Evaluation of Effect of Different Safety Training Styles on Mental Workloads Using Electroencephalography

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Abstract –

In the construction industry, diverse safety training styles, such as verbal instructions, pictorial representations, radio-based, video, Virtual Reality (VR), and Augmented Reality (AR) training, have been employed to improve workers' hazard recognition. However, the impact of these varied training styles on mental workload has been understudied. This research aims to investigate two primary aspects: (1) the influence of different safety training styles on participants' mental workloads, and (2) the variation in mental workload across different training phases. For this purpose, an experimental study was conducted with 20 participants (10 males and 10 females), who were randomly assigned to receive safety instructions either through reading or listening. The training was divided into four phases, each focusing on a specific hazard. Participants' brain activity was monitored using electroencephalography (EEG), and their mental workloads were assessed based on engagement and arousal indices. The results indicated no significant differences in engagement and arousal indexes between the reading and listening groups. However, variations in mental states were observed across different training phases, with increasing arousal levels noted as the training progressed. This study offers insights into the efficiency of different safety training styles and provides valuable recommendations for designing more effective safety training programs to enhance hazard recognition in the construction industry.

Keywords –

Safety training styles; EEG; Engagement index; Arousal index

1 Introduction

The construction industry is a vital component of the global economy, characterized by its dynamic and often high-risk work environments [1]. The construction industry continues to report a significant number of workplace accidents and fatalities each year [2]. This situation underscores the critical need for effective safety measures and training programs tailored to address the unique hazards of construction sites.

Traditionally, construction safety training has relied on conventional methods such as the dissemination of printed manuals and verbal instruction [3]. However, the effectiveness of these methods has often been questioned, particularly in terms of the engagement. Recently, the industry have seen a shift towards more interactive and multimedia-based training approaches, including the use of auditory training tools [4]. However, there remains a lack of comprehensive data to assess the overall impact of these diverse training styles.

Effective safety training in the construction industry is not merely a regulatory requirement but also a fundamental aspect of ensuring workers' safety and preventing accidents [5]. The complexity of construction work and the diversity of risks present on construction sites, make comprehensive safety training indispensable. In addition, effective safety training programs are essential to enhance construction safety, which can contribute to reducing the incidence of workplace accidents.

While there is a consensus on the importance of safety training, there is a noticeable gap in research regarding the differences of workloads when people receive different safety training methods. Traditional evaluation methods have primarily focused on subjective assessments or post-training performance metrics. The application of neurophysiological tools, such as Electroencephalogram (EEG), remains largely unexplored. This gap hinders the development of evidence-based training programs that can enhance safety in the construction sector.

EEG presents a novel approach to understanding and evaluating training effectiveness by providing objective measures of cognitive engagement [6]. Although EEG has been successfully employed in cognitive research to assess learning processes, its application in evaluating construction safety training is pioneering. By analyzing EEG data, this research aims to uncover the workloads of effective learning in safety training, offering a new method to training evaluation.

This study seeks to evaluate and compare the workloads among people undergoing different forms of safety training, specifically traditional manual reading versus auditory training methods. The objective is to determine the differences of workload when people receive different training styles. The research questions were formulated as following:

Research question (RQ 1): Do people show different level of workloads when receiving different safety training styles?

Research question (RQ 2): How do people's workloads change at different phases?

2 Literature Review

2.1 Construction safety training styles

The construction industry, characterized by its inherently hazardous environment, necessitates the implementation of robust safety training methods to mitigate workplace accidents and fatalities [1]. There has been a concerted effort to develop and refine effective safety training techniques to address this need. A variety of safety training programs have been integrated into the construction sector, each with its unique approach and methodology.

Traditional safety training within the construction domain typically relies on verbal instructions and pictorial representations [3]. This approach often involves job hazard identification conducted by professionals utilizing two-dimensional drawings, photographs, or static representations, supplemented by verbal explanations [7]. Such methods are foundational but may have limitations in conveying complex scenarios.

Radio-based training, while less prevalent, provides an auditory learning experience that can be particularly effective in reinforcing verbal instructions. Video training, conversely, has seen a surge in popularity due to its capacity to visually demonstrate procedures and scenarios. A notable example of this is the OSHA-10hr video training program, widely recognized in the construction industry [8].

