediate sizes.

Fig. 11 presented line plots of ADI values across stages, providing an overview of ADI changes over different stages. Notably, for configuration one, B-U-related ADI in stage B1 exceeded those in stage A, indicating that augmented stimuli improved B-U.

Repeated measures ANOVA was conducted to examine the effects of augmented stimuli on ADI between stage A-B1. The Table 7 revealed a significant main effect of augmented stimuli on ADI for most of the hazards.

4.1.2. ERP evidence

The cross-participants averaged ERP waveforms and scalp maps were used to visualize the effects of the augmented stimuli and toolbox meeting on brain activity in both B-U and T-D. As a result, 600 (2 tasks × 2 attentional processes × 5 hazards × 2 configurations × 15 channels) ERP waveforms and scalp maps were plotted. Owing to the constraint on available space, we presented a selection of key findings below. Fig. 12 presented the ERP waveforms for task two, B-U, H7, configuration one, and channel O2. The three lines represented ERP waveforms during stages A, B1, and C. Notably, the P3a component isolated from these waveforms showed that its amplitude in stage B1 was higher than in stage A. This suggested that the augmented stimuli triggered stronger brain activity in stage B1. The ERP scalp maps in Fig. 13, which corresponded to Fig. 12, further indicated that Channel O2 showed lower activity in Stage A.

Repeated measures ANOVA was conducted to examine the effects of augmented stimuli on 50 % area amplitude. As shown in Table 8, the results indicated a significant main effect of augmented stimuli on 50 % area amplitude between stages A-B1 ($P < 0.05$).

The absence of statistically significant ERP components amplitude across some channels may arise from multiple factors beyond artifacts. Methodologically, ERP components are inherently small in amplitude

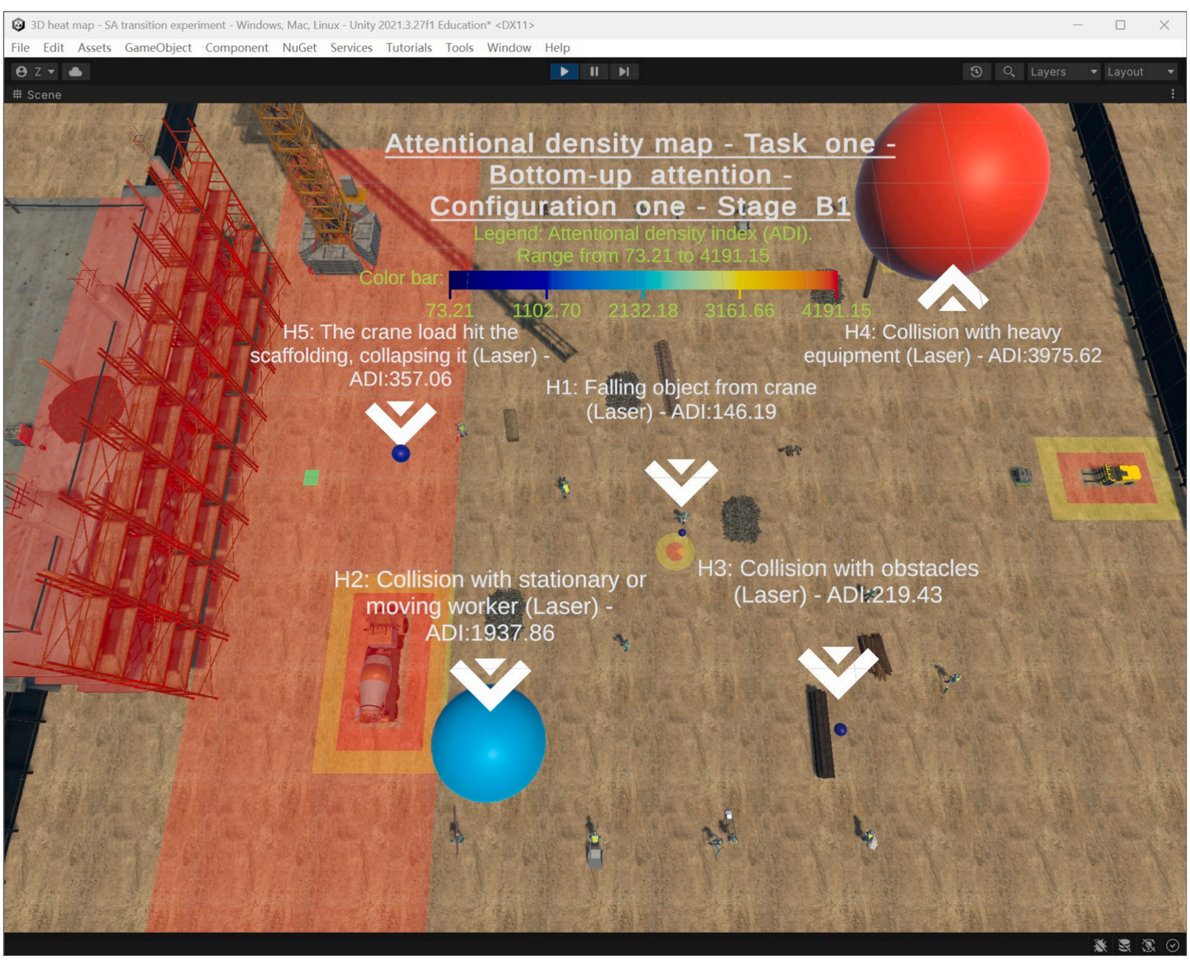


Fig. 10. Attentional density map – task one – stage B1.

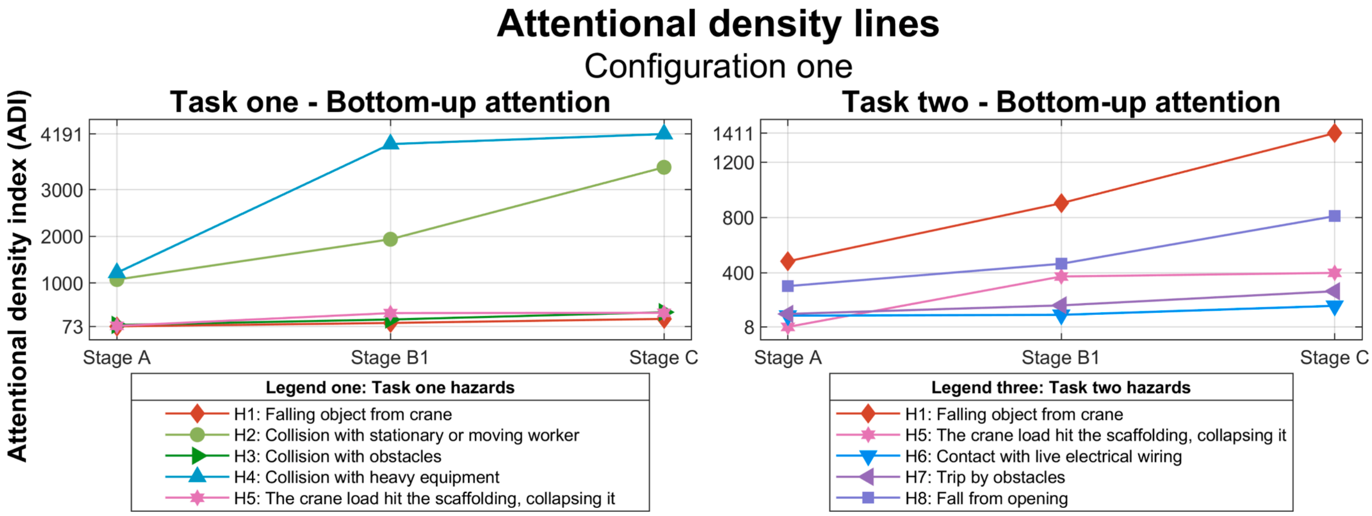


Fig. 11. B-U attentional density lines.

