Feasibility Study to Identify Brain Activity and Eye-Tracking Features for Assessing Hazard Recognition Using Consumer-Grade Wearables in an Immersive Virtual Environment

Mojtaba Noghabaei, S.M.ASCE[1]; Kevin Han, Ph.D., A.M.ASCE[2]; and Alex Albert, Ph.D., A.M.ASCE[3]

Abstract: Hazard recognition is vital to achieving effective safety management. Unmanaged or unrecognized hazards on construction sites can lead to unexpected accidents. Recent research has identified cognitive failures among workers as being a principal factor associated with poor hazard recognition levels. Therefore, understanding cognitive correlates of when individuals recognize hazards versus when they fail to recognize hazards will be useful in combating poor hazard recognition. Such efforts are now possible with recent advances in electroencephalograph (EEG) and eye-tracking technologies. This paper presents a feasibility study that combines EEG and eye tracking in an immersive virtual environment (IVE) to predict when safety hazards will be successfully recognized during hazard recognition efforts using machine learning techniques. Workers wear a virtual reality (VR) head-mounted device (HMD) that is equipped with an eye-tracking sensor. Together with an EEG sensor, brain activities and eye movements are recorded as the workers navigate a simulated virtual construction site and recognize safety hazards. Through an experiment and a feature extraction and selection process, 13 best features out of 306 features from EEG and eye tracking were selected to train a machine learning model. The results show that EEG and eye tracking together can be leveraged to predict when individuals will recognize safety hazards. The developed IVE can be potentially used to first identify hazard types that are correlated with higher arousal and valence. Also, the developed IVE can be potentially used to evaluate the correlation among arousal, valence, and hazard recognition. **DOI:** **10.1061/(ASCE)CO.1943-7862.0002130.**

Author keywords: Virtual reality; Electroencephalograph (EEG); Eye tracking; Safety training; Brain sensing.

Introduction

Over 60,000 fatal injuries in the construction industry are reported around the world each year (Jeelani et al. 2017b; Lingard 2013). In particular, fatal construction injuries in the US increased by over 16% from 2011 to 2015 (BLS 2015). The cost associated with such incidents exceeds $48 billion in the US alone (Jeelani et al. 2017b) and decreases the profit margin of construction projects. These incidents can adversely affect project success and jeopardize the economic stability of small companies (Zou and Sunindijo 2015). Research indicates that low levels of hazard recognition and management in the construction industry contribute to poor safety performance (Jeelani et al. 2017c). For example, research has demonstrated that more than 57% of construction hazards go unrecognized by workers (Bahn 2013; Perlman et al. 2014; Zhang 2017). Therefore, various efforts have advocated the adoption of proper safety training programs (Li et al. 2015; Rozenfeld et al. 2010) to enhance construction hazard recognition skill. Researchers have also suggested leveraging technologies such as virtual reality (VR) (Zhao and Lucas 2015), brain sensing (Hwang et al. 2018), and eye tracking (Hasanzadeh et al. 2017) to identify cognitive and physiological behaviors of workers during hazard recognition tasks, focusing on analysis and improvement of individual workers. Furthermore, studies have illustrated that using eye tracking and VR in personalized safety training programs can significantly improve workers' hazard recognition skills as eye tracking provides important insights about visual search patterns (Jeelani et al. 2017c) and VR provides a higher sense of presence compared with traditional two-dimensional (2D) screens (Alshaer et al. 2017). However, the use of eye tracking in isolation provides limited insight into the mental processes associated with effective hazard recognition. These processes can be addressed by brain-sensing (i.e., EEG).

EEG sensors can collect brainwave signals during visual hazard recognition tasks, allowing classification and identification of brain activities that are associated with superior hazard recognition levels. Classification can help trainers provide more accurate and personalized feedback to workers, which ultimately will lead to better safety performance (Hwang et al. 2018). Also, researchers have found that workers experience emotional changes while they are working in a hazardous environment (Hwang et al. 2018). These findings demonstrate that combining eye-tracking technology with brain sensing can be used to predict the hazard recognition performance of workers.

This paper presents a feasibility study that combines a VR head-mounted device (HMD) with an embedded eye tracker and a consumer-grade EEG sensor (the reliability of which is discussed in the section "Background") for predicting workers' ability to

[1]Ph.D. Candidate, Dept. of Civil, Construction, and Environmental Engineering, North Carolina State Univ., Raleigh, NC 27695-7908 (corresponding author). ORCID: https://orcid.org/0000-0002-2248-1840. Email: snoghab@ncsu.edu

[2]Assistant Professor, Dept. of Civil, Construction, and Environmental Engineering, North Carolina State Univ., Raleigh, NC 27695-7908. ORCID: https://orcid.org/0000-0002-2995-8381. Email: kevin_han@ncsu.edu

[3]Associate Professor, Dept. of Civil, Construction, and Environmental Engineering, North Carolina State Univ., Raleigh, NC 27695-7908. Email: alex_albert@ncsu.edu

Note. This manuscript was submitted on July 23, 2020; approved on April 12, 2021; published online on July 12, 2021. Discussion period open until December 12, 2021; separate discussions must be submitted for individual papers. This paper is part of the ***Journal of Construction Engineering and Management***, © ASCE, ISSN 0733-9364.

recognize safety hazards (e.g., whether a worker detects hazards). Workers wear this HMD and EEG sensor while performing a hazard recognition task on an immersive virtual construction site. This platform allows synchronous analyses of brain activity and eye movement in an immersive virtual environment (IVE). The recorded data from the eye tracker and EEG sensor are analyzed and classified using a machine learning technique that recognizes the pattern of brain activities and eye movements. Through a greedy feature selection process, 13 out of 306 features of EEG and eye tracking were found to be the best for for use in prediction of hazard recognition. The findings of this feasibility study can lead to future safety training programs and future research directions, as discussed in this paper. The paper's main contributions are as follows:

- Introduction of the first feasibility study that combines VR HMD, eye tracking, and brain waves (EEG) for hazard recognition performance. To the authors' best knowledge, this study is the first attempt to combine eye tracking, EEG, and VR HMD in the same framework for the construction domain (Table 1).
- Identification of best features (EEG and eye tracking) to use to predict workers' ability to recognize hazards (e.g., whether a worker detects hazards) through greedy feature selection. The number of extracted features from EEG and eye tracking is large and a long recording time can lead to very large data sets to be

Table 1. Related research

Study	Year	Summary	Limitations and recommendations	EEG device	Participants	Key features			
						EEG	Eye tracker	AR/VR	Safety
Chumerin et al. (2013)	2012	Analysis of SSVEP responses recorded with EEG in games	80% accuracy achieved in game control	Emotiv	20	✓	—	—	—
Van Vliet et al. (2012)	2012	90% accuracy for video game control using EEG	—	Emotiv	4	✓	—	—	—
Liu et al. (2012)	2012	SSVEP-based BCI with 95% accuracy	—	Emotiv	4	✓	—	—	—
Aspinall et al. (2015)	2013	EEG analysis of human behavior during physical activity	EEG can be used outdoors	Emotiv	12	✓	—	—	—
Ren et al. (2014)	2014	Sensitivity of neuromeric application fidelity to EEG data	—	Emotiv	20	✓	—	—	—
Elsawy et al. (2014)	2014	P300 classification with 90% accuracy	—	Emotiv	3	✓	—	—	—
Lin et al. (2014)	2014	Use of consumer-level EEG for real-life BCI SSVEP applications	Consumer-level EEG can be used in real-life scenarios	Emotiv	17	✓	—	—	—
Saha et al. (2014)	2014	Classification of olfactory stimulus from EEG response	—	Emotiv	25	✓	—	—	—
Wang et al. (2016)	2015	Memory workload assessment	—	Emotiv	9	✓	—	—	—
Perez Vidal et al. (2016)	2016	EEG control of robotic arm	—	Emotiv	20	✓	—	—	—
Wu (2017)	2016	Improved BCI calibration	—	Emotiv	18	✓	—	—	—
Barham et al. (2017)	2017	Similarity of latency and peak amplitude of N200 and P300 components between consumer-level and advanced EEG devices	Consumer-level EEG promoted as accurate	Emotiv	15	✓	—	—	—
Majid Mehmood et al. (2017)	2017	Emotion recognition using EEG and deep learning	—	Emotiv	21	✓	—	—	—
Bhatti et al. (2019)	2019	EEG optimal feature selection	—	Emotiv	5	✓	—	—	—
Casson and Trimble (2018)	2018	Effect of color priming using EEG	—	Emotiv	26	✓	✓	—	—
He et al. (2019)	2019	Feasibility of consumer-level EEG to differentiate cognitive task loads	Consumer-level EEG can collect high-quality data	Muse	37	✓	✓	—	—
Ergan et al. (2019)	2019	EEG and eye tracking for quantifying human experience in architectural spaces	—	Emotiv	33	✓	✓	—	—
Khushaba et al. (2013b)	2013	Combined EEG and eye tracker for safety research	—	BioSemi	17	✓	✓	—	✓
Azevedo et al. (2014)	2013	Analysis of human behavior related to markets	Combining EEG and eye tracking improves analysis accuracy	Emotiv	18	✓	—	✓	—
Coogan and He (2018)	2015	Combined EEG and VR to classify physical modality	—	Emotiv	10	✓	—	✓	—
Huang et al. (2019)	2018	First use of VR and EEG together	VR can serve as real environment	—	31	✓	—	✓	—
Putze (2019)	2019	Improved cognition using EEG training in Unity	Combining VR and EEG provides deeper experimental insights	Emotiv	20	✓	—	✓	—

Table 1. (*Continued.*)

Study	Year	Summary	Limitations and recommendations	EEG device	Participants	Key features			
						EEG	Eye tracker	AR/VR	Safety
Zhao et al. (2020)	2019	Use of VR + EEG for art applications	BCI can be successfully used with AR/VR	—	—	✓	—	✓	—
Wang et al. (2019)	2020	Similarity of SSVEP on 2D screen to AR	AR can be used for SSVEP experiments	—	10	✓	—	✓	—
Chen et al. (2016)	2019	EEG for improving safety	—	Emotiv	10	✓	—	—	✓
Wang et al. (2017)	2016	Use of brain waves to assess mental workload	Brain waves should be used to monitor workers' physical activities	Emotiv	5	✓	—	—	✓
Jeelani et al. (2018)	2017	Use of EEG sensors to monitor construction workers' perceived risk	EEG can be used on construction sites	Emotiv	10	✓	—	—	✓
Zhang (2017)	2018	Automated and scale personalized training using eye tracker	VR can be combined with eye tracking	—	6	—	✓	—	✓
Savage et al. (2013)	2017	VR-based training for mining industry	—	—	—	—	—	✓	✓
This study	—	Combining EEG, VR, and eye tracking for automated personalized feedback in construction safety training	—	Emotiv	30	✓	✓	✓	✓

processed for any machine learning methods. Therefore, 13 essential features were selected from 306 features through greedy feature selection without compensating for accuracy. This paper suggests that EEG and eye tracking together are strong predictors of hazard recognition performance.