Recent technological advancements in VR and AR have led to significant innovations in construction safety training. Xu and Zheng [9] have developed an immersive, interactive multiplayer-based training platform utilizing VR technology, aimed at enhancing workers' safety awareness. This platform represents a shift towards more engaging and realistic training environments.

Furthering this trend, Li et al. [10] introduced an optimization-centric methodology for creating personalized training scenarios within a VR framework, specifically designed for construction safety education. Their research demonstrated that participants receiving personalized guidance in the VR setting showed more significant improvements in hazard identification skills.

Additionally, the study by Pereira et al. [11] explored the development of a virtual reality environment that augments real-world training resources, such as those provided by OSHA's Susan Harwood Grant. This approach underscores the potential of VR in replicating and enhancing traditional training methods.

In summary, the construction industry has witnessed the application of a diverse array of safety training methods, ranging from conventional techniques to cutting-edge VR and AR-based platforms. These methods collectively contribute to the overarching goal of enhancing construction safety, underscoring the industry's commitment to reducing accidents and fatalities through innovative and effective training solutions.

2.2 Application of EEG on construction issues

The advent of wearable sensing technologies has significantly broadened the scope for enhancing safety and health measures in the construction industry [12]. These technologies comprise a wide range of devices, such as Inertial Measurement Units (IMU), Electrocardiography (ECG), Photoplethysmography (PPG) sensors, Electrodermal Activity (EDA), Electromyography (EMG) sensors, eye-tracking technology, and Electroencephalography (EEG). Among these, EEG stands out for its unique benefits in addressing safety issues in construction: (1) Real-time cognitive state monitoring; (2) Non-intrusive nature; and (3) Training effectiveness assessment.

The significance of EEG in studying construction safety issues is increasingly recognized in research. Jebelli et al. [13] developed a method for automatically identifying stress levels in construction workers by analyzing EEG signals, paving the way for early stress detection. Wang et al. [14] introduced a novel approach combining kinematic data with EEG to derive vigilance measurement indices, enhancing understanding of workers' risk perception and safety management on construction sites. Additionally, Wang et al. [15] created a technique for monitoring mental fatigue in workers using EEG signals and machine learning, facilitating real-time and continuous fatigue assessment, thereby improving safety management practices.

This section underscores the state-of-the-art state in construction safety training methods and the application of EEG in addressing construction-related issues. However, there remains a gap in research regarding the impact of different safety training methods on workers' workload. Addressing this gap, the current study aims to employ EEG technology to measure the workload experienced by individuals subjected to various training methods, thereby contributing to the optimization of safety training in the construction industry.

3 Methodology

This section presents the methodology of this study, including participant, experimental procedure, EEG signal pre-processing, and feature selection. Figure 1 presented the process of this study.

3.1 Participants

In this study, 21 people were invited from the university to participate in the experiment. Among them, one was excluded because of the missing data. Finally, the eligible sample size is 20, including 10 (female) and 10 (male). All participants range from 18 to 40 years, including 18-25(3), 26-30 (11), and 31-40 (6). In addition, all participants not only have normal or corrected-to-normal vision and hearing but also normal mental health.

While inviting 20 participants to an EEG study on the effects of safety training on mental workload is a good starting point, especially for pilot studies or exploratory research, this number may be on the lower end for ensuring robust statistical power, detecting small to moderate effect sizes, and achieving generalizable results.

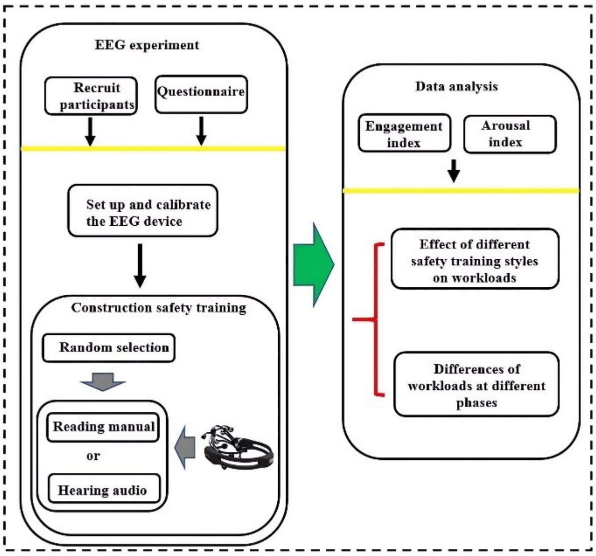


Figure 1. Procedure of this study

3.2 Experiment procedure and apparatus

Before the formal experiment, the participants were required to complete the questionnaire regarding their basic information, including gender, age, and their mental health. Then, the staff then prepared the device and attached the electrodes on the participant's scalp. During the process of calibration, participants were required to relax. The formal experiment started when the quality of EEG signal reaches 100%.