Table 7
ANOVA results for augmented stimuli of ADI in configuration one.

Stages	Cognitive process	Task	Hazard	Augmented stimuli		
				P value	F-statistic	Effect size
A-B1	Bottom-up attention	T-1	H1	0.064	3.558	0.56
			H2	<0.0001	35.221	0.76
			H3	<0.0001	37.053	0.96
			H4	<0.0001	40.577	0.85
			H5	<0.0001	20.374	0.90
		T-2	H1	<0.0001	22.457	0.72
			H5	<0.0001	30.417	0.99
			H6	<0.01	8.934	0.75
			H7	<0.01	11.006	0.76
			H8	<0.0001	24.220	0.80

and susceptible to variability, requiring longer recording times or more trials to isolate signals. Individual differences in neurophysiological responsiveness could impact the isolation of ERP components. Additionally, uncontrolled confounders (e.g., participant fatigue, motivation fluctuations, or residual carry-over effects between stages despite mitigations) may introduce noise.

4.1.3. A summary of results

The results provided neuropsychological evidence for the effectiveness of augmented stimuli and toolbox meetings in improving B-U and hazard recognition performance. ET revealed a significant main effect of augmented stimuli on ADI for all hazards, indicating that augmented stimuli improved B-U-related attention distribution. Similarly, ERP results showed that the P3a component isolated from ERP waveforms had higher amplitude in stage B1 compared to stage A, suggesting stronger brain activity in response to augmented stimuli. Overall, these findings suggested that augmented stimuli could enhance both B-U and hazard recognition abilities.

4.2. Effects of safety toolbox meeting on top-down attention

4.2.1. Eye tracking evidence

Fig. 14 presented the attentional density map for task two, T-D, configuration two, stage C. Fig. 15 presented line plots of ADI values cross stages. For configuration two, T-D-related ADI in stage B2 surpassed those in stage A, indicating that the safety toolbox meeting enhanced T-D.

Repeated measures ANOVA was conducted to examine the effects of safety toolbox meetings on ADI between stages A-B2. Table 9 indicated a significant effect of safety toolbox meeting on ADI for half hazards ($P < 0.01$).

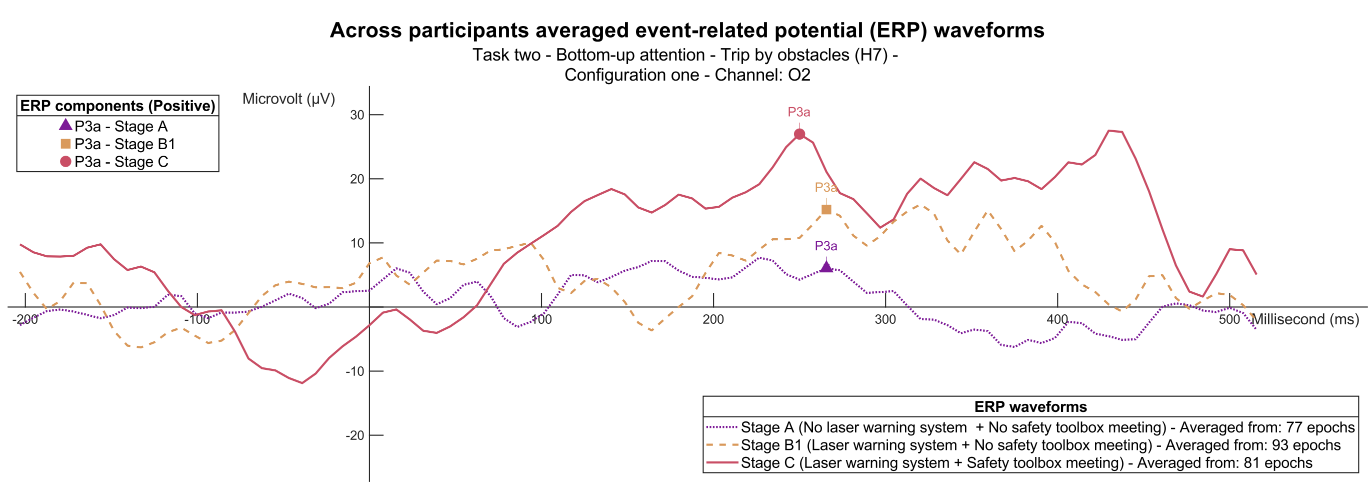


Fig. 12. P3a ERP component: waveform analysis cross stage A, B1, and C.

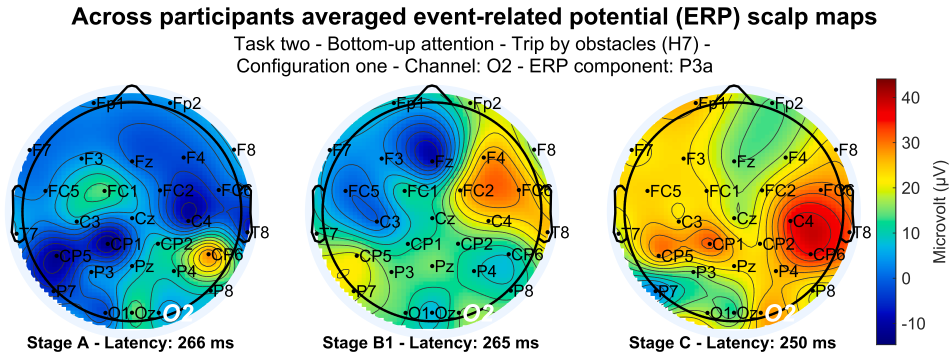


Fig. 13. P3a ERP component on O2 channel: scalp map visualization cross stage A, B1, and C.

Table 8
ANOVA results for augmented stimuli of 50% area amplitude in configuration one.