- Validation against the neuroscience literature to ensure that the research findings are in alignment with its findings. According to the literature, occipital lobe channels (e.g., O1 and O2) correlate with a sense of danger (Joseph 1990; Mesulam 2000; Walker et al. 2007) Other channels, such as FC5 and AF3, correlate with visual perception (Joseph 1990; Mesulam 2000; Walker et al. 2007). In Fig. 1 these areas of the brain are enclosed by dashed lines (unenclosed channels are not directly corresponding to hazard detection). The research results here agree with the literature.
- Presentation of a system that can improve the adoption of EEG sensors in the construction industry. EEG technology has not been fully exploited in the construction industry due to the difficulty of data collection. This study can potentially improve EEG utilization since researchers can create new VR simulations in a controlled environment and collect data. Where data collection without VR simulations can be challenging, the proposed system may enhance it and ease EEG data collection as well.

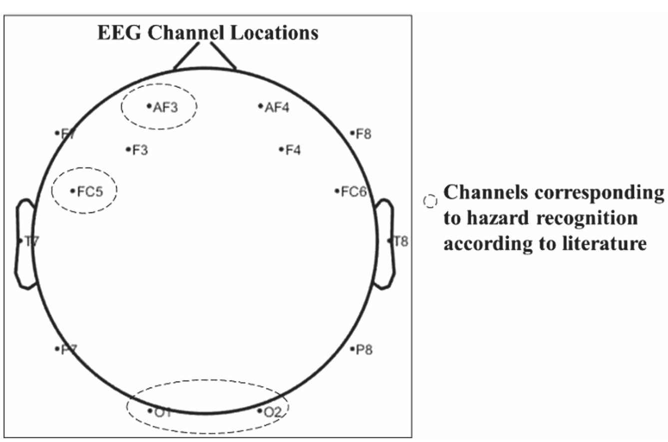

Fig. 1. Channel locations corresponding to hazard recognition.

Background

This section focuses on studies of enabling technologies (EEG, eye tracking, and VR HMD) for the proposed work. Table 1 summarizes the area of the work, limitations, and enabling technologies used. As can be seen, this paper is the first attempt to use a fusion of EEG, eye tracking, and VR HMD for safety improvement purposes. Table 1 shows 29 articles from journals with high impact factors in the related field (13 from IEEE journals); 22 of them used consumer-grade EEG devices, and 21 used the same EEG sensor used in the present research.

Studies have demonstrated the practicality of consumer EEG device use in domains such as brain–computer interaction (BCI) and assessment of workload and human behavior (Chumerin et al. 2013; Liu et al. 2012; Van Vliet et al. 2012; Wang et al. 2016). For example, many studies have focused on the analysis of steady-state visually evoked potentials (SSVEPs) and event-related potentials (ERPs) (Barham et al. 2017). SSVEP is a resonance phenomenon that can be observed in the occipital and parietal lobes of the brain when a subject looks at a light source flickering at a constant frequency. ERP is the direct result of a specific sensory, cognitive, or motor event (Elsawy et al. 2014; Lin et al. 2014; Liu et al. 2012). Accordingly, researchers have suggested that the examination of EEG signals can offer profound insights into human behavior (Bhatti et al. 2019; Majid Mehmood et al. 2017; Saha et al. 2014). These classifications can be used to analyze brain activity during a physical task (Aspinall et al. 2015) and improve BCI (Perez Vidal et al. 2016; Wu 2017). Apart from such examinations, to broaden the analysis level of EEG signals, researchers have proposed fusing EEG and eye trackers (Casson and Trimble 2018). These researchers have analyzed eye movement and brainwave patterns of subjects for assessing cognitive load during driving (He et al. 2019), and assessing human experience in evaluating architectural designs (Ergan et al. 2019). Also, a combination of EEG and VR has been proposed researchers to design detailed experiments (Azevedo et al. 2014; Coogan and He 2018; Khushaba et al. 2013a). Recent advancements in EEG analysis (Chen et al. 2016; Wang et al. 2017, 2019) and eye tracking (Jeelani et al. 2019) have created new insights for the construction industry and, more specifically, safety.

VR in Hazard Recognition

Researchers have developed safety training platforms using VR to offer personalized feedback for improving safety training outcomes (Moore et al. 2019). The outcomes indicate that safety training programs that use VR provide high-fidelity simulations for workers. In general, VR can present better spatial perception than conventional visualization methods such as 2D screens (Balali et al. 2018; Noghabaei and Han 2020). Consequently, it can help in improving the quality of training (Noghabaei et al. 2019, 2020; Noghabaei and Han 2021).

More particularly, Grabowski and Jankowski (2015), in a pilot study, used VR to enhance the safety and occupational health of mining workers. Safety experts trained the workers and tested different motion-tracking systems, HMD, joysticks, and training scenarios. The results illustrated that VR technology can be an effective platform for safety training and a substitute for on-site training. By substituting VR training for on-site training, unnecessary exposure of trainees to mining environment risks and dangers can be prevented. Also, researchers have developed a VR training system for the mining industry and demonstrated that increasing immersion using hand motion trackers can enhance training systems (Zhang 2017). Pedram et al. (2017) assessed VR safety training systems and showed that these systems create a significant positive learning experience. In addition, researchers in the field of construction have proposed fusing EEG and VR technologies to assess humans' behavior in virtually designed areas (Ergan et al. 2019; Zou et al. 2019). Overall, research suggests that VR can be a useful tool for improving current safety training programs.

EEG Sensors in Hazard Recognition

In addition to VR, many researchers have focused on the use of EEG sensors and neurological sensors to enhance construction safety using mental and physical workload assessment. Construction researchers have often questioned the feasibility of adopting EEG sensors on construction sites since these devices are sensitive, and small movements can generate artifacts in the obtained data (Wang et al. 2017). To solve this problem, Jebelli et al. (2018) demonstrated that it is feasible to use an EEG device on a construction site to monitor workers' valance and arousal. Also, researchers have used EEG sensors for measuring construction workers' emotional state during construction tasks (Hwang et al. 2018). Chen et al. (2016) developed a wearable EEG monitoring helmet and showed that mental workload can be used as an essential indicator of workers' vulnerability to hazards on a construction site. EEG sensors have the potential to be used in construction; however, due to the difficulty of data collection and artifact removal, this technology is not yet fully exploited. The present study has advantages over conventional EEG studies that allow it to potentially improve EEG utilization in practice. It uses VR simulation in lab space to collect data in a controlled environment with limited exposure to extrinsic artifacts. In contrast in conventional EEG studies without VR simulations, EEG data collection can be vulnerable to extrinsic artifacts and often cannot be used for training. The proposed system will potentially solve data collection deficiencies and provide an easier way for researchers to collect EEG data in a controlled environment.

Eye Tracking for Identifying Visual Search Patterns in Hazard Recognition

Visual search processes are prevalent in workplaces. For instance, law enforcement agents scan luggage at airport checkpoints (Biggs and Mitroff 2015), or a bridge supervisor evaluates channel components to identify structural shortcomings (Estes and Frangopol 2003). To effectively analyze visual search patterns, investigators have started using eye-tracking technology that monitors eye movements during visual search processes. Eye-tracking technology has been used to evaluate the visual search patterns of construction workers during risk identification undertakings (Alruwaythi et al. 2017). Comprehension of these links can be valuable in the determination of visual search shortcomings leading to ineffective hazard identification. Furthermore, this knowledge can be employed in evaluating the efficiency of strategic measures to enhance visual search arrangements and construction risk recognition.

In addition to visual search patterns, pupil diameter is an important predictor of hazard recognition. The literature strongly supports the idea that an increase in pupil diameter is an indicator of increased cognitive load (Shi et al. 2020b; van der Wel and van Steenbergen 2018). Also, researchers have indicated that pupil diameter is related to information processing and understanding (Giannakos et al. 2019; Liao et al. 2021). Similarly, researchers have suggested that changes in pupil diameter reflect emotional arousal and alertness triggered by visual detection of sensory stimuli, and that pupil diameter increases when a subject processes emotionally engaging stimuli (Bradley et al. 2008; Qian et al. 2009). Lastly, (Liao et al. 2021) pointed out that pupillary activation is induced by hazard recognition; fall hazards induce the most pupillary activation.

Methods

The main objective of the present research was to identify brain activity and eye-tracking features that are associated with the successful recognition of safety hazards. Therefore, a platform consisting of an eye tracking–enabled HMD and an EEG sensor was used to collect eye movements and brain activity. This platform simulated a virtual construction site where participants were asked to identify hazards by pressing a button when they detected one. Meanwhile, eye movements and brain waves were collected. The platform used the button press as a trigger for synchronizing signals and to determine whether a participant was able to detect a hazard. The research methods are shown in Fig. 2 and the structure of this section follows the steps illustrated.

Hazard Simulation in VR

The initial step was to simulate a construction site in a VR environment using a three-dimensional (3D) engine, Unity, which is widely used in the architectural, engineering, and construction (AEC) industry for VR simulations (Unity3D 2020) as well as in educational and neuroscientific applications (Coogan and He 2018). Ten hazards, provided in Table 2, were simulated in a virtual construction environment. These hazards are responsible for roughly 80% of construction-related fatalities (Helander 1991; Jeelani et al. 2017a). A detailed construction site was modeled based on real construction sites, and hazards were simulated to create a realistic virtual

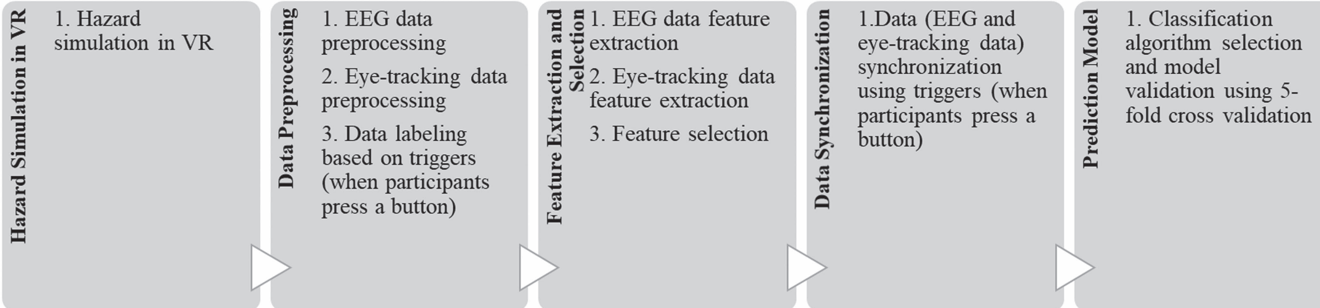

Fig. 2. Method overview.

Table 2. Hazards in the simulated virtual environment

Hazard No.	Hazard type	Description
1	Fall	Unprotected object near edge
2	Electrical	Unprotected electric cables without proper conduit
3	Trip	Unprotected ladder
4	Fall	Unprotected barrel near edge
5	Chemical	Unmarked barrel without lid containing unknown chemical fluid
6	Trip	Unprotected bricks on ground
7	Electrical	Unprotected junction box without proper protection
8	Chemical	Unprotected igneous chemical fluids
9	Chemical	Unmarked bucket without lid containing unknown chemical fluid
10	Pressure	Gas cylinder without proper restraints in work zone

environment. Fig. 3(a) is a first-person view of the simulated site, and Fig. 3(b) is a view of a chemical hazard (Hazard 5). Fig. 3(c) is a view of the simulated area. The next step was data acquisition and preprocessing as detailed in the following subsection.