During the formal experiment, the participant was randomly assigned a task, which required the participant to read a safety training manual or hear a safety training audio to enhance the safety awareness. Figure 2 shows an example of the test set up. Both of the two training styles have the same content and the only difference between them is the presentation style. The training concentrates on different hazards at construction sites to enhance people' safety awareness. This training was divided into four phases each phrase corresponds to one common hazard: phase 1- fall hazard, phase 2- tripping hazard, phase 3-electrical hazard, and phase 4- caught-in/between hazard. For example, phase 1 in the safety training manual describes the fall hazard and presents an example of this hazard through a figure. The selection of fall hazards, tripping hazards, electrical hazards, and caught-in/between hazards for inclusion in safety training programs is based on their ubiquity and potential severity within workplace environments, reflecting a strategic approach to mitigating prevalent risks that contribute significantly to workplace accidents and injuries. Time window for each phase depends on the length of the description. For example, phases 1 about the fall hazard lasts 30 seconds because it has 56 words and the audio play speed is 120 words/ minute. There is a five-second relaxation period between the two phases. The detailed procedure of the experiment was presented in Figure 3.

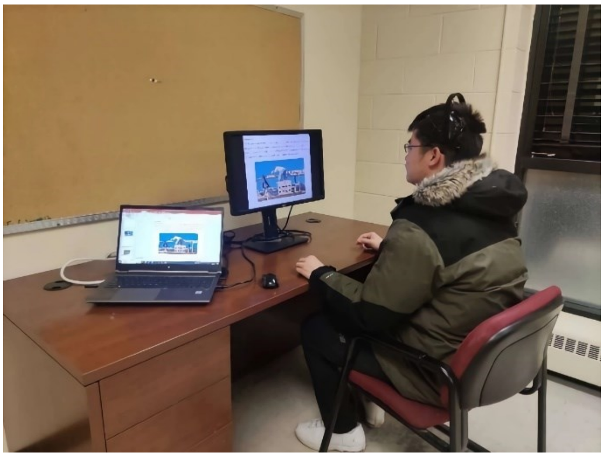


Figure 2. An example of the test setup

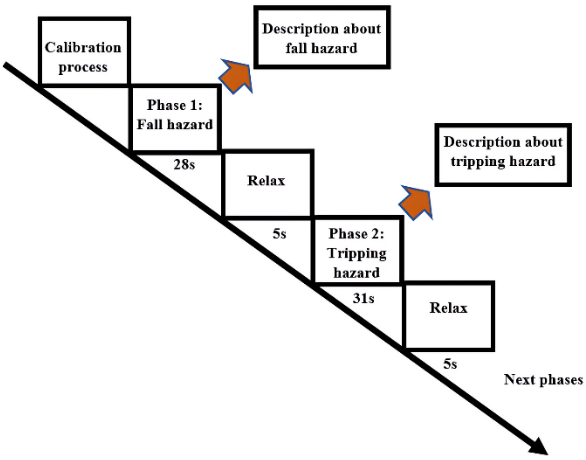


Figure 3. Experiment procedure

In this study, brain activity of the participants was meticulously monitored and recorded using the EMOTIV EPOC+ 14-Channel Headset, a wireless EEG signal amplifier. This device operates at a sampling frequency of 256 Hz, ensuring high-resolution data capture. The continuous EEG signals were acquired through 14 strategically placed electrodes (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4). Two additional electrodes function as referential anchors, specifically aligned with the P3 and P4 regions. These are designated as the Driven Right Leg (DRL) and Common Mode Sense (CMS), respectively, playing critical roles in enhancing signal fidelity and mitigating interference. Figure 4 shows the position of 14 electrodes of Emotive EEG device [16].