Stages	Cognitive process	Task	Hazard	ERP component	Channel	Augmented stimuli		
						P value	F-statistic	Effect size
A-B1	Bottom-up attention	T-2	H1	P3a	P4	<0.05	4.428	0.5
			H7	N2pc	Oz, P7, P8, PO10	<0.05	4.331 ~ 6.762	0.52 ~ 0.92
				P3a	O2, P7, PO10	<0.05	4.960 ~ 6.447	0.64 ~ 0.7
	Top-down attention	T-1	H2	P1	CP6, O1, O2, Oz, P4, P8, PO10, PO9	<0.05	4.036 ~ 8.470	0.24 ~ 0.66
				P3	CP6, O1, O2, Oz, P3, P4, P7, P8	<0.05	4.046 ~ 7.924	0.26 ~ 0.68
				P3b	CP6, O1, O2, Oz, P3, P4, P7, P8, PO10, Pz	<0.05	4.066 ~ 8.062	0.27 ~ 0.67
			H3	P1	F8, FC6, FT10, T8	<0.05	4.298 ~ 8.525	0.66 ~ 0.99
				P3b	FT9	<0.05	4.816	0.48
			H4	P1	C3, C4, CP1, CP2, CP5, FC2, FC6, P3, Pz	<0.05	4.064 ~ 7.371	0.14 ~ 0.31
				P3	PO10	<0.05	4.172	0.35
		T-2	H1	P3	C3, C4, CP2, CP6, Cz, F3, F4, F8, FC2, FC5, FC6, FT10, Fz, P4, T8	<0.05	6.129	0.36 ~ 0.63
				P3b	C3, C4, CP2, CP6, Cz, F3, F4, F8, FC2, FC5, FC6, FT10, Fz, P4, T8	<0.05	4.514 ~ 7.011	0.6 ~ 0.84
			H5	P3	C4, F4	<0.05	4.051 ~ 4.06	1
				P3b	P4	<0.05	4.019	1
			H7	P1	O1	<0.05	4.019	0.3
			H8	P1	FC6, Fp1, Fp2	<0.05	4.113 ~ 4.613	0.52 ~ 0.91
				P3	FC6, Fp1, Fp2, Pz, T7, T8	<0.05	4.480 ~ 6.614	0.35 ~ 0.7
				P3b	Fp1, Fp2, T7	<0.05	4.298 ~ 6.821	0.6 ~ 0.65

4.2.2. *ERP evidence*

Fig. 16 illustrated the ERP waveforms for task one, T-D, H2, configuration two, channel Cz. The three lines represented ERP waveforms in stages A, B2, and C. Notably, the T-D-related ERP component (P3b) isolated from the ERP waveforms showed that the 50 % area amplitude of the component in Stage B2 was higher than in Stage A. This indicated that T-D in Stage B2 was stronger than in Stage A. The ERP scalp maps in Fig. 17, corresponding to Fig. 16, indicated that Channel Cz in Stage A was lower than in Stage B2.

Repeated measures ANOVA was conducted to examine the effects of toolbox meetings on 50 % area amplitude between Stage A-B2. As presented in Table 10, the results revealed a significant main effect of toolbox meetings on 50 % area amplitude between Stage A and B2 ($P < 0.05$).

4.2.3. *A summary of results*

The results provided neuropsychological evidence for the effectiveness of safety toolbox meetings in improving T-D and hazard recognition performance, particularly in task one. ET data revealed a significant main effect of toolbox meetings on ADI for half of the hazards, indicating that T-D-related attention distribution increased after the toolbox meeting. ERP results suggested stronger brain activity related to T-D after the toolbox meeting. Overall, these findings suggested that safety toolbox meetings could enhance both T-D and hazard recognition abilities.

Fig. 14. Attentional density map – task two – stage B2.

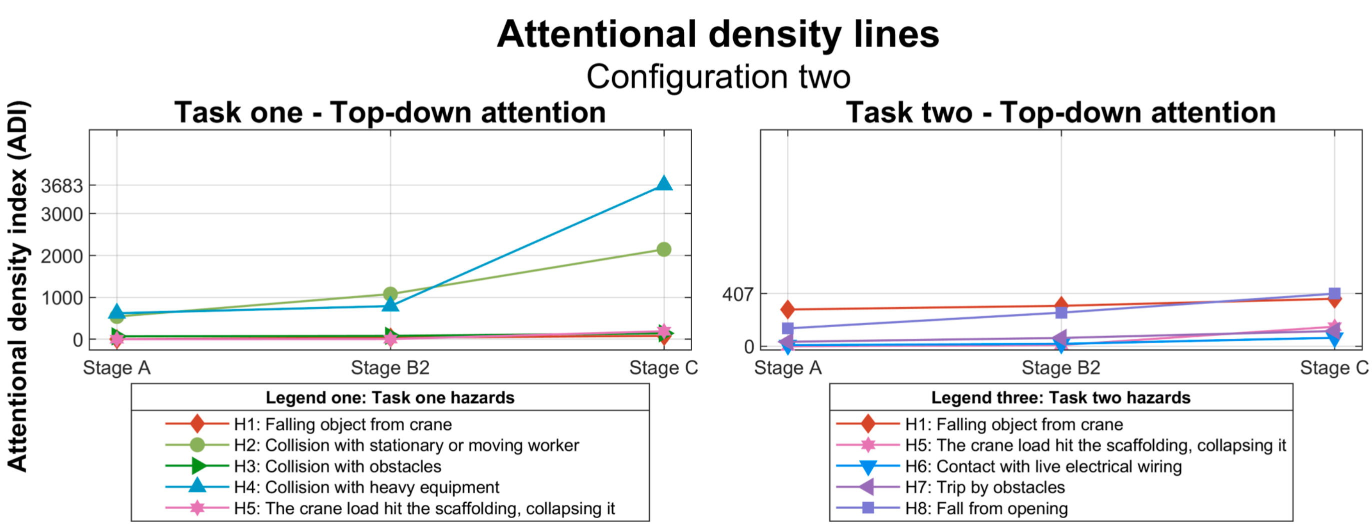


Fig. 15. T-D attentional density lines.

4.3. Impacts of the interactions between augmented B-U and T-D on hazard recognition

4.3.1. Eye tracking evidence

Fig. 18 and Fig. 19 presented the attentional density map for stage C. ADI in Fig. 18 and Fig. 19 were higher than in Fig. 10 and Fig. 14, indicating the interplay of augmented stimuli and safety toolbox meeting improved B-U and T-D.

Cross all stages, the combined data from Fig. 20 and Fig. 21 showed that both B-U and T-D-related ADI in stage C were higher than those in stages A, B1, and B2. Furthermore, within each stage, T-D-related ADI values were consistently lower than their B-U-related ADI, indicating that not all B-U-related attention was controlled by T-D.

From Fig. 20 and Fig. 21, the results in task one showed significant variability in hazard awareness across different types of hazards, with falling objects from cranes (H1) and forklifts colliding with obstacles (H3) proving challenging even with the assistance of the augmented stimuli and toolbox meeting. Fig. 20 and Fig. 21 revealed that, without any intervention, the hazards of forklifts colliding with stationary or moving workers (H2) and forklifts colliding with heavy equipment (H4) exhibited high ADI. However, both augmented stimuli and toolbox meeting interventions still improved ADI. Notably, the augmented

Table 9
ANOVA results for toolbox meeting of ADI in configuration two.