Data Preprocessing

This section discusses data acquisition and preprocessing for the two sensors—brain waves (EEG) and eye tracking. In the first two subsections, artifact removal from the EEG signal and details of the eye tracker are discussed. In the final and third subsection, EEG and eye-tracking data labeling using triggers (button presses) is described.

EEG

An Emotiv EPOC$^+$ 14-channel wireless EEG headset (Emotiv, San Francisco, California) was used to obtain the EEG data stream. A high-end EEG device would not have been practical since it requires device manipulation and takes time to set up (i.e., applying gel to 32/64 EEG nodes). The reliability of EPOC$^+$, artifact removal, and the data it generates are detailed in Appendix S1.

Eye-Tracking

To acquire eye-tracking data in VR, the HTC Vive Pro Eye VR headset (HTC, New Taipei City, Taiwan) was used [Fig. 4(a)]. The reliability of this device and the data generated are detailed in the section "Discussion and Future Work." Raw eye-tracking data were

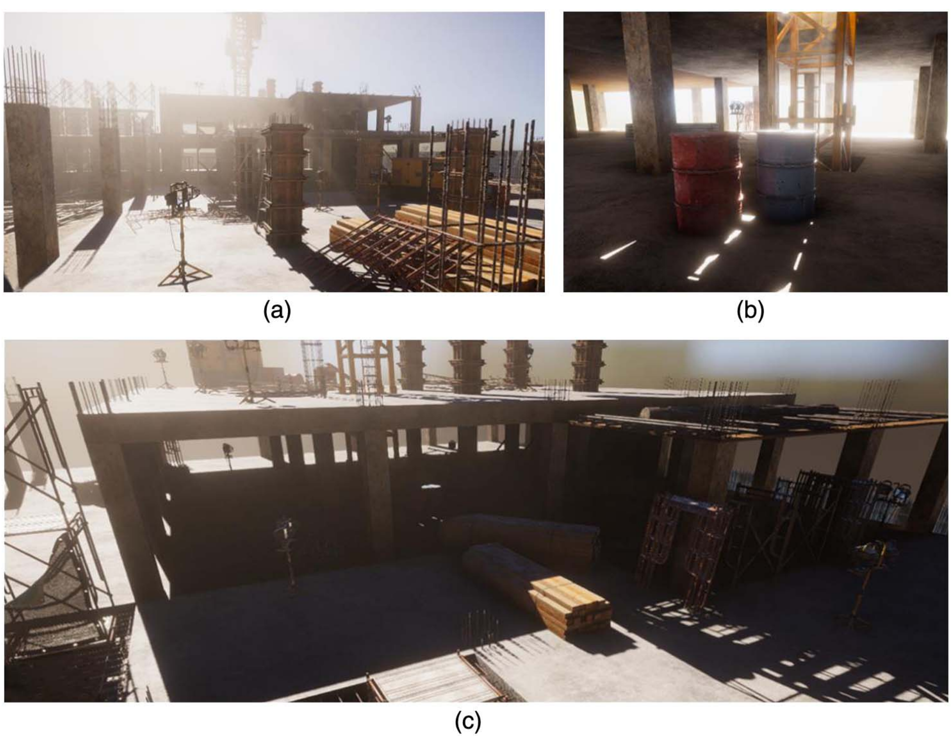

Fig. 3. 3D simulated environment: (a) first-person view; (b) Hazard 5; and (c) simulated site.

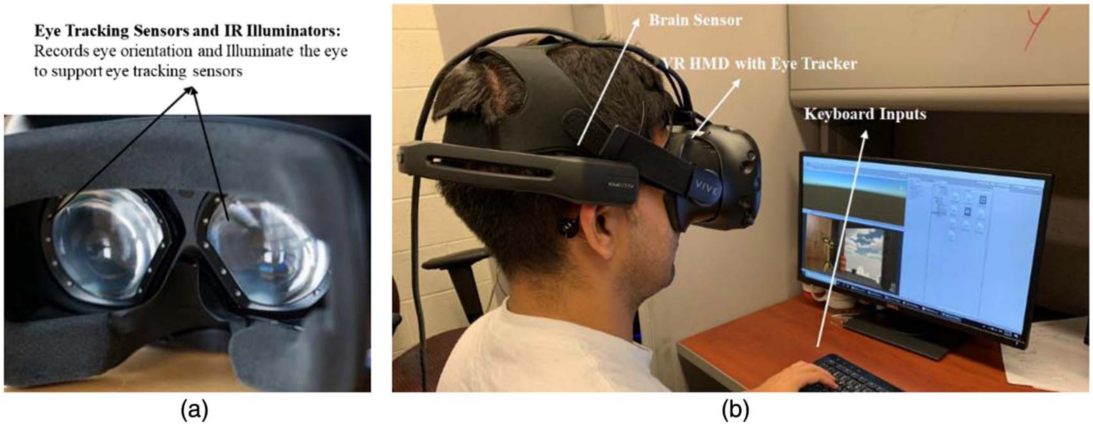

Fig. 4. Data collection process: (a) HMD with eye tracker; and (b) participant wearing EEG sensor and HMD (reproduced from Noghabaei and Han 2020, © ASCE).

acquired from a developed code within Unity known as Tobii, which identified the sighted object at each moment and recorded the data in its eye-tracking data stream. The device has an accuracy of 0.5°and a 110° trackable field of view. It can collect gaze origin, gaze direction, pupil position, and absolute pupil size with less than 10 ms of latency, and it has 10 infrared (IR) illuminators and an eye-tracking sensor for each eye. Fig. 4(b) shows a participant wearing an EEG sensor and HMD at the same time as instructed by the manufacturer. Fig. 4(b) shows the participant pressing a button on the keyboard as he identifies hazards.

Data Labeling Based on Triggers

Labeling is an essential step in training data for supervised learning. One method is to partition the data into various windows and define a single continuous segment that spans an entire action sequence (i.e., fixed windowing). Features are then extracted as detailed in the section "Feature Extraction and Selection" from these windowed segments and used in a machine-learning algorithm to classify a fixed-length testing segment (Fig. 5). This method is commonly used for EEG signal annotation; however, in this study it was applied to both eye-tracking and EEG signal streams for data annotation. To label the data, participants were asked to press a controller button as they detected hazards. Immediately a trigger was sent to the EEG device and a message was recorded in the eye-tracking data. These markers could be used for both signal synchronization (of EEG and eye-tracking data) and data labeling. The object at which the participant was looking was marked in the data. If he or she detected a nonhazardous object as a hazard, the recording was not valid and was removed. However, if he or she detected the hazard correctly, the recording was used for training. Fig. 5 illustrates the process of labeling data in a fixed time interval or window size (during which a feature is extracted from the signals).

Feature Extraction and Selection

The extraction of relevant features is a critical component in the high accuracy of machine learning algorithms. In machine learning, a feature is an individual measurable property or characteristic of the phenomenon being observed (Bishop 2006). Direct use of raw data for classification results in poor performance (Lan et al. 2007; Sherafat et al. 2019a, b). Therefore, only essential features should be extracted. The following two subsections describe the process of feature extraction and the third discusses the process of selecting just the essential features from those extracted.

EEG

EEG signals are classified according to their frequency and amplitude, as well as the location of the EEG channel where the data are recorded. EEG signal frequency refers to repetitive rhythmic activity measured in hertz. A frequency band is an interval in the frequency domain, delimited by a lower and an upper frequency. EEG signals can be classified in frequency ranges (delta: 0.5–4 Hz, theta: 4–7.5 Hz, alpha: 7.5–13 Hz, low beta: 13–15 Hz, beta: 15–20 Hz, high beta: 20–38 Hz, and gamma: ≥ 38 Hz). EEG signal bands with lower frequencies are related to more profound thoughts such as in meditation (Savage et al. 2013). Table 3 summarizes the features extracted from the EEG data. The total number of extracted features from all EEG signal channels was 296.

Eye-Tracking

When an individual engages in any visual search activity, two primary behaviors are observed, saccades and fixations (Holmqvist et al. 2011; Jeelani et al. 2018, 2019). According to the literature, fixations are positions where the pupil is stationary. These stationary positions show focusing attention on or visual processing of a specific object, location, or stimulus in the environment (Holmqvist et al. 2011). The rapid movements of the pupil between two fixation points are known as saccades. During saccades, minimal data are absorbed.

Since hazard recognition is a visual search activity and it requires attention, saccades and fixations can be used as essential features for data classification purposes. The authors extracted the following features [based on previous studies on eye tracking for hazard recognition (Jeelani et al. 2019)] from raw eye-tracking data. Table 4 provides formulas for computing these features.

- Fixation count (FC): hazard recognition requires high levels of attention. When an individual detects a hazard, many fixations should have happened before reporting the detection. The number of these fixations within a period can be used as a feature. This feature is called FC.
- Fixation time (FT): the attention level of an individual shows the total time spent on a fixation point (e.g., a particular location, object, or stimulus).
- Mean fixation duration (MFD): average of fixation duration is one of the most important visual search tasks (Shic et al. 2008). A higher level of mean fixation duration is associated with higher mental activity (Shic et al. 2008).

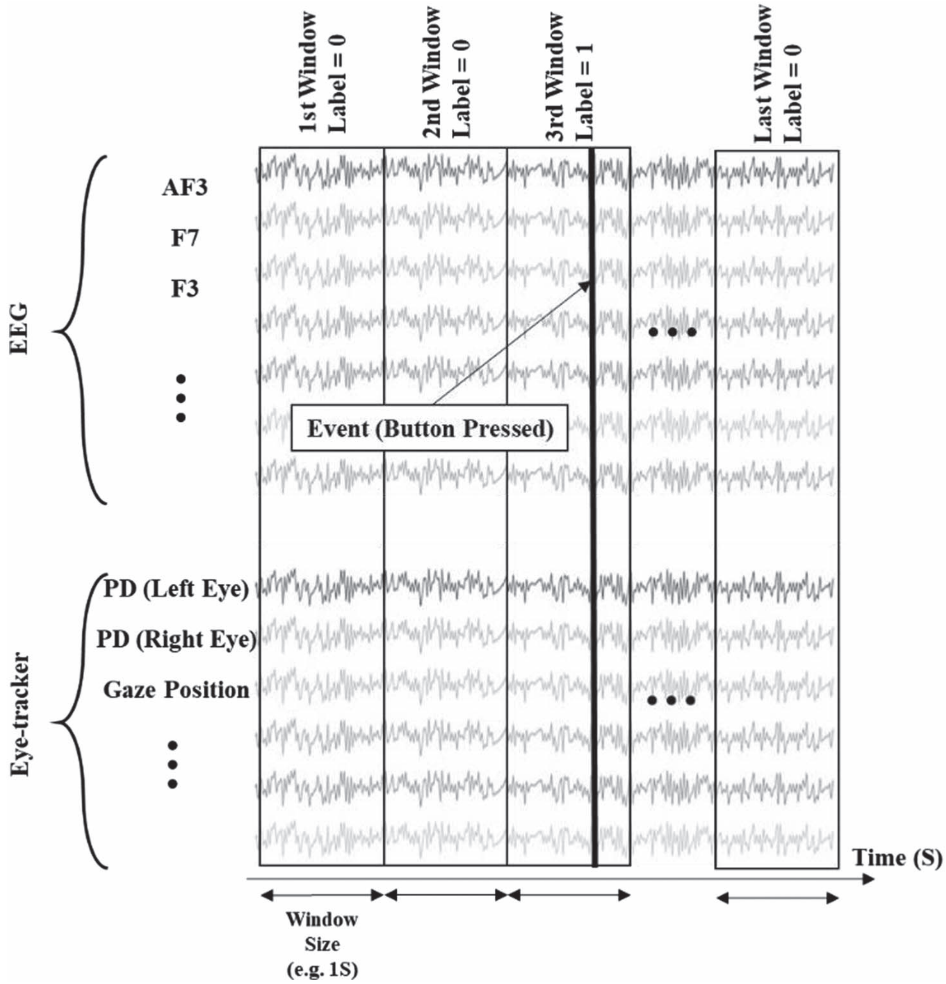

Fig. 5. Data annotation using fixed window approach.