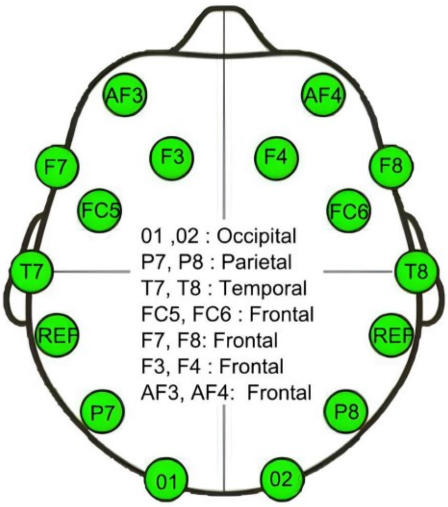


Figure 4. Location of the 14 electrodes of Emotive EEG device

The device is worn compliance with the International 10-20 system. This system is globally recognized for its standardized approach in electrode placement on the scalp, primarily aimed at facilitating accurate mapping of brain regions, with a specific emphasis on the cerebral cortex. The EEG signal was referenced using the P3 and P4 electrodes, a method that ensures reliable and stable signal quality by reducing noise and enhancing the accuracy of cerebral activity measurement.

3.3 EEG signal pre-processing

The raw EEG data often contains various types of noise and artifacts, making pre-processing a critical step to ensure the accuracy and reliability of EEG analysis [17]. When the EEG starts recording the brain activities, the user is required to record baseline, including relax with your eyes open and relax with your eyes closed. This step stems from the following reasons: (1) The EMOTIV EEG devices, like many other EEG systems, require calibration to the individual user's brain wave patterns. Opening and closing the eyes can help the device in calibrating and recognizing the user's unique brainwave patterns. This process ensures that the device accurately captures and interprets the EEG data; (2) Artifacts Detection: Eye movements, including blinks, can cause artifacts in EEG recordings. By asking the user to open and close their eyes, the system can identify and potentially filter out these artifacts from the actual brainwave data. This helps in improving the accuracy of the EEG readings; (3) Baseline Establishment: The difference in brain activity when the eyes are open versus when they are closed (such as changes in alpha waves) can be significant. This contrast helps in setting a baseline to better understand and interpret subsequent brain activity during the EEG recording.

The initial processing of EEG data involves the application of a bandpass filter, specifically within the frequency range of 1–30 Hz. This filtering stage is a critical component in EEG data pre-processing, as the raw EEG signals typically encompass a variety of fluctuating time-dependent curves, incorporating multiple channels and frequency bands that are not pertinent to the intended analysis. The primary function of filtering is to eliminate extraneous noise and to isolate the signal of interest from a specified frequency band for subsequent examination. A bandpass filter is particularly instrumental in this context, as it allows the passage of signals within a designated frequency range—here, 1–30 Hz—while attenuating signals that fall outside this spectrum. Employing a bandpass filter in the 1–30 Hz range is a common practice in the initial stages of EEG signal processing, given that the data of relevance are predominantly contained within these frequencies.

3.4 Feature selection

Cognitive or mental workload, integral to understanding human performance and learning, reflects the mental effort required to perform tasks, influenced by task complexity, individual capabilities, and environmental factors [18]. It is assessed through subjective self-reports, behavioral metrics, and physiological indicators, offering insights into the demands placed on cognitive resources [19]. Training outcomes significantly affect cognitive workload, with effective training reducing workload over time through skill acquisition and efficiency gains [20]. Adaptive training, tailored to individual differences and optimized through strategic feedback, can enhance learning efficiency and effectiveness, demonstrating the critical interplay between cognitive workload management and optimized training designs for improved task performance and learning.

Engagement index and arousal index are often considered key predictors of successful learning outcomes [21]. Engaged learners are typically more attentive, motivated, and invested in the learning process, which can lead to better understanding, retention, and application of the learned material. Higher engagement indices are usually associated with more focused attention and active cognitive processing, which are crucial for effective learning [22, 23]. High level of arousal index represents that the phase is more stimulating but low arousal index indicates that process is arousal [24]. Therefore, this study adopted engagement index to measure the participants' brain activities. It is calculated as follows:

$$Engagment\ index = \beta / (\alpha + \theta) \qquad (1)$$

$$Arousal\ index = (\beta(F4) + \beta(F3)) / ((\alpha(F4) + \alpha(F3)) \qquad (2)$$

Where, θ, α, β, and represents the EEG frequency bands, namely 4-8 Hz, 8-12 Hz, and 12-30 Hz.