Stages	Cognitive process	Task	Hazard	Toolbox meeting		
				P value	F-statistic	Effect size
A-B2	Top-down attention	T-1	H1	0.064	3.564	0.98
			H2	<0.0001	20.712	0.77
			H3	<0.05	4.980	0.70
			H4	<0.0001	28.640	0.77
			H5	<0.0001	0.000	0.00
		T-2	H1	<0.01	9.225	0.68
			H5	0.321	1.000	1.00
			H6	0.122	2.462	0.76
			H7	0.054	3.866	0.80
			H8	<0.0001	19.320	0.82

stimuli had a more significant impact on H4 and crane load hitting scaffolding (H5), whereas the toolbox meeting only slightly improved it. In contrast, hazards such as H1 and H3 exhibited low ADI by participants across all stages, with no significant effects observed from augmented stimuli and toolbox meeting interventions. This may have been attributed to the complex interaction of cranes and scaffolds involved in H1 and H5, as well as the fact that H1, H3, and H5 were outside the participants' normal line of sight, making them harder to perceive.

In task two, as shown in Fig. 20 and Fig. 21, although the same H1 and H5 were present, the ADI patterns differed from those in task one. For H1, the ADI was very high without any measures, and augmented stimuli and toolbox meetings statistically significantly increased the ADI. The difference in ADI trends between task one and task two for H1 may have been attributed to the distance between participants and the heavy load on the crane. Specifically, in task two, this distance was much smaller than in task one, making it easier for participants to notice heavy objects above their heads. For the hazards involving contact with live electrical wiring (H6) and tripping over obstacles (H7), these hazards exhibited very low ADI at stage A, and the effects of augmented stimuli and toolbox meeting were not significant. Finally, for falls from openings (H8), the toolbox meeting proved effective. Although augmented stimuli had no specific design for H8, the ADI still improved. This may have been due to the augmented stimuli designed for other hazards, which improved safety awareness among participants.

Repeated measures ANOVA was conducted to examine the effects of the interplay of augmented stimuli and toolbox meetings on ADI between stages B1-C and B2-C. The results are presented in Table 11. The interaction effect between augmented stimuli and toolbox meetings on ADI was found to be significant for most hazards ($P < 0.05$).

4.3.2. ERP evidence

In Fig. 12 and Fig. 13, the amplitude of the P3a component was highest in stage C, followed by stage B1, and then stage A. This suggested that the augmented stimuli and toolbox meeting showed stronger brain activity in stage C than in stages B1 and A. The ERP scalp maps in Fig. 13, which corresponded to Fig. 12, further indicated that Channel O2 showed lower activity in Stage A compared to Stage B1, with Stage C showing even higher activity. Similar results were observed in Fig. 16 and Fig. 17, where the 50 % area amplitude of P3b in Stage C was higher than in Stage B2, which was also higher than in Stage A.

Repeated measures ANOVA was conducted to examine the effects of

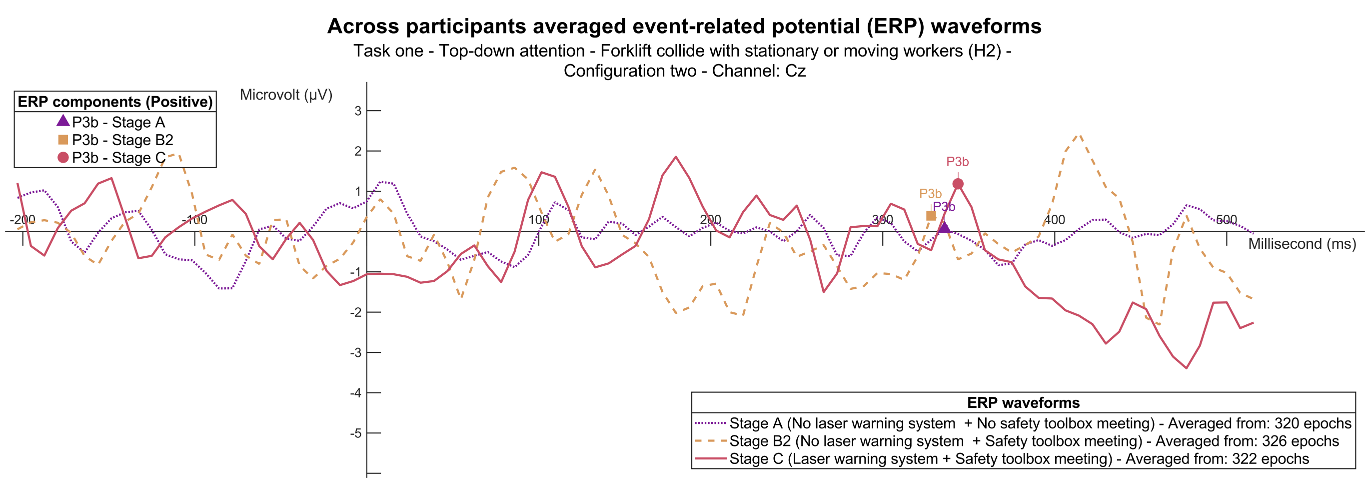


Fig. 16. P3b ERP component: waveform analysis cross stage A, B2, and C.

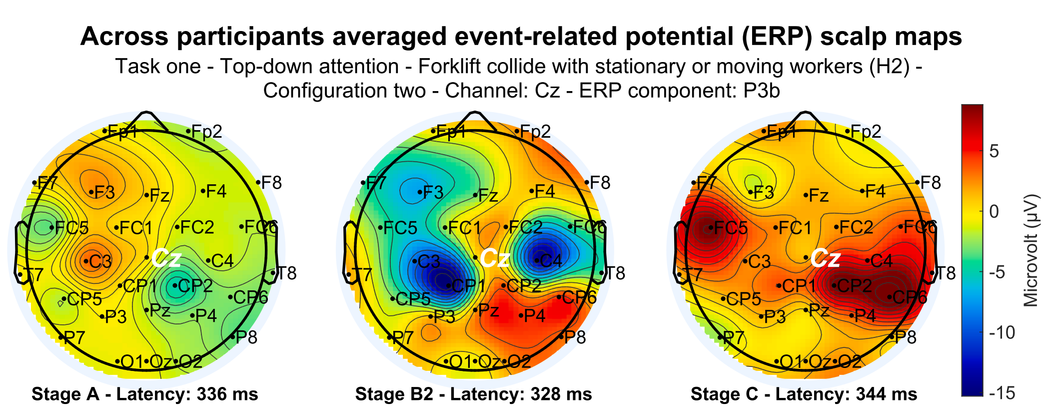


Fig. 17. P3b ERP component on Cz channel: scalp map visualization cross stage A, B2, and C.

Table 10
ANOVA results for toolbox meeting of 50% area amplitude in configuration two.