Table 3. EEG signal–extracted features

Feature	Description	Equation
Maximum	Maximum amplitude for channel j in range x–y	$\max(EEG_j^{x:y})$
Minimum	Minimum amplitude for channel j in range x–y	$\min(EEG_j^{x:y})$
Mean value	Average amplitude for channel j in range x–y	$\frac{\sum_{i=x}^{y} EEG_j^i}{y-x}$
Maximum of frequency range	Maximum amplitude for channel j with frequency range (delta or ...) within specified period in range x–y	$\max(EEG_j^{x:y})\forall f \in [\alpha,\beta,\gamma,\delta,\theta]$
Minimum of frequency range	Minimum amplitude for channel j with frequency within specified period in range x–y	$\min(EEG_j^{x:y})\forall f \in [\alpha,\beta,\gamma,\delta,\theta]$
Mean value of frequency range	Average amplitude for channel j with frequency within specified period in range x–y	$\text{avg}(EE_j^{x:y})\forall f \in [\alpha,\beta,\gamma,\delta,\theta]$
Valence (Blaiech et al. 2013)	Happiness level	$\frac{\alpha(\text{F4})}{\beta(\text{F4})} - \frac{\alpha(\text{F3})}{\beta(\text{F3})}$
Arousal (Blaiech et al. 2013)	Excitement level	$\frac{\alpha(\text{AF3}+\text{AF4}+\text{F3}+\text{F4})}{\beta(\text{AF3}+\text{AF4}+\text{F3}+\text{F4})}$

Note: Frequency ranges (Hz): delta: 0.5–4; theta: 4–7.5; alpha: 7.5–13; low beta: 13–15; beta: 15–20; high beta: 20–38; and gamma: ≥ 38.

- Saccade velocity (SV): SV is correlated with low arousal and engagement level during a visual search activity; it is also associated with fatigue level and lethargy (Di Stasi et al. 2014).
- Pupil diameter (PD): pupillary response indicates change in the pupil size with the oculomotor cranial nerve (Ellis 1981). Studies have shown that pupil size varies based on the level of interest in visual stimuli (Hess and Polt 1960).

Selection

In this study, the high frequency of collected data from the EEG (128 Hz) and eye tracking (120 Hz) and the high number of features per data point were generated from the raw data. There were 248 data points (128 for the EEG and 120 for the eye tracker) per second. A recording of the collected data per person for a 30-min training session would generate 446,400 data points for 306 features

Table 4. Eye-tracking extracted features

Feature	Equation
FC	No of fixations
FT	$\sum_{i=1}^{n}[E(f_1 - Sf_1)]$
MFD	$\frac{FT}{FC}$
SV	$\frac{\text{Average number of pixels}}{\text{Movement time}}$
PD	—

(296 for EEG + 10 for eye tracking), with each data point including 306 features. As more data from more sessions with more people can lead to a very large data set, computation becomes expensive. Therefore, a reduction in the input dimension is very important.

Moreover, the accuracy of the classification algorithms might be negatively affected without feature selection (Chu et al. 2012). Redundant attributes can mislead the algorithms by introducing noise in the data (Sherafat et al. 2020). The solution in this study was greedy forward selection for subset selection (Fig. 6). In this approach, a subset with fixed cardinality is extracted from the feature set. All remaining features are added to each subset and evaluated separately. Finally, the feature with the best evaluation function is selected and added to the subset with fixed cardinality. Greedy forward selection allows identifying the best feature at each step. Therefore, it provides valuable information about which features are more important than others. In this study, the accuracy of a nonlinear model was used as an evaluation function since it was faster than other evaluation functions (i.e., mean square error). In greedy forward selection, the number of calling evaluation functions is determined using the following equation, where n is the total number of features:

$$\text{Number of calling evaluation functions} = \frac{n \times (n+1)}{2} \tag{1}$$

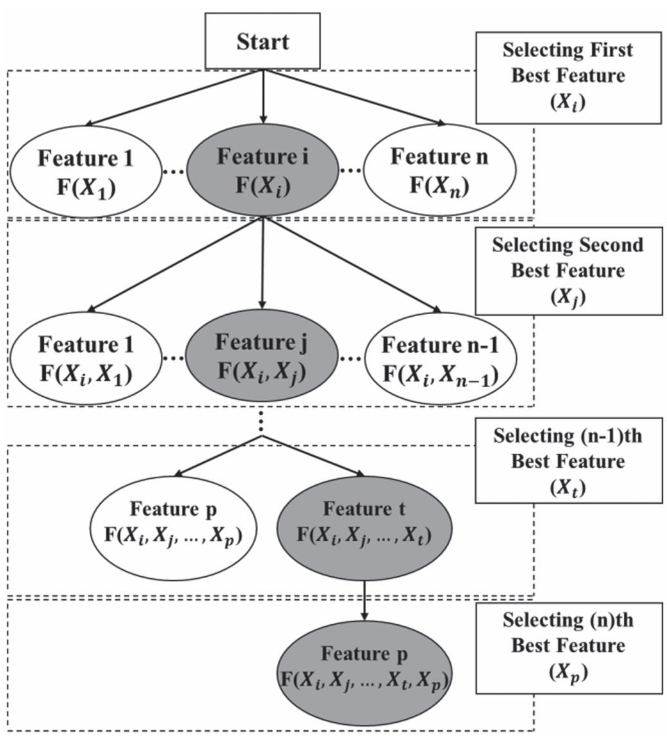

Fig. 6. Schematic of greedy feature selection.

Data Synchronization

Data synchronization was essential in providing reliable data for this study. Recordings from eye tracking and EEG signals were synchronized using MATLAB's version 2018a EYE-EEG toolbox (Dimigen et al. 2011). The synchronization process is further detailed in Appendix S1.

Prediction Model

To classify the data, supervised machine learning algorithms were compared. In this paper, k-nearest neighbor (k-NN) and support vector machine (SVM) with different types of similarity functions [linear, cubic, quadratic, radial basis function (RBF), and Gaussian] were compared. k-NN is a memory-based algorithm that uses the entire database for prediction based on a similarity measure in the instance space (Altman 1992). Memory-based algorithms find a set of nearby data points in the instance space with similar features, known as neighbors. To predict the label of a new data point, a group of nearby neighbors referred to as the neighborhood is formed. k-NN is based on the assumption that the nearby data points in the instance space have the same class.

SVM is widely used in supervised machine learning and data mining (Burges 1998). It is an appropriate classifier for neurological data class actions (Rani et al. 2006). SVM creates hyperplanes that separate data points of a binary classification problem, applying iterative learning to converge these hyperplanes into one optimal hyperplane that maximizes the margin between data points of two classes. In machine learning (especially SVM), kernel methods are commonly used (Hofmann et al. 2008). These are a class of algorithms for pattern analysis that transform data into another dimension that has a clear dividing margin between data classes. In this study, Gaussian and RBF kernels were tested because they are well known for yielding accurate classification compared with other kernels.

In addition to k-NN and SVM, the authors tested the data with Gaussian discriminant analysis (GDA), hidden Markov models (HMM), decision tree, and logistic regression. However, the preliminary results of the classification were discouraging and therefore are not reported here. Lastly, fivefold cross validation was performed to validate obtained classification accuracies.

Experimental Setup

Subjects and Data Acquisition

According to studies on EEG data, reliable inferences can be made in EEG experiments with 10–20 participants (Melnik et al. 2017). Accordingly, 24 studies that similarly used the Emotiv EEG sensor had an average of 14.2 participants as shown in Fig. 7. The data in the current study were collected from 30 participants. Following the two-sigma rule, the number of participants in this study was more than 95% of similar studies. The subjects were graduate students at North Carolina State University due to the difficulty of conducting this experiment (e.g., wearing both EEG and VR HMD) and accessing construction workers of this sample size. All subjects in the study were male and had an average age of 28.5 with an average working experience of 3.4 years in the construction industry and no history of mental disorder or any eye-related problems. Bear in mind that the results of this study should not be different between construction workers and students since the focus was on determining whether a combination of EEG and eye tracking would accurately predict hazard recognition, and the feasibility of using a combination of EEG and eye tracking in VR.

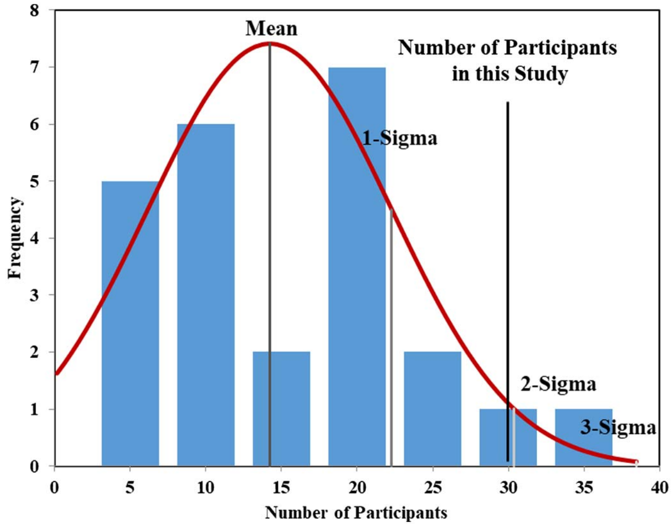

Fig. 7. Frequency of sample size in 24 studies that used Emotiv EEG sensor versus sample size in this study.

