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Predicting workers' inattentiveness to struck-by hazards by monitoring biosignals during a construction task: A virtual reality experiment

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ABSTRACT

At construction workplaces, workers should be consistently attentive to approaching and nearby safety hazards. However, workers tend to allocate most of their attentional resources to a work task and often exhibit inattentive behaviors to hazards, which may lead to serious injuries and fatalities. Predicting construction workers' inattentiveness is thus critical to preventing accidents in construction workplaces. With the advent of biosensing technologies, the potential of using biosignals to predict human behaviors has been proven in various fields of study. However, to date there has been little discussion about utilizing biosignals to predict construction workers' inattentive behaviors. To this end, this study examines whether construction workers' inattentive behaviors can be predicted by assessing biosignal reactivity. A virtual road construction environment was created and used for an experiment to expose participants to a repeated struck-by hazard without risking actual injury. Participants' biosignals (i.e., electrodermal activity, pupil dilation, and saccadic eye movement) and physical engagement in inattentive behaviors were collected and analyzed. The results of statistical analyses revealed significant differences in biosignal reactivities between participants' attentive behaviors (i.e., paying attention to the hazard) and inattentive behaviors (i.e., ignoring the hazard). The outcomes of the machine learning-based behavior classification also indicate the usefulness of predicting inattentive behaviors by monitoring workers' biosignals during a construction task and provide a foundation for the utilization of biosignals in safety management to prevent accidents resulting from inattentive behaviors.

1. Introduction

The construction industry has always been considered to be one of the most high-risk industries [1–3]. In 2018, more than 1,000 fatalities were reported from the construction industry in the United States [4]. Despite countless efforts to improve construction safety, the majority of fatalities and injuries in construction workplaces still occur due to workers' unsafe behaviors [5–9]. Insufficient attention to potential risks associated with workplace hazards is a major contributing factor to workers' unsafe behaviors [10,11]. In construction workplaces, workers become complacent with hazards that they are exposed to frequently [12–14]. This often causes workers to underestimate the risks, become inattentive to the hazards, and engage in unsafe behaviors [15,16]. Typically, warning signals are provided to induce worker alertness to nearby hazards, but repeated exposures to warning signals also cause workers to be less attentive or habituated to those signals. To this end, measuring workers' attentiveness and predicting their inattentive behaviors are critical to the development of closed-loop interventions that continuously provide feedbacks until workers recover their attention to hazards and/or warning signals [11,17,18].

The recent development in the field of biosensing technology (e.g., electrodermal activity (EDA), electroencephalography [EEG], electrocardiogram [ECG], and eye tracking) has led to a growing interest in the use of wearable sensors in measuring worker attentiveness [19,20]. Researchers have focused on observing changes in biosignals when a participant encounters a hazard during an experiment and compared participants' biosignals when they were in "without hazard" conditions and in "with hazard" conditions. Several studies have found that workers show heightened biosignal reactivity when they are exposed to workplace hazards [11,17,21]. Choi et al. [17] found that short-term changes in EDA show significant differences between low- and high-risk activities. Specifically, Wang et al. [11] demonstrated that

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workers' vigilance—sustained attention to an external threat—is observable through EEG signal analysis. These studies have accumulated evidence indicating the potential causality between heightened reactivities in biosignals and attentiveness by identifying the association between abnormalities in biosignals and exposure to hazards. However, little research has been conducted on predicting inattentive behaviors that are caused by failures to be attentive to frequently presented warning signals or repeatedly encountered workplace hazards in a construction environment. To this end, this study examines the computational approaches to predict workers' inattentive behaviors to hazards by using biosignals collected while warning signals are employed prior to their encounters with hazards.

To achieve the research objective, an experiment was conducted in a laboratory setting. The major considerations in the experimental design were how to expose participants to a repeated workplace hazard without risking actual injury and observe their attentiveness to it. Thus, a virtual reality environment was created and used for the experiment, during which participants were asked to perform a road-cleaning task and repeatedly exposed to the risk of being struck by a construction vehicle. Participants' physical responses and biosignal reactivitties to the hazard were measured by using eye-tracking sensors and a wearable EDA sensor. Through the statistical analysis, significant relationships between participants' physical inattentive behaviors and reactivities in biosignals are identified. Finally, the usefulness of predicting inattentive behaviors using biosignals is demonstrated by applying a supervised learning-based classification. The findings provide a foundation for the utilization of biosignals in safety interventions and training to prevent accidents caused by workers' inattentive behaviors during a construction task.

2. Research background

2.1. Inattentive behaviors and habituation to workplace hazards

Previous studies in construction safety have focused on explaining workers' unsafe behaviors from a cognitive psychology perspective. These researchers claimed that workers' inattention to hazards is one of the significant precursors of workplace accidents [22–24]. Performing a construction task demands constant attention to surrounding hazards [21,25]. However, during a construction task, workers tend to pay more attention to the task and less attention to hazards because of limited attention capacity [26,27]. Wickens [27] determined that humans' attentional resources are limited. Therefore, in workplaces, while simultaneously performing multiple tasks (e.g., performing a task vs. watching