Stages	Cognitive process	Task	Hazard	ERP component	Channel	Toolbox meeting		
						P value	F-statistic	Effect size
A-B2	Bottom-up attention	T-1	H2	N2pc	F7	<0.05	4.672	0.88
				P3a	F7	<0.05	4.66	0.85
			H3	N2pc	F7, FT9	<0.05	4.886 ~ 5.625	0.69 ~ 0.71
				P3a	F7, FT9	<0.05	4.547 ~ 5.275	0.75
		T-2	H6	N2pc	Fp2	<0.05	4.052	0.99
			H7	N2pc	O1, O2, Oz	<0.05	4.102 ~ 4.126	0.89 ~ 0.9
			H8	N2pc	C3, CP1, CP2, CP5, Cz, F3, F4, FC1, FC2, Fp2, FT10, Fz	<0.05	4.029 ~ 7.248	0.52 ~ 0.71
				P3a	CP1, Cz, FC1, FC2, Fp2, FT10, Fz	<0.05	4.025 ~ 6.695	0.61 ~ 0.76
	Top-down attention	T-1	H2	P3b	Cz	<0.05	4.773	0.92
			H3	P1	Fp1	<0.05	4.045	0.76
			H4	P1	FT10, PO10, PO9	<0.05	4.515 ~ 6.085	0.43 ~ 0.75
				P3b	F7, FC5	<0.05	4.149 ~ 4.226	0.31 ~ 0.45
		T-2	H1	P3	Fp1	<0.05	4.141	0.7
			H6	P1	CP1, P8	<0.05	4.103 ~ 5.339	0.43 ~ 0.49
			H8	P3	Fp1, Fp2	<0.05	4.301 ~ 4.326	0.47 ~ 0.62
				P3b	PO10	<0.05	4.909	0.58

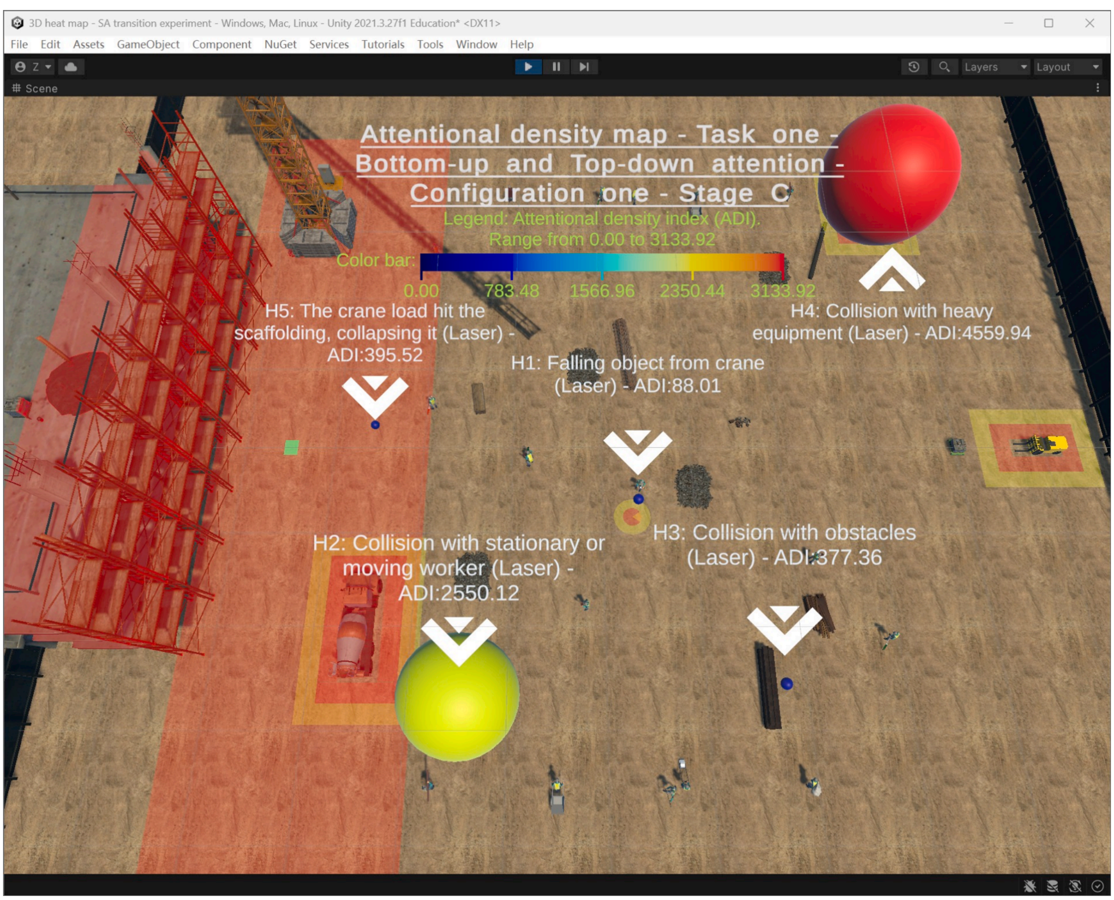


Fig. 18. Attentional density map – task one – stage C.

the interplay of augmented stimuli and toolbox meetings on 50 % area amplitude between stages B1-C and B2-C, as shown in Table 12. The interaction effect between augmented stimuli and toolbox meetings was found to be significant for 50 % area amplitude ($P < 0.05$). This result suggested that the simultaneous use of both augmented stimuli and toolbox meetings led to improved brain activity compared to using them in isolation.

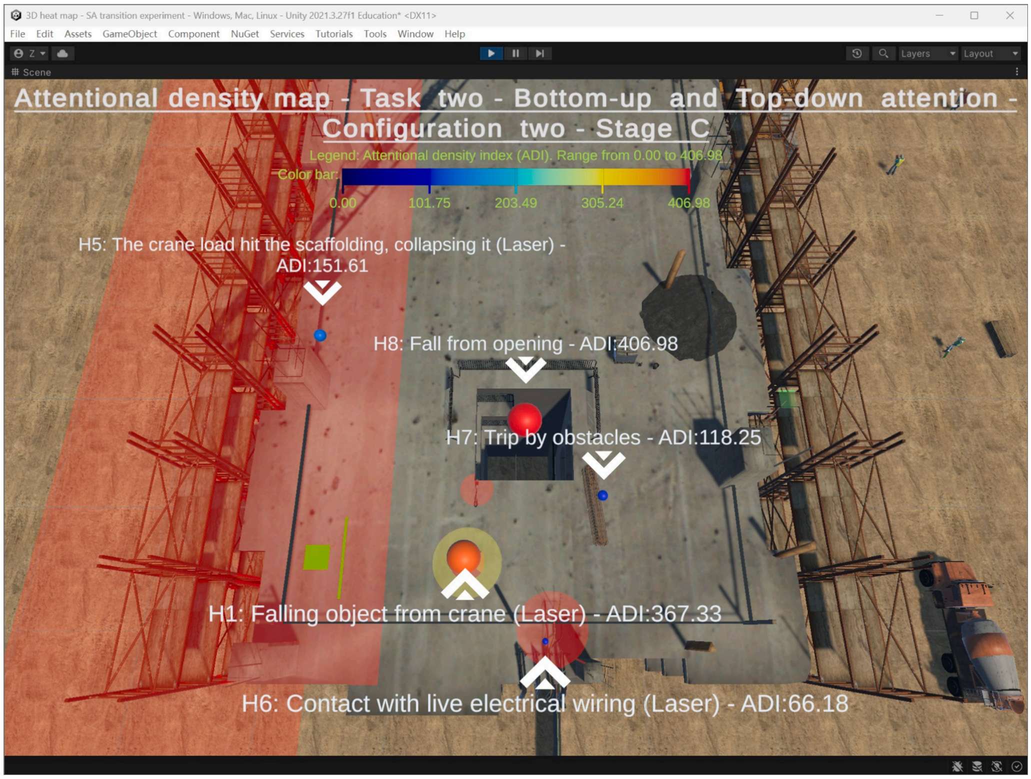


Fig. 19. Attentional density map – task two – stage C.