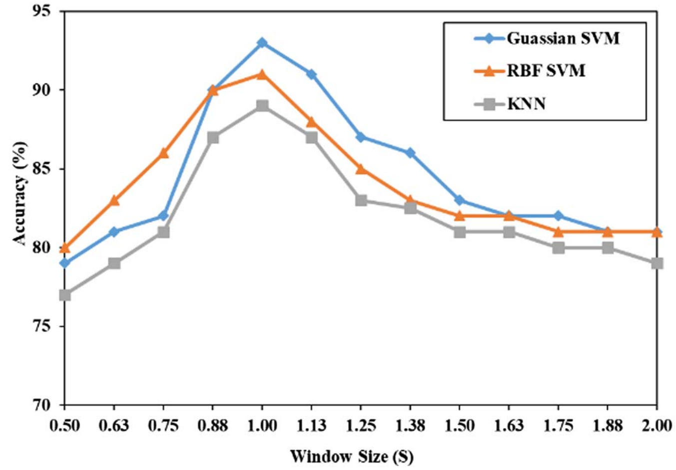

Fig. 8. Classification accuracy for different algorithms and time intervals.

To ensure that the participants were familiar with construction hazard recognition, a very brief introduction to safety in construction was given The introduction contained information about what is considered a hazard. EEG and eye-tracking signals were obtained from each participant. in ten trials with a 1-min rest between trials, which is a standard protocol in brain-sensing experiments. To reduce errors related to the sequence effect (also known as the learning effect) (Wang et al. 2017), hazard locations were changed in each trial. In this experiment, the learning effect meant brain signals affected by previous trials in the experiment. Also, each trial was limited to 30 s to make sure that the participants were focusing on the hazard recognition task. Limiting experiment time to 30 s guaranteed high synchronization accuracy. Also, the objective of this experiment was not to ensure that the participants detected all of the hazards. In fact, the experiment was designed so that that participants focused on critical hazards rather than all hazards to properly capture brain and pupillary responses.

The participants were asked to attend the experimental session with washed and dried hair. They were asked not to use hair wax, gel, conditioner, or spray as wet hair and hair treatments would generate higher impedances. Before each experiment, all electrodes were cleaned using a cloth. After cleaning, electrode gel/conductive paste was applied to the electrodes. Then the HMD was placed on top of the EEG device. Before starting the experiment, all experimental details (i.e., how to press keys, how to perform device calibration, and the number of trials) were discussed with the participants. Fig. 4(b) shows a participant in a VR environment.

Device Calibration

Before performing the experiment, the eye-tracking device was calibrated by asking the participants to look at the red dots in the VR simulation. The calibration method is known as five-point calibration and was performed as instructed by the manufacturer. Then EEG calibration was performed as instructed by the manufacturer of the EEG device.

Experimental Results

All features were extracted from preprocessed data with different window sizes, as shown in Fig. 5. The extracted data directly used in the classification algorithms and the classification accuracies are reported in Fig. 8. Fivefold cross validation was performed, and the results of the selected algorithms were compared. The classification accuracy for each algorithm was the true-positive rate plus the true-negative rate. The sum of these two numbers from a confusion matrix provided the classification accuracy for each algorithm. Fig. 8 shows that the best window size for achieving the highest accuracy was 1 s, which was selected for further data analyses. Since the accuracies of the selected algorithms were close (90%–93%), further investigations were necessary to select the best one. This finding fit with previous studies showing that humans detect hazards as fast as 390–600 ms after they see them (Crundall et al. 2012; Matheson 2019). The window approach minimized the effects of the time lag between brain and eye responses to any stimulus as it extracted features from a 1-s range of data. To compare the algorithms (k-NN, Gaussian SVM, and RBF SVM), receiver operating characteristic (ROC) charts for each algorithm were drawn. Fig. 9 shows the ROC curves for the selected algorithms.

Based on the ROC curves, Gaussian kernel SVM was the best algorithm since it had the most area under the curve (AUC) and the highest accuracy (93%). Therefore, it was selected for further analyses. To describe the performance of a classification algorithm, a confusion matrix is prepared. Fig. 10 shows that the confusion matrix for Gaussian kernel SVM had an accuracy of 93%. Another critical measure of classification accuracy is f-measure (F1 score in Fig. 10), defined as the weighted harmonic mean of precision and recall. This score shows the balance between precision and recall and therefore detects uneven class distribution. It reaches its best value at 1 and worst at 0. for Gaussian kernel SVM, the f-measure was 0.94. As shown in Fig. 10, true positives, false positives, true negatives, and false negatives were divided by the total number of samples and reported as ratios.

To find the most important features based on the collected data, greedy sequential feature selection was performed (discussed in the section "Feature Selection"). The data were divided into four groups of features: (1) eye tracking, (2) EEG, (3) selection from the first two groups, and (4) both EEG and eye tracker. Then greedy feature selection was performed on all four groups.

Fig. 11(a) shows the accuracy of the best features selected by greedy feature selection for the first group (eye tracking). It indicates that it was possible to achieve 74% accuracy in classification using eye-tracking data only. According to the graph, accuracy reached a plateau after the first five features (second column of Table 5).

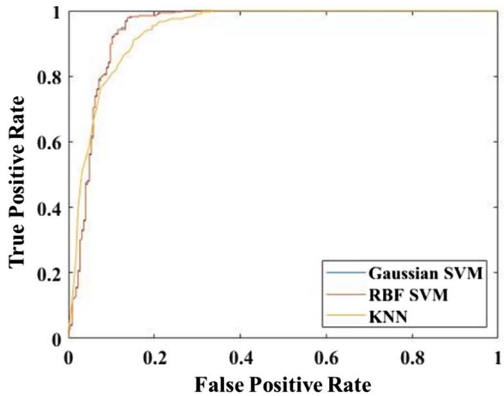

Fig. 9. ROC curve for different classification algorithms.

		True Condition			
		Hazard Identified	Hazard Not Identified		
Predicted Condition	Hazard Identified	618 (0.343)	93 (0.052)	Precision = 0.868	
	Hazard Not Identified	28 (0.016)	1061 (0.589)		
		Recall = 0.956		Accuracy = 0.932	F1 Score = 0.941

Fig. 10. Confusion matrix for Gaussian SVM for 1-s interval.

Therefore, these five features were selected from eye tracking to be combined with the selected EEG features. Fig. 11(b) shows the accuracy of the 14 best features from the EEG (Table 5). These features reached about 82% accuracy while overall accuracy reached a plateau of around 83%. Fig. 11(c) shows sequential forward feature selection with 5 eye-tracking and 14 EEG features (Table 5) selected from the first two groups.

Fig. 11(d) shows the accuracy of combined best features from all EEG and eye-tracking features, which plateaued at around 93%. The figure also shows an accuracy of 93% with 13 best features (Table 5), indicating that the 13 best features from EEG and eye tracking had high accuracy compared with all 306 features. In fact, a large number of features might mislead the prediction model and act as noise in the input data. Therefore, it was necessary to use meaningful features rather than all features.

The 13 best features were used to reason about participants' ability to recognize hazards as further discussed in the following section. According to the results presented in Table 6, the prediction model had the best performance in trip hazards (Hazards 3 and 6) and the lowest performance in chemical hazards (Hazards 5, 8, and 9). This finding suggests that trip hazards produce stronger sensory stimulation than chemical hazards.

Implications of Results Compared with Findings from the Literature

The findings of this research contribute to the safety literature and have important implications for theory and practice. For instance, the results show that from the 13 best features 3 from eye tracking (PD and FT) and 10 from EEG signal bands can be effectively used to predict whether safety hazards will be recognized by workers.

The results show an average classification accuracy of 93% for visual hazard recognition, indicating that EEG and eye-tracking signals together are more sophisticated predictors of awareness of surrounding hazards when compared with accuracies achieved independently by EEG (83%) and eye tracking (74%). Therefore, while previous research efforts used only eye tracking to assess

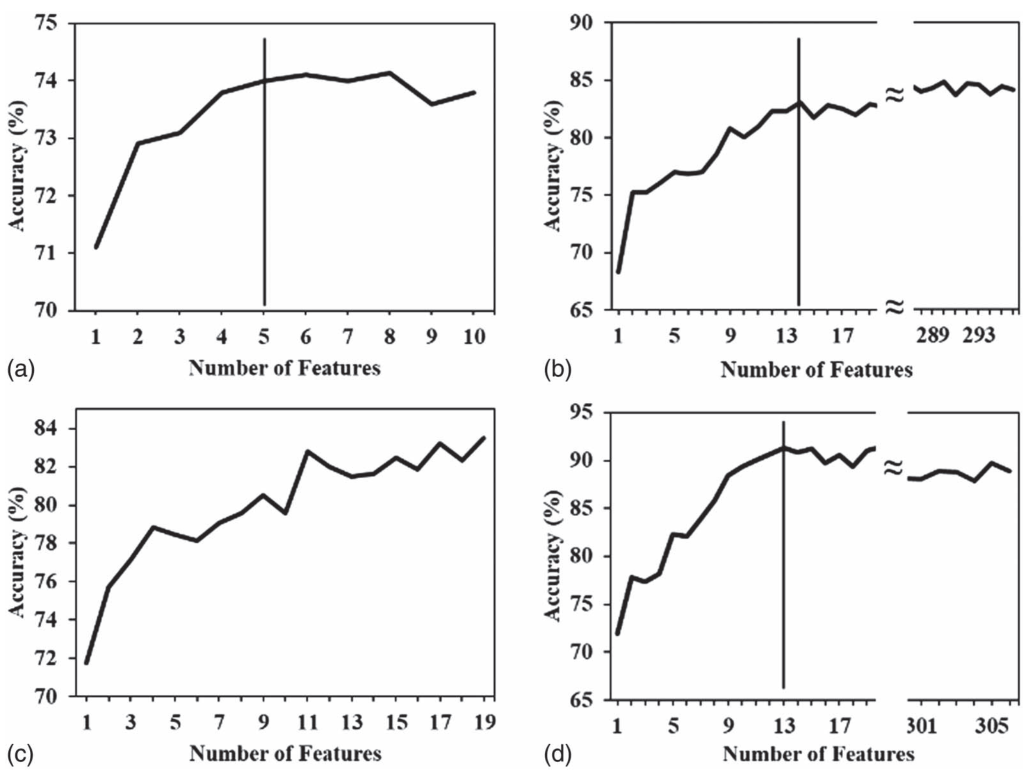

Fig. 11. Sequential forward feature selection: (a) eye-tracking features; (b) EEG features; (c) selected EEG and eye-tracking features from EEG + eye tracking; and (d) all features.