The process for extracting the three frequency bands from the EEG signal involves several steps. Initially, a one-second segment of the EEG signal is processed using a Fast Fourier Transform. This method facilitates the separation of the signal into distinct frequency bands: theta (θ), alpha (α), and beta (β). Subsequently, a composite value representing these three bands is calculated. This is achieved by aggregating their respective values across the measured regions of the brain.

In the final step, the EEG engagement index and arousal index at a given instant time is determined. This is accomplished by calculating the average of each ratio within a sliding window preceding the instant T. This approach provides a dynamic measure of workloads, reflecting changes over the observed period.

4 Result and Analysis

This section presents result about the effect of different training styles on people, which responds to two RQs.

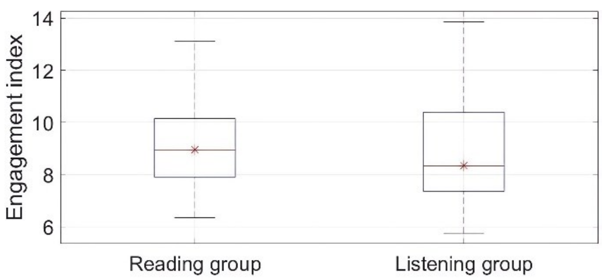
4.1 Learning outcome

Table 1 shows the EEG descriptive for two metrics, including engagement index and arousal index.

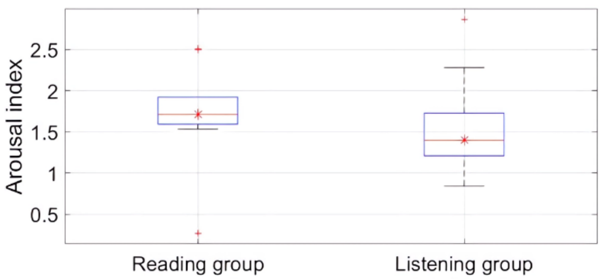
Figure 5 demonstrates the engagement index and arousal index of each group on different safety training styles. A Mann- Whitney U test was conducted to test the difference of the index between two groups. As the p-value =0.33 > 0.05, engagement index in reading group (*mdn*=8.95) and listening group (*mdn*=8.34) do not show significant differences between the reading and listening groups. Arousal index performs the similar result.

Table 1 EEG descriptive for each index

Indices	Training styles	Mean	SD	SEM
Engagement	Reading	9.10	1.88	0.56
index	Listening	8.95	2.54	0.76
Arousal	Reading	1.72	0.62	0.19
Index	Listening	1.57	0.59	0.18



(a) Engagement index between two groups

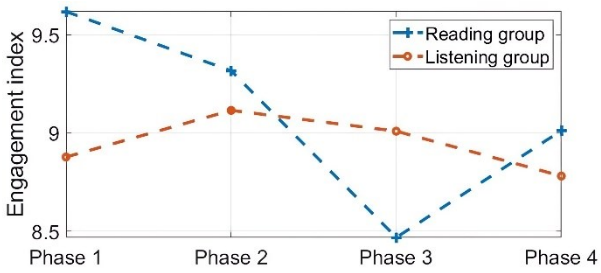


(b) Arousal index between two groups

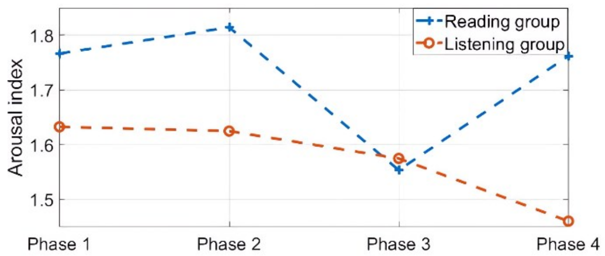
Figure 5. Engagement index and arousal index between reading and listening groups

4.2 Workloads at different phases

Figure 6 shows the workloads at different phases. According to the figure, people have lowest engagement index at phase 3 when reading the manual and at phase 4 when listening the safety manual. For the arousal index, people have lowest arousal value at phase 3 when reading. When listening to the manual, arousal index goes down as the learning process proceeds.