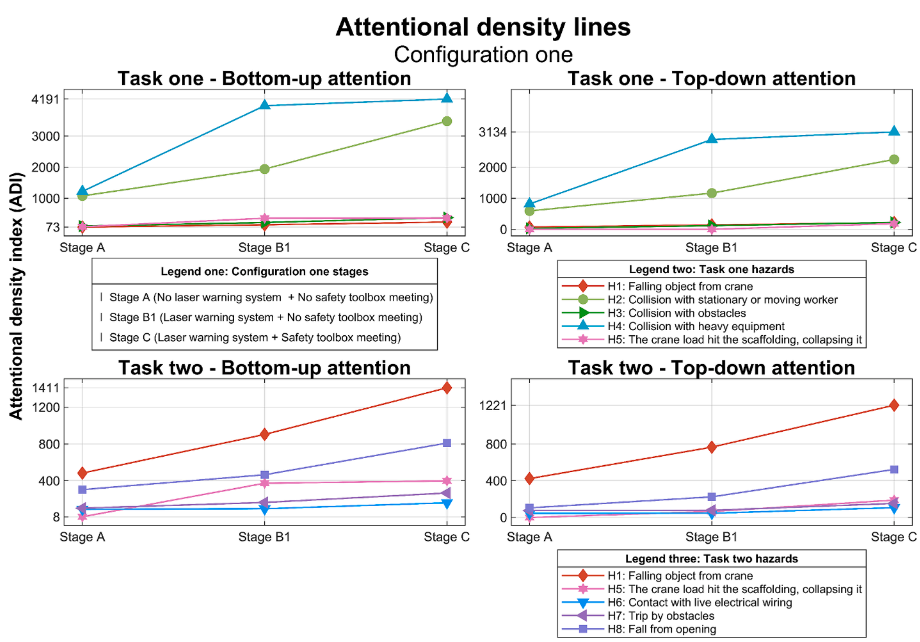


Fig. 20. Configuration one attentional density lines.

4.3.3. *Hazard recognition evidence*

Repeated measures ANOVA was conducted to examine the effects of augmented stimuli and toolbox meetings on HRI between stages A-B1, A-B2, B2-C, and B2-C. The results are presented in Table 13. The results indicated a significant main effect of augmented stimuli on HRI between stages A and B1 ($P < 0.0001$). Moreover, the analysis revealed a significant main effect of toolbox meetings on HRI ($P < 0.01$). The interplay of augmented stimuli and toolbox meetings was found to be statistically significant in both tasks for all configurations ($P < 0.0001$).

4.3.4. *A summary of results*

The results provided neuropsychological evidence for the effectiveness of the interplay of augmented stimuli and toolbox meetings in improving B-U, T-D, and hazard recognition performance. ET data showed that the interplay between augmented stimuli and toolbox meetings statistically significantly improved B-U and T-D-related attention distribution in configuration one. ERP evidence also demonstrated stronger brain activity in response to the combination of augmented stimuli and toolbox meetings compared to using them

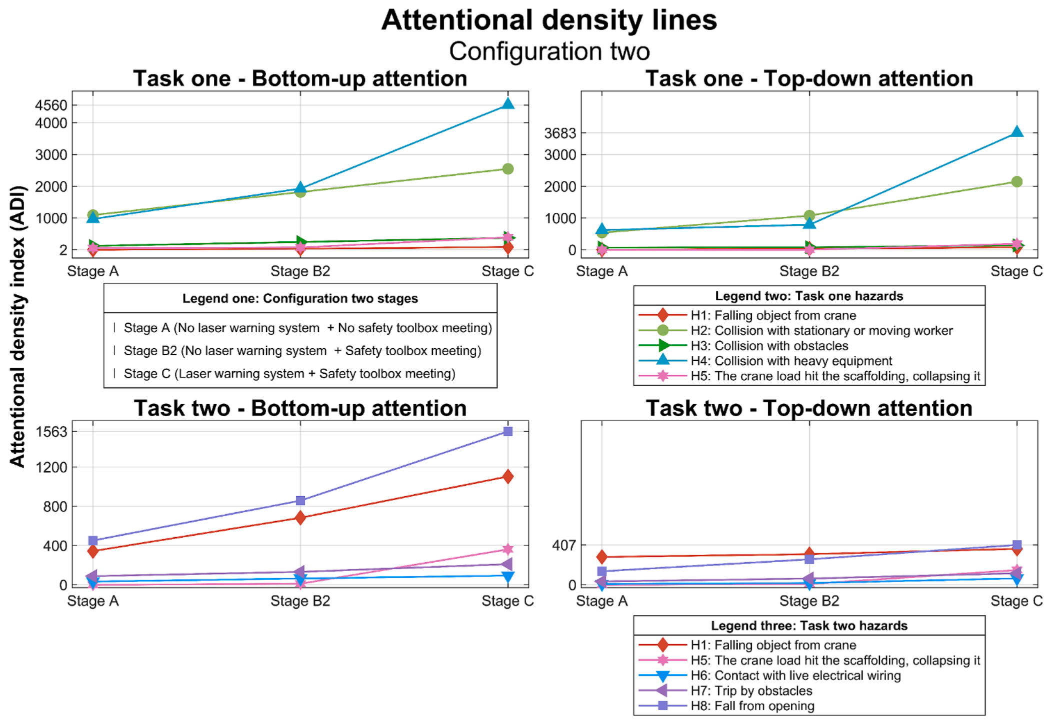


Fig. 21. Configuration two attentional density lines.

separately. HRI revealed a statistically significant effect of the interplay of augmented stimuli and toolbox meetings on hazard recognition performance in configuration one, task one, indicating that their combined use was more effective than using either alone. Overall, these findings indicated that the combined effect of augmented stimuli and toolbox meetings yielded a statistically significant improvement in B-U, T-D, and hazard recognition compared to utilizing either intervention in isolation.