Table 5. Selected features from sequential forward feature selection in four scenarios

Feature No.	Eye tracking	EEG	Selected EEG + eye tracking	EEG + eye tracking
1	FT average[a]	Maximum of FC5 channel in gamma band[b]	FT average[a]	FT average[a]
2	PD average for right eye[a]	Minimum of AF3 channel[b]	PD average for right eye[a]	Maximum of FC5 channel in gamma band[b]
3	PD average for left eye[a]	Maximum of P8 channel[c]	PD average for left eye[a]	Minimum of F4 channel in delta band[c]
4	PD maximum for right eye[a]	Maximum of AF3 channel[b]	Minimum of F8 channel in gamma band[c]	PD average for right eye[a]
5	PD maximum for left eye[a]	Maximum of F4 channel in delta band[c]	Minimum of O2 channel in theta band	Maximum of AF3 channel in delta band[b]
6	—	Minimum of P7 channel[c]	PD maximum for left eye[a]	Maximum of T7 channel in alpha band[c]
7	—	Maximum of FC5 channel in delta band[b]	Maximum of F4 channel in delta band[c]	PD average for left eye[a]
8	—	Maximum of T8 channel in gamma band[c]	PD average for right eye[a]	Minimum of F4 channel in gamma band[c]
9	—	Maximum of P7 channel in gamma band[c]	Minimum of P7 channel[c]	Minimum of O2 channel[b]
10	—	Minimum of O2 channel in theta band[b]	Maximum of FC5 channel in gamma band[b]	Minimum of O1 channel in alpha band[b]
11	—	Minimum of F8 channel in gamma band[c]	Minimum of AF3 channel[b]	Minimum of F7 channel[c]
12	—	Minimum of F4 channel in gamma band[c]	Maximum of FC5 channel in delta band[b]	Maximum of FC5 channel in delta band[b]
13	—	Maximum of F7 channel in theta band[c]	Minimum of O1 channel in alpha band[b]	Minimum of P7 in high beta band[c]
14	—	Minimum of O1 channel in alpha band[b]	Minimum of F4 channel in gamma band[c]	—
15	—	—	Maximum of AF3 channel[b]	—
16	—	—	Maximum of T8 channel in gamma band[c]	—
17	—	—	Maximum of F7 channel in theta band[c]	—
18	—	—	Maximum of P7 channel in gamma band[c]	—

[a]Eye-tracking features.
[b]EEG features from AF3, FC5, O1, and O2.
[c]EEG features.

Table 6. Results of prediction model

Categories	Hazard No. 1	2	3	4	5	6	7	8	9	10
Successful predictions	92	51	71	79	52	53	61	38	54	67
Unsuccessful predictions	4	3	1	4	3	1	4	3	2	3
Successful predictions (%)	95.8	94.4	98.6	95.1	94.5	98.1	93.8	92.6	96.4	95.7
Successful cases (%)	5.41	2.97	4.09	4.50	3.00	3.14	3.58	2.26	3.16	3.79
Successful cases	487	267	368	405	270	283	322	203	284	341

Note: Results are for test set (Rows 1–3) for time windows in which subjects successfully recognized a hazard, and for number of successful cases in the entire data set (Rows 3–5).

hazard recognition, the present study demonstrates that the integration of EEG with eye tracking offers additional information when analyzing the hazard recognition behavior. Additional statistical analyses to find the difference between successful and unsuccessful hazard recognition must be taken up in future studies before this study's findings can be implemented in practice.

Moreover, the results show that brain activity in the occipital lobe is correlated with visual hazard recognition. Accordingly, Joseph (1990), Mesulam (2000), and Walker et al. (2007) showed that activities in occipital lobe channels (e.g., O1 and O2) correlate with a sense of danger. Other channels, such as FC5 and AF3, correlate with visual perception tasks (Joseph 1990; Mesulam 2000; Walker et al. 2007). Five out of the 10 best EEG features were from Channels O1, O2, FC5, and AF3. Fig. 12 shows these features, which were also among the 13 best features. The circles with dashed lines are areas related to hazard perception according to the literature. These results demonstrate that the activation of certain channels during hazard recognition efforts is indicative of hazard detection.

Discussion and Future Work

The findings of this research show the feasibility of using EEG and eye tracking together to detect workers' ability to recognize hazards, and can be potentially integrated into safety training programs. Before they can be used in practice, however, a number of research questions need to be addressed. For instance, human behaviors (e.g., lack of concentration, selective attention) can affect hazard recognition. Training interventions that are mindful of this may improve workers' hazard recognition skills as well as their safety performance. Also, this study, as the first to EEG in a VR simulation,

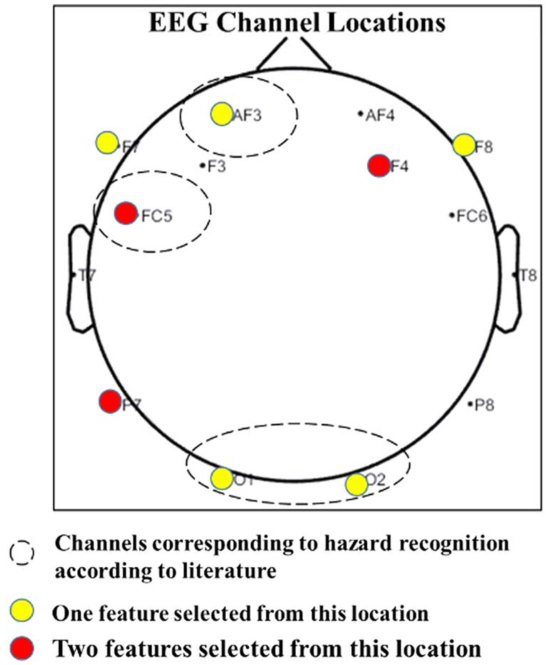

Fig. 12. Features selected by sequential forward feature selection versus channels corresponding to hazard recognition.

can make the process of data collection easier, as in this framework custom simulations can be produced and EEG signals can be analyzed accordingly. Using EEG and VR together and making data collection easier can potentially boost the adoption of EEG technology in the construction industry. Lastly, to improve prediction, more sophisticated preprocessing can be applied to the EEG and eye-tracking data. Potential improvement areas are baseline correction, noise removal, and EEG and eye-tracking synchronization (Shi et al. 2020a; Winn et al. 2018).

The question of how brain wave and eye movement patterns differ between highly skilled and less skilled workers needs to be also addressed before the findings of this study can be used in practice. Such a comparison can provide essential insights into the way skilled workers perceive danger as well as important insights for safety researchers in creating more advanced safety training. Mainly, the future of this research can be split into three main directions (Fig. 13):

- Correlation of arousal and valence, or arousal alone, extracted from EEG signals with hazard recognition to clarify what emotions predict success. Safety training programs that intensify these emotions can potentially improve outcomes.
- Correlation of hazard types with intense emotions. For example, fall hazards might produce fear, which can reduce worker vulnerability to them.
- Identification of hazard types that subjects fail to detect to provide safety managers with a clearer vision of those that require more intervention.

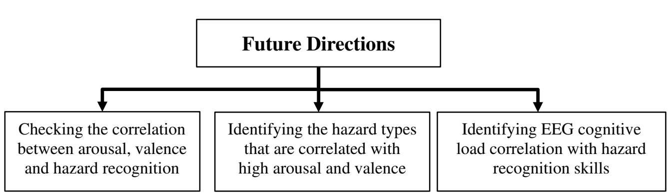

Fig. 13. Future research directions.

This study is a step toward automating personalized feedback generation using brain wave and eye movement patterns, which can improve safety performance (Moore et al. 2019). In practice, most training sessions are conducted by an instructor who is not able to provide personalized feedback to many workers. The approach presented in this paper can be extended to automation of prior work on personalized safety training that provides personalized feedback to workers as part of a training program (Jeelani et al. 2018). For example, when workers pay attention to a particular safety hazard as captured by an eye tracker, but do not mentally process the hazard as captured by brain waves, they may not be aware of the risks associated with that hazard. Human trainers and/or an automated training system can use this information to identify particular hazards and hazard types that workers do not mentally process and provide feedback to improve workers' mental processing.

Conclusions

A combination of visual search and brain wave analyses offers safety trainers and educators valuable information. Through a feature selection process, this study identified 13 best EEG and eye-tracking features that are related to hazard recognition. It presented an approach for extracting features from high-frequency EEG and eye-tracking data, and pointed out the feasibility of analyzing these features, even though the data sets generated can be quite large. The proposed system can be used for data collection in a simulated environment and potentially make data collection easier.

According to the study findings, high cognitive loads in an occipital lobe within the brain correlate with successful visual hazard recognition. This conclusion matches findings from the neuroscience literature showing that activity in occipital lobe channels (e.g., O1 and O2) correlate with a sense of danger (Joseph 1990; Mesulam 2000; Walker et al. 2007). Eye tracking and EEG provide deep insights into how a worker's brain and eye react during visual search. Analyzing both eye movement and brain waves in an integrated platform can lead to higher classification accuracy, showing that combined EEG and eye-tracking signals (93% accuracy) are more sophisticated predictors of awareness of surrounding hazards when compared with the accuracy achieved by EEG (83%) or that achieved by eye tracking (74%) independently. These findings have important implications for construction research and practice. Specifically, they can enhance current safety training programs (and ongoing research efforts) by assessing worker biometrics in real time to provide personalized feedback.

Several lessons emerged from this study. For instance, combining EEG and eye-tracking sensors with VR is an important breakthrough for safety researchers because they can simulate custom safety scenarios and have a predictive measure of workers' ability to recognize different hazard types. The are three significant directions in which future studies may go. First, researchers might use this platform to correlate arousal, valence, and hazard recognition performance. Second, they may use the proposed platform in identifying hazard types that correlate with high arousal and valence. And third, they can extend the platform to correlate EEG cognitive load with hazard recognition skills to determine low mental cognitive load situations on the construction site.

Data Availability Statement

Some or all data, models, or codes that support the findings of this study are available from the corresponding author upon reasonable request.

Acknowledgments

This work is partially funded by the National Institute for Occupational Safety and Health (NIOSH, T42-OH008673). Any opinions, findings, conclusions, or recommendations presented in this paper are those of the authors and do not reflect the views of NIOSH or the individuals acknowledged above.

Supplemental Materials

Appendix S1 is available online in the ASCE Library (www.ascelibrary.org).

References

Alruwaythi, O. F., M. H. Sears, and P. M. Goodrum. 2017. "The impact of engineering information formats on craft worker eye gaze patterns." In *Proc., Computing in Civil Engineering 2017*, 9–16. Reston, VA: ASCE.

Alshaer, A., H. Regenbrecht, and D. O'Hare. 2017. "Immersion factors affecting perception and behaviour in a virtual reality power wheelchair simulator." *Appl. Ergon.* 58 (Jan): 1–12. https://doi.org/10.1016/j.apergo.2016.05.003.

Altman, N. S. 1992. "An introduction to kernel and nearest-neighbor nonparametric regression." *Am. Stat.* 46 (3): 175–185.

Aspinall, P., P. Mavros, R. Coyne, and J. Roe. 2015. "The urban brain: Analysing outdoor physical activity with mobile EEG." *Br. J. Sports Med.* 49 (4): 272–276. https://doi.org/10.1136/bjsports-2012-091877.

Azevedo, A. S., J. Jorge, and P. Campos. 2014. "Combining EEG data with place and plausibility responses as an approach to measuring presence in outdoor virtual environments." *Presence Teleoperators Virtual Environ.* 23 (4): 354–368. https://doi.org/10.1162/PRES_a_00205.

Bahn, S. 2013. "Workplace hazard identification and management: The case of an underground mining operation." *Saf. Sci.* 57 (Aug): 129–137. https://doi.org/10.1016/j.ssci.2013.01.010.