(a) Engagement index at different phases



(b) Arousal index at different phases

Figure 6. Workloads at different phases

Engagement index and arousal index can measure the immersion level while learning. High level of engagement is an indicator to reflect the level of stressful state. In addition, high level of arousal index represents that the phase is more stimulating but low arousal index indicates that process is arousal. According to the result, this study found that 1) people have the most relaxed mental state at phase 3 while reading but at phase 4 while listening; 2) In general, as the learning process proceeds, individuals experience a progressive enhancement in their mental tranquillity; 3) the hazard at phase 3 is more stimulating while reading but at phase 4 when listening; 4) As the listening learning process continues, the hazard becomes more and more stimulating, which means more and more arousal.

The study on the differential impact of reading and listening on engagement and arousal indices during construction safety training reveals nuanced insights into learner responses. It indicates that the mode of content delivery—whether visual or auditory—significantly influences learners' mental states and their perceived stimulation from the material. Specifically, learners exhibit a more relaxed state during phase 3 while reading and during phase 4 while listening, suggesting that content complexity and delivery mode interact uniquely with individual psychological responses. Furthermore, the progressive enhancement in mental tranquility across the learning process highlights the importance of acclimatization to the training material, while the increased arousal in listening scenarios underscores the cumulative engagement effect of auditory delivery. These findings point to the critical role of individual learning preferences, content delivery methods, and the inherent characteristics of the training material in designing effective safety training programs, emphasizing the need for tailored approaches that consider the diverse responses of learners to optimize training outcomes.

The study underscores the multifaceted nature of learning engagement and arousal, influenced by factors that include individual learning preferences, prior knowledge and experience, and environmental conditions. Individual learning preferences play a pivotal role, as they dictate how learners process and engage with information, whether through auditory or visual means. Participants' prior knowledge and experience with the subject matter can also significantly affect their response to the training, potentially reducing stress and increasing comprehension. Lastly, environmental factors, such as the presence of distractions and the physical or digital nature of the learning environment, contribute to the overall effectiveness of safety training by influencing learners' ability to focus and engage with the content. In conclusion, these factors highlight the necessity of adopting a nuanced and learner-centered approach in the design and implementation of safety training programs to enhance efficacy and learner outcomes.

5 Conclusion

This research aimed to evaluate the cognitive workloads associated with various safety training methodologies, utilizing electroencephalography (EEG) technology. To achieve this, an experimental framework was established to monitor and record cerebral activity in participants during the training sessions. The primary metrics for assessing cognitive workload were the engagement index and the arousal index. The findings of this study revealed two key insights: firstly, there was no statistically significant variation in the engagement index and arousal index between participants engaged in reading-based and listening-based training methods; secondly, the study observed differential cognitive workloads among phases, particularly noting that as the learning process proceeds, there was a corresponding rise in mental tranquillity, suggesting a more profound cognitive processing. These results have significant implications for the design of more effective safety training programs, potentially enhancing workers' ability to recognize and respond to hazards in their work environment.

This study illuminates the impact of different safety training styles on learner engagement and arousal within the construction industry, highlighting the potential for tailored training approaches. By demonstrating that reading and listening variably affect mental states and stimulation levels across different phases of safety training, the research suggests a strategic blending of content delivery methods to optimize learning outcomes. This approach not only accommodates diverse learning preferences but also utilizes the instructional strengths of each training styles to enhance learner engagement, reduce stress, and improve safety protocol. Such insights advocate for a more informed and adaptive design of safety training programs in the construction industry, aiming to foster safer work environments.

This study, while yielding insightful findings, is subject to certain limitations that must be acknowledged. Firstly, the participant pool was a little small, comprising only 20 individuals. This limited sample size may not adequately represent the broader population, potentially affecting the generalizability of the results. Additionally, the participants were not frontline construction workers, a factor that could influence the applicability of the findings to the intended target group. Moreover, the study's reliance on just two metrics – the engagement index and the arousal index – to assess cognitive workloads might not capture the full spectrum of cognitive responses to safety training.

For future research, several avenues are suggested to enhance the understanding of cognitive workloads during safety training. These include: (1) investigating the detailed trends in cognitive workload throughout the duration of safety training sessions; (2) employing a more comprehensive set of indices to measure cognitive workloads, thereby providing a more nuanced understanding of the cognitive processes involved; (3) examining the effectiveness of various safety training modalities, such as video, VR and AR in order to determine the most effective methods for imparting safety knowledge and skills. These future studies could significantly contribute to the optimization of safety training strategies, particularly in high-risk industries like construction.

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