5. Discussion

This paper aims to investigate the effects of the interplay between T-D and B-U attention on hazard recognition. Attention was measured by eye tracking and EEG, which improved validity and reliability. Results suggest that both B-U and T-D play a crucial role in hazard recognition on construction sites. It is indicated that the augmented stimuli statistically significantly improved B-U attention, while toolbox meetings statistically significantly improved T-D attention. It is evident that the interplay between T-D and B-U attention can statistically significantly improve workers' hazard recognition performance.

This paper tested how salient stimuli impact workers' attention allocation. Results are consistent with classic attention theories (Eysenck and Keane, 2020). that augmented stimuli naturally draw worker's attention and facilitate hazard recognition. The bottom-up process starts with attention capture and sensory input. Hazard recognition is based on the prerequisite that once a worker attends to the object, she or he would understand and recognize the hazard. However, this may not always be the case. For complex and dynamic hazardous scenarios that involve multiple objects, preliminary attention and perception are not sufficient. Nevertheless, the results suggest that stimulus-driven attention can be deliberately shaped and enhanced by digital technologies. As demonstrated and proved in the experiment, stimuli (e.g., visual and auditory cues) can be carefully crafted and enabled by digital technologies.

On the other hand, safety toolbox meetings play an essential role in developing and reinforcing workers' safety goal, commitment, and expectation. The goal-directed effects, as a form of attentional control, drive workers to allocate attentional resources to hazards. From a behavior science perspective, this top-down process is intentional and effortful, driven by internal motivations. The importance of safety goal in shaping safety behavior has been clearly investigated in previous research (Guo et al., 2018a, 2018b, 2015; Zhang et al., 2023b). This paper provided clear psychophysiological evidence to support the result that when workers internalize safety goals, they are more likely to remain vigilant, recognize potential hazards, and take proactive steps to mitigate risks. In addition, the results highlight that traditional safety practices still play a critical role in site safety management.

5.1. Contributions and implications

This paper made both theoretical and methodological contributions to the research on cognitive aspects of hazard recognition in construction settings. On the theoretical level, this paper provided evidence that the interplay between B-U and T-D can significantly improve workers' hazard recognition performance. As aforementioned, prior research has examined the role of various attentional mechanisms, such as sustained attention (Wang et al., 2019, 2017), visual attention (Cheng et al., 2021; Hasanzadeh et al., 2017a, 2017b; Liao et al., 2021), selective attention (Hasanzadeh et al., 2017a) and divided attention (Hasanzadeh et al., 2017a). The results of this paper improved our understanding of the mechanisms that control selective attention and the source of guidance over attention orientation. By demonstrating that T-D and B-U processes can work together rather than in isolation, this research contributes a key theoretical insight: attentional orientation in hazardous construction environments is neither fully determined by external stimuli nor entirely controlled by internal cognitive sets.

On the methodological level, unlike previous studies that employed advanced techniques such as IVR, ET, and EEG in static or 2D screen-based scenarios (Li et al., 2023; Wang et al., 2024; Zhu et al., 2022), this research allows participants to explore and interact with a dynamic scenario in real-time. This immersive approach enables individuals to make their own decisions and navigate through the environment freely, providing a more nuanced understanding of how they respond to changing situations and hazards.

Table 11
ANOVA results for augmented stimuli and toolbox meeting of ADI.

Stages	Cognitive process	Task	Hazard	Augmented stimuli and toolbox meeting		
				P value	F-statistic	Effect size
B1-C	Bottom-up attention	T-1	H1	<0.05	4.282	0.77
			H2	<0.0001	26.701	0.71
			H3	<0.0001	20.867	0.71
			H4	<0.0001	33.704	0.71
			H5	<0.0001	21.744	0.70
		T-2	H1	<0.001	14.729	0.73
			H5	<0.0001	30.014	0.73
			H6	<0.01	11.264	0.72
			H7	<0.001	16.487	0.68
			H8	<0.0001	30.712	0.75
	Top-down attention	T-1	H1	0.054	3.871	0.77
			H2	<0.0001	27.015	0.72
			H3	<0.0001	23.682	0.79
			H4	<0.0001	28.315	0.74
			H5	<0.0001	21.213	0.79
		T-2	H1	<0.001	12.189	0.74
			H5	<0.0001	28.149	0.77
			H6	<0.01	8.394	0.73
			H7	<0.01	11.505	0.68
			H8	<0.0001	26.109	0.76
B2-C	Bottom-up attention	T-1	H1	<0.05	6.174	0.88
			H2	<0.0001	27.514	0.75
			H3	<0.0001	27.317	0.89
			H4	<0.0001	23.617	0.85
			H5	<0.0001	29.058	0.90
		T-2	H1	<0.0001	29.063	0.72
			H5	<0.0001	35.672	0.99
			H6	<0.01	7.675	0.86
			H7	<0.01	10.144	0.68
			H8	<0.0001	31.391	0.72
	Top-down attention	T-1	H1	<0.05	6.174	0.88
			H2	<0.0001	30.705	0.76
			H3	<0.0001	19.325	0.90
			H4	<0.0001	33.111	0.83
			H5	<0.0001	21.294	1.00
		T-2	H1	<0.0001	25.922	0.73
			H5	<0.0001	22.109	0.99
			H6	<0.05	6.563	0.91
			H7	<0.05	6.970	0.69
			H8	<0.0001	20.174	0.75

Previous studies on hazard perception have been limited by traditional methods of data analysis, which often result in static representations of dynamic phenomena (Hasanzadeh et al., 2017a, 2017a; Kim et al., 2021; Liao et al., 2021). Specifically, researchers have relied on static heatmaps or bar charts, which oversimplify the spatiotemporal interplay between B-U and T-D attentional processes (Cheng et al., 2021; Hasanzadeh et al., 2017a). In contrast, this research leverages innovative visualization tools, such as the attentional density index map and lines, to provide a 3D spatial–temporal representation of attentional allocation. Regarding practical implications, this paper highlights and calls for an integrated approach to improving worker's hazard recognition performance. By combining digital-technology-enabled stimuli with safety-goal-oriented training and managerial practices, construction firms and safety professionals can more effectively guide workers' attention. For instance, on-site digital alerts and augmented cues can provide immediate, visually compelling prompts to notice potential hazards, while regular toolbox talks, mentoring, and leadership reinforcement of safety goals can ensure workers remain internally motivated and attentive. This dual focus represents a design-thinking perspective that seeks to improve both the physical and mental environments. On the one hand, advanced digital interfaces and strategically placed cues shape how workers perceive and respond to their surroundings. On the other, sustained safety training, clear goal-setting, and ongoing feedback reshape workers' internal decision-making frameworks, making it more natural for them to prioritize safety and hazard detection.

5.2. Limitations and future research

Four limitations should be considered when interpreting and applying the findings of this study. First, the EEG signal can be contaminated with significant artifacts caused by participants' movements during the experiment, such as walking and head movements. These artifacts may introduce noise into the data, potentially affecting the accuracy and reliability of the EEG results. Nevertheless, the researchers employed Independent Component Analysis (ICA) and filtering techniques to remove as much artifact-related noise as possible from the EEG data. It is worth noting that our primary focus is on the eye movement data collected using HTC VIVE, with EEG serving as supplementary evidence to support our findings. While the measures taken to clean the EEG data were rigorous, some residual noise may still remain, and this should be acknowledged when interpreting the results.