Balali, V., M. Noghabaei, A. Heydarian, and K. Han. 2018. "Improved stakeholder communication and visualizations: Real-time interaction and cost estimation within immersive virtual environments." In *Proc., Construction Research Congress 2018*, 522–530. Reston, VA: ASCE.

Barham, M. P., G. M. Clark, M. J. Hayden, P. G. Enticott, R. Conduit, and J. A. G. Lum. 2017. "Acquiring research-grade ERPs on a shoestring budget: A comparison of a modified EMOTIV and commercial SynAmps EEG system." *Psychophysiology* 54 (9): 1393–1404. https://doi.org/10.1111/psyp.12888.

Bhatti, M. H., J. Khan, M. U. G. Khan, R. Iqbal, M. Aloqaily, Y. Jararweh, and B. Gupta. 2019. "Soft computing-based EEG classification by optimal feature selection and neural networks." *IEEE Trans. Ind. Inf.* 15 (10): 5747–5754. https://doi.org/10.1109/TII.2019.2925624.

Biggs, A. T., and S. R. Mitroff. 2015. "Improving the efficacy of security screening tasks: A review of visual search challenges and ways to mitigate their adverse effects." *Appl. Cognit. Psychol.* 29 (1): 142–148. https://doi.org/10.1002/acp.3083.

Bishop, C. 2006. *Pattern recognition and machine learning*. Berlin: Springer.

Blaiech, H., M. Neji, A. Wali, and A. M. Alimi. 2013. "Emotion recognition by analysis of EEG signals." In *Proc., 13th Int. Conf. on Hybrid Intelligent Systems (HIS 2013)*, 312–318. New York: IEEE.

BLS (Bureau of Labor Statistics). (2015). *Survey of occupational injuries and illnesses*. Washington, DC: BLS.

Bradley, M. M., L. Miccoli, M. A. Escrig, and P. J. Lang. 2008. "The pupil as a measure of emotional arousal and autonomic activation." *Psychophysiology* 45 (4): 602–607. https://doi.org/10.1111/j.1469-8986.2008.00654.x.

Burges, C. J. C. 1998. "A tutorial on support vector machines for pattern recognition." *Data Min. Knowl. Discovery* 2 (2): 121–167. https://doi.org/10.1023/A:1009715923555.

Casson, A. J., and E. V. Trimble. 2018. "Enabling free movement EEG tasks by eye fixation and gyroscope motion correction: EEG effects of color priming in dress shopping." *IEEE Access* 6: 62975–62987. https://doi.org/10.1109/ACCESS.2018.2877158.

Chen, J., X. Song, and Z. Lin. 2016. "Revealing the 'Invisible Gorilla' in construction: Estimating construction safety through mental workload assessment." *Autom. Constr.* 63 (Mar): 173–183. https://doi.org/10.1016/j.autcon.2015.12.018.

Chu, C., A.-L. Hsu, K.-H. Chou, P. Bandettini, and C. Lin. 2012. "Does feature selection improve classification accuracy? Impact of sample size and feature selection on classification using anatomical magnetic resonance images." *NeuroImage* 60 (1): 59–70. https://doi.org/10.1016/j.neuroimage.2011.11.066.

Chumerin, N., N. V. Manyakov, M. Van Vliet, A. Robben, A. Combaz, and M. M. Van Hulle. 2013. "Steady-state visual evoked potential-based computer gaming on a consumer-grade EEG device." *IEEE Trans. Comput. Intell. AI Games* 5 (2): 100–110. https://doi.org/10.1109/TCIAIG.2012.2225623.

Coogan, C. G., and B. He. 2018. "Brain-computer interface control in a virtual reality environment and applications for the Internet of Things." *IEEE Access* 6: 10840–10849. https://doi.org/10.1109/ACCESS.2018.2809453.

Crundall, D., P. Chapman, S. Trawley, L. Collins, E. Van Loon, B. Andrews, and G. Underwood. 2012. "Some hazards are more attractive than others: Drivers of varying experience respond differently to different types of hazard." *Accid. Anal. Prev.* 45 (Mar): 600–609. https://doi.org/10.1016/j.aap.2011.09.049.

Dimigen, O., W. Sommer, A. Hohlfeld, A. M. Jacobs, and R. Kliegl. 2011. "Coregistration of eye movements and EEG in natural reading: Analyses and review." *J. Exp. Psychol. Gen.* 140 (4): 552–572. https://doi.org/10.1037/a0023885.

Di Stasi, L. L., M. B. McCamy, S. L. Macknik, J. A. Mankin, N. Hooft, A. Catena, and S. Martinez-Conde. 2014. "Saccadic eye movement metrics reflect surgical residents' fatigue." *Ann Surg.* 259 (4): 824–829. https://doi.org/10.1097/SLA.0000000000000260.

Ellis, C. J. 1981. "The pupillary light reflex in normal subjects." *Br. J. Ophthalmol.* 65 (11): 754–759. https://doi.org/10.1136/bjo.65.11.754.

Elsawy, A. S., S. Eldawlatly, M. Taher, and G. M. Aly. 2014. "Performance analysis of a principal component analysis ensemble classifier for EMOTIV headset P300 spellers." In *Proc., 2014 36th Annual Int. Conf. of the IEEE Engineering in Medicine and Biology Society, EMBC 2014*, 5032–5035. New York: IEEE.

Ergan, S., A. Radwan, Z. Zou, H. Tseng, and X. Han. 2019. "Quantifying human experience in architectural spaces with integrated virtual reality and body sensor networks." *J. Comput. Civ. Eng.* 33 (2): 04018062. https://doi.org/10.1061/(ASCE)CP.1943-5487.0000812.

Estes, A. C., and D. M. Frangopol. 2003. "Updating bridge reliability based on bridge management systems visual inspection results." *J. Bridge Eng.* 8 (6): 374–382. https://doi.org/10.1061/(ASCE)1084-0702(2003)8:6(374).

Giannakos, M. N., K. Sharma, I. O. Pappas, V. Kostakos, and E. Velloso. 2019. "Multimodal data as a means to understand the learning experience." *Int. J. Inf. Manage.* 48 (Oct): 108–119. https://doi.org/10.1016/j.ijinfomgt.2019.02.003.

Grabowski, A., and J. Jankowski. 2015. "Virtual reality-based pilot training for underground coal miners." *Saf. Sci.* 72 (Feb): 310–314. https://doi.org/10.1016/j.ssci.2014.09.017.

Hasanzadeh, S., B. Esmaeili, and M. D. Dodd. 2017. "Measuring the impacts of safety knowledge on construction workers' attentional allocation and hazard detection using remote eye-tracking technology." *J. Manage. Eng.* 33 (5): 1–17. https://doi.org/10.1061/(ASCE)ME.1943-5479.0000526.

He, D., B. Donmez, C. C. Liu, and K. N. Plataniotis. 2019. "High cognitive load assessment in drivers through wireless electroencephalography and the validation of a modified N-back task." *IEEE Trans. Hum.-Mach. Syst.* 49 (4): 362–371. https://doi.org/10.1109/THMS.2019.2917194.

Helander, M. G. 1991. "Safety hazards and motivation for safe work in the construction industry." *Int. J. Ind. Ergon.* 8 (3): 205–223. https://doi.org/10.1016/0169-8141(91)90033-I.

Hess, E. H., and J. M. Polt. 1960. "Pupil size as related to interest value of visual stimuli." *Science* 132 (3423): 349–350. https://doi.org/10.1126/science.132.3423.349.

Hofmann, T., B. Schölkopf, and A. J. Smola. 2008. "Kernel methods in machine learning." *Ann. Stat.* 36 (3): 1171–1220.

Holmqvist, K., M. Nyström, R. Andersson, R. Dewhurst, H. Jarodzka, and J. Van de Weijer. 2011. *Eye tracking: A comprehensive guide to methods and measures*. Oxford, UK: Oxford University Press.

Huang, Z., A. Javaid, V. K. Devabhaktuni, Y. Li, and X. Yang. 2019. "Development of cognitive training program with EEG headset." *IEEE Access* 7: 126191–126200. https://doi.org/10.1109/ACCESS.2019.2937866.

Hwang, S., H. Jebelli, B. Choi, M. Choi, and S. Lee. 2018. "Measuring workers' emotional state during construction tasks using wearable EEG." *J. Constr. Eng. Manage.* 144 (7): 04018050. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001506.

Jebelli, H., S. Hwang, and S. Lee. 2018. "EEG-based workers' stress recognition at construction sites." *Autom. Constr.* 93 (Sep): 315–324. https://doi.org/10.1016/j.autcon.2018.05.027.

Jeelani, I., A. Albert, R. Azevedo, and E. J. Jaselskis. 2017a. "Development and testing of a personalized hazard-recognition training intervention." *J. Constr. Eng. Manage.* 143 (5): 04016120. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001256.

Jeelani, I., A. Albert, and J. A. Gambatese. 2017b. "Why do construction hazards remain unrecognized at the work interface?" *J. Constr. Eng. Manage.* 143 (5): 04016128. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001274.

Jeelani, I., A. Albert, K. Han, and R. Azevedo. 2019. "Are visual search patterns predictive of hazard recognition performance? Empirical investigation using eye-tracking technology." *J. Constr. Eng. Manage.* 145 (1): 04018115. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001589.

Jeelani, I., K. Han, and A. Albert. 2017c. "Development of immersive personalized training environment for construction workers." In *Proc., Computing in Civil Engineering 2017*, 407–415. Reston, VA: ASCE.

Jeelani, I., K. Han, and A. Albert. 2018. "Automating and scaling personalized safety training using eye-tracking data." *Autom. Constr.* 93 (Sep): 63–77. https://doi.org/10.1016/j.autcon.2018.05.006.

Joseph, R. 1990. *Neuropsychology, neuropsychiatry, and behavioral neurology*. Berlin: Springer.

Khushaba, R. N., C. Wise, S. Kodagoda, J. Louviere, B. E. Kahn, and C. Townsend. 2013a. "Consumer neuroscience: Assessing the brain response to marketing stimuli using electroencephalogram (EEG) and eye tracking." *Expert Syst. Appl.* 40 (9): 3803–3812. https://doi.org/10.1016/j.eswa.2012.12.095.

Khushaba, R. N., C. Wise, S. Kodagoda, J. Louviere, B. E. Kahn, and C. Townsend. 2013b. "Consumer neuroscience: Assessing the brain response to marketing stimuli using electroencephalogram (EEG) and eye tracking." *Expert Syst. Appl.* 40 (9): 3803–3812. https://doi.org/10.1016/j.eswa.2012.12.095.

Lan, T., D. Erdogmus, A. Adami, S. Mathan, and M. Pavel. 2007. "Channel selection and feature projection for cognitive load estimation using ambulatory EEG." *Comput. Intell. Neurosci.* 2007: 074895. https://doi.org/10.1155/2007/74895.

Li, H., M. Lu, G. Chan, and M. Skitmore. 2015. "Proactive training system for safe and efficient precast installation." *Autom. Constr.* 49 (Jan): 163–174. https://doi.org/10.1016/j.autcon.2014.10.010.

Liao, P. C., X. Sun, and D. Zhang. 2021. "A multimodal study to measure the cognitive demands of hazard recognition in construction workplaces." *Saf. Sci.* 133 (Jan): 105010. https://doi.org/10.1016/j.ssci.2020.105010.

Lin, Y. P., Y. Wang, and T. P. Jung. 2014. "Assessing the feasibility of online SSVEP decoding in human walking using a consumer EEG headset." *J. Neuroeng. Rehabil.* 11 (1): 119. https://doi.org/10.1186/1743-0003-11-119.

Lingard, H. 2013. "Occupational health and safety in the construction industry." *Constr. Manage. Econ.* 31 (6): 505–514. https://doi.org/10.1080/01446193.2013.816435.

Liu, Y., X. Jiang, T. Cao, F. Wan, P. U. Mak, P. I. Mak, and M. I. Vai. 2012. "Implementation of SSVEP based BCI with Emotiv EPOC." In *Proc., IEEE Int. Conf. on Virtual Environments, Human-Computer Interfaces, and Measurement Systems, VECIMS*, 34–37. New York: IEEE.

Majid Mehmood, R., R. Du, and H. J. Lee. 2017. "Optimal feature selection and deep learning ensembles method for emotion recognition from human brain EEG sensors." *IEEE Access* 5: 14797–14806. https://doi.org/10.1109/ACCESS.2017.2724555.

Matheson, R. 2019. "Study measures how fast humans react to road hazards." *MIT News*, August 7, 2019.

Melnik, A., P. Legkov, K. Izdebski, S. M. Kärcher, W. D. Hairston, D. P. Ferris, and P. König. 2017. "Systems, subjects, sessions: To what extent do these factors influence EEG data?" *Front. Hum. Neurosci.* 11: 150. https://doi.org/10.3389/fnhum.2017.00150.

Mesulam, M. M. 2000. *Principles of behavioral and cognitive neurology*. Oxford, UK: Oxford Univ. Press.

Moore, H. F., R. Eiris, M. Gheisari, and B. Esmaeili. 2019. "Hazard identification training using 360-degree panorama vs. virtual reality techniques: A pilot study." In *Proc., Computing in Civil Engineering 2019: Visualization, Information Modeling, and Simulation*, 55–62. Reston, VA: ASCE.

Noghabaei, M., K. Asadi, and K. Han. 2019. "Virtual manipulation in an immersive virtual environment: Simulation of virtual assembly." In *Proc., Computing in Civil Engineering: Visualization, Information Modeling, and Simulation*, 95–102. Reston, VA: ASCE.

Noghabaei, M., and K. Han. 2020. "Hazard recognition in an immersive virtual environment: Framework for the simultaneous analysis of visual search and EEG patterns." In *Proc., of Construction Research Congress 2020*, 934–943. Reston, VA: ASCE. https://doi.org/10.1061/9780784482865.099.

Noghabaei, M., and K. Han. 2021. "Object manipulation in immersive virtual environments: Hand motion tracking technology and snap-to-fit function." *Autom. Constr.* 124 (Apr): 103594. https://doi.org/10.1016/j.autcon.2021.103594.

Noghabaei, M., A. Heydarian, V. Balali, and K. Han. 2020. "Trend analysis on adoption of virtual and augmented reality in the architecture, engineering, and construction industry." *Data* 5 (1): 26. https://doi.org/10.3390/data5010026.

Pedram, S., P. Perez, S. Palmisano, and M. Farrelly. 2017. *Evaluating 360-virtual reality for mining industry's safety training*, 555–561. Cham, Switzerland: Springer.

Perez Vidal, A. F., M. A. Oliver Salazar, and G. Salas Lopez. 2016. "Development of a brain-computer interface based on visual stimuli for the movement of a robot joint." *IEEE Lat. Am. Trans.* 14 (2): 477–484. https://doi.org/10.1109/TLA.2016.7437182.

Perlman, A., R. Sacks, and R. Barak. 2014. "Hazard recognition and risk perception in construction." *Saf. Sci.* 64 (Apr): 22–31. https://doi.org/10.1016/j.ssci.2013.11.019.

Putze, F. 2019. "Methods and tools for using BCI with augmented and virtual reality." In *Brain art*, 433–446. Cham, Switzerland: Springer.

Qian, M., M. Aguilar, K. N. Zachery, C. Privitera, S. Klein, T. Carney, and L. W. Nolte. 2009. "Decision-level fusion of EEG and pupil features for single-trial visual detection analysis." *IEEE Trans. Biomed. Eng.* 56 (7): 1929–1937. https://doi.org/10.1109/TBME.2009.2016670.

Rani, P., C. Liu, N. Sarkar, and E. Vanman. 2006. "An empirical study of machine learning techniques for affect recognition in human–robot interaction." *Pattern Anal. Appl.* 9 (1): 58–69. https://doi.org/10.1007/s10044-006-0025-y.

Ren, Z., X. Qi, G. Zhou, and H. Wang. 2014. "Exploiting the data sensitivity of neurometric fidelity for optimizing EEG sensing." *IEEE Internet Things J.* 1 (3): 243–254. https://doi.org/10.1109/JIOT.2014.2322331.

Rozenfeld, O., R. Sacks, Y. Rosenfeld, and H. Baum. 2010. "Construction job safety analysis." *Saf. Sci.* 48 (4): 491–498. https://doi.org/10.1016/j.ssci.2009.12.017.

Saha, A., A. Konar, A. Chatterjee, A. Ralescu, and A. K. Nagar. 2014. "EEG analysis for olfactory perceptual-ability measurement using a recurrent neural classifier." *IEEE Trans. Hum.-Mach. Syst.* 44 (6): 717–730. https://doi.org/10.1109/THMS.2014.2344003.

Savage, S. W., D. D. Potter, and B. W. Tatler. 2013. "Does preoccupation impair hazard perception? A simultaneous EEG and eye tracking study." *Transp. Res. Part F Traffic Psychol. Behav.* 17 (Feb): 52–62. https://doi.org/10.1016/j.trf.2012.10.002.

Sherafat, B., C. R. Ahn, R. Akhavian, A. H. Behzadan, M. Golparvar-Fard, H. Kim, Y.-C. Lee, A. Rashidi, and E. R. Azar. 2020. "Automated methods for activity recognition of construction workers and equipment: State-of-the-art review." *J. Constr. Eng. Manage.* 146 (6): 03120002. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001843.

Sherafat, B., A. Rashidi, Y. C. Lee, and C. R. Ahn. 2019a. "A hybrid kinematic-acoustic system for automated activity detection of construction equipment." *Sensors* 19 (19): 4286. https://doi.org/10.3390/s19194286.

Sherafat, B., A. Rashidi, Y.-C. Lee, and C. R. Ahn. 2019b. "Automated activity recognition of construction equipment using a data fusion approach." In *Proc., Computing in Civil Engineering 2019: Data, Sensing, and Analytics*, 1–8. Reston, VA: ASCE.

Shi, Y., J. Du, and D. A. Worthy. 2020a. "The impact of engineering information formats on learning and execution of construction operations: A virtual reality pipe maintenance experiment." *Autom. Constr.* 119 (Nov): 103367. https://doi.org/10.1016/j.autcon.2020.103367.

Shi, Y., J. Du, and Q. Zhu. 2020b. "The impact of engineering information format on task performance: Gaze scanning pattern analysis." *Adv. Eng. Inf.* 46 (Oct): 101167. https://doi.org/10.1016/j.aei.2020.101167.

Shic, F., B. Scassellati, and K. Chawarska. 2008. "The incomplete fixation measure." In *Proc., 2008 Symp. on Eye Tracking Research and Applications—ETRA '08*, 111. New York: ACM Press.

van der Wel, P., and H. van Steenbergen. 2018. "Pupil dilation as an index of effort in cognitive control tasks: A review." In *Psychonomic bulletin and review*. New York: Springer.

van Vliet, M., A. Robben, N. Chumerin, N. V. Manyakov, A. Combaz, and M. M. Van Hulle. 2012. "Designing a brain-computer interface controlled video-game using consumer grade EEG hardware." In *Proc., 2012 ISSNIP Biosignals and Biorobotics Conf.: Biosignals and Robotics for Better and Safer Living*, 1–6. New York: IEEE.

Walker, J. E., G. P. Kozlowski, and R. Lawson. 2007. "A modular activation/coherence approach to evaluating clinical/QEEG correlations and for guiding neurofeedback training: Modular insufficiencies, modular excesses, disconnections, and hyperconnections." *J. Neurothe.* 11 (1): 25–44. https://doi.org/10.1300/J184v11n01_03.

Wang, D., J. Chen, D. Zhao, F. Dai, C. Zheng, and X. Wu. 2017. "Monitoring workers' attention and vigilance in construction activities through a wireless and wearable electroencephalography system." *Autom. Constr.* 82 (Oct): 122–137. https://doi.org/10.1016/j.autcon.2017.02.001.

Wang, D., H. Li, and J. Chen. 2019. "Detecting and measuring construction workers' vigilance through hybrid kinematic-EEG signals." *Autom. Constr.* 100 (Apr): 11–23. https://doi.org/10.1016/j.autcon.2018.12.018.

Wang, S., J. Gwizdka, and W. A. Chaovalitwongse. 2016. "Using wireless EEG signals to assess memory workload in the n-back task." *IEEE Trans. Hum.-Mach. Syst.* 46 (3): 424–435. https://doi.org/10.1109/THMS.2015.2476818.

Winn, M. B., D. Wendt, T. Koelewijn, and S. E. Kuchinsky. 2018. "Best practices and advice for using pupillometry to measure listening effort: An introduction for those who want to get started." *Trends Hear* 22. https://doi.org/10.1177/2331216518800869.

Wu, D. 2017. "Online and offline domain adaptation for reducing BCI calibration effort." *IEEE Trans. Hum.-Mach. Syst.* 47 (4): 550–563. https://doi.org/10.1109/THMS.2016.2608931.

Zhang, H. 2017. "Head-mounted display-based intuitive virtual reality training system for the mining industry." *Int. J. Min. Sci. Technol.* 27 (4): 717–722. https://doi.org/10.1016/j.ijmst.2017.05.005.

Zhao, D., and J. Lucas. 2015. "Virtual reality simulation for construction safety promotion." *Int. J. Inj. Control Saf. Promot.* 22 (1): 57–67. https://doi.org/10.1080/17457300.2013.861853.

Zhao, X., C. Liu, Z. Xu, L. Zhang, and R. Zhang. 2020. "SSVEP stimulus layout effect on accuracy of brain-computer interfaces in augmented reality glasses." *IEEE Access* 8: 5990–5998. https://doi.org/10.1109/ACCESS.2019.2963442.

Zou, P., and R. Y. Sunindijo. 2015. *Strategic safety management in construction and engineering*. Hoboken, NJ: Wiley.

Zou, Z., X. Yu, and S. Ergan. 2019. "Visualization (ND, VR, AR)." In *Proc., Computing in Civil Engineering 2019*, 169–176. Reston, VA: ASCE.