The second limitation is that within-subject experimental design may still be subject to carry-over effects (Cacioppo et al., 2007, p. 814), where participants' performance in one stage could influence their behavior in subsequent stages. Although the three scenarios presented distinct variations in terms of augmented stimuli and goals (e.g., safety goals were not mentioned on stages A and B1), the potential for carry-over effects cannot be entirely eliminated. To mitigate these effects, a 10-minute rest period was implemented between each stage, during which the experiment conductor explicitly instructed participants to clear their minds and relax. Despite these precautions, future studies could consider a between-subjects design to further minimize the risk of carry-over effects.

The third limitation is that the study was conducted in a controlled VR environment. The results should be applied to real-world construction sites with caution. While VR offers a highly immersive and controllable setting for experimentation, it may not fully replicate the complexities and unpredictability of real-world construction sites. Factors such as environmental distractions, physical hazards, and the dynamic nature of real-world tasks are difficult to simulate in a VR setting. As such, the generalizability of the findings to real-world scenarios should be approached with caution. Future research could validate these findings by conducting field studies on actual construction sites to assess the transferability of the results.

Finally, the sample size and demographic characteristics of the participants may also limit the generalizability of the findings. The study relied on a specific group of participants, which may not fully represent the broader population of construction workers or individuals in other high-risk industries. Expanding the sample size and diversifying the participant pool in future studies could enhance the external validity of the results.

6. Conclusion

This study contributes significantly to understanding the interplay between B-U and T-D in hazard recognition on construction sites. The findings demonstrate that both B-U and T-D processing play critical roles in recognizing hazards, and that the combination of interventions targeting these two processes has a synergistic effect on hazard recognition. Results also highlight the importance of considering individual hazard types when implementing attention-based interventions, as well as the limitations of using eye-tracking and ERP in measuring attention allocation and brain activity.

The implications of this research are far-reaching, with potential applications in construction safety management and hazard recognition. By tailoring attention-based interventions to specific hazards and taking into account the complex interactions between B-U and T-D processing, safety managers can develop more effective strategies for reducing hazards and improving worker safety on construction sites. Furthermore, this study underscores the need for a more comprehensive

Table 12
ANOVA results for augmented stimuli and toolbox meeting of 50% area amplitude.

Stages	Cognitive process	Task	Hazard	ERP component	Channel	Augmented stimuli and toolbox meeting		
						P value	F-statistic	Effect size
B1-C	B-U	T-1	H1	N2pc	FT10	<0.05	4.182	0.67
			H3	N2pc	C3, C4, CP1, CP5, CP6, Cz, F3, F4, F8, FC1, FC2, FC6, Fp1, Fp2, FT10, Fz, O1, P3, P4, P8, T7, T8	<0.05	4.227 ~ 8.617	0.52 ~ 0.85
				P3a	C3, C4, CP1, CP5, CP6, Cz, F3, F4, F8, FC1, FC2, FC5, FC6, Fp1, Fp2, FT10, Fz, P3, P4, P8, T7, T8	<0.05	4.038 ~ 8.866	0.47 ~ 0.78
		T-2	H5	N2pc	PO10	<0.05	6.428	0.62
				P3a	PO10	<0.01	7.099	0.64
			H7	P3a	O2	<0.05	4.118	0.78
			H8	N2pc	F4, FT10	<0.05	4.014 ~ 4.475	0.41 ~ 0.47
				P3a	F4, FT10	<0.05	4.37 ~ 5.089	0.4 ~ 0.47
	T-D	T-1	H3	P1	F3, F7	<0.05	5.28 ~ 6.527	0.74 ~ 0.85
				P3	CP6, F3, F7, FC1, O1, O2, Oz, P3, P4, P8, T7	<0.05	4.064 ~ 5.791	0.59 ~ 0.92
				P3b	CP6, F7, FC1, O1, P4, P8, T7	<0.05	4.279 ~ 5.914	0.67 ~ 0.86
		T-2	H5	P3	Fp1, Fp2	<0.05	4.969 ~ 5.003	0.9 ~ 0.94
				P3b	Fp1, Fp2	<0.05	4.852 ~ 5.319	0.88
			H6	P3b	C3, Cz	<0.05	5.592 ~ 6.033	0.32 ~ 0.37
B2-C	B-U	T-1	H1	N2pc	Fp1	<0.05	4.068	1
			H4	N2pc	Cz, P8	<0.05	5.115 ~ 7.043	0.15 ~ 0.24
				P3a	Cz, P8	<0.05	4.103 ~ 4.643	0.15 ~ 0.26
			H5	N2pc	P3	<0.05	4.711	1
				P3a	P3	<0.05	4.13	1
	T-D	T-1	H1	P3	FC2, FC6, FT10	<0.05	4.245 ~ 4.396	0.77 ~ 0.93
				P3b	CP6, F3, F4, FC2, FC5, FC6, FT10	<0.05	4.046 ~ 5.602	0.61 ~ 0.97
			H2	P1	Fp1	<0.05	4.324	0.34
			H4	P3b	Cz	<0.05	4.011	0.105
				P1	PO9	<0.05	5.072	0.11
		T-2	H1	P3	FT10	<0.05	4.869	0.4
			H7	P3	C4, FC2, FC6, Fz, T8	<0.05	4.088 ~ 5.311	0.2 ~ 0.48
				P3b	C4, F8, FC6, Fz, T8	<0.05	4.308 ~ 5.528	0.21 ~ 0.57
			H8	P1	CP5, FC5, FC6, O1, O2, Oz, P4, P7, P8, PO10	<0.05	4.250 ~ 8.337	0.24 ~ 0.57

Table 13
ANOVA results for augmented stimuli and toolbox meeting of 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

understanding of attention and hazard recognition, incorporating multiple sources of information to gain a nuanced picture of how workers process information and allocate their attention.

The findings of this research also have broader implications for occupational health and safety (OHS) management in general. By understanding the cognitive processes underlying hazard recognition, OHS professionals can develop more effective interventions aimed at reducing workplace hazards and improving worker safety. The results of this paper demonstrate the importance of considering both B-U and T-D processing when designing these interventions. They also highlight the need for a multidisciplinary approach to OHS research that incorporates insights from neuroscience, psychology, and other fields.

In conclusion, this study provides valuable insights into the interplay between bottom-up and top-down attention in hazard recognition on construction sites. The findings have significant implications for construction safety management and hazard recognition and underscore the need for a more comprehensive understanding of attention and hazard recognition.

CRediT authorship contribution statement

Zhe Zhang: Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Brian H.W. Guo:** Writing – review & editing, Supervision, Resources, Methodology, Conceptualization. **Zhenan Feng:** Writing – review & editing, Supervision, Methodology. **Yang Miang Goh:** Writing – review & editing, Methodology, 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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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ssci.2025.106841.

Data availability

Data will be made available on request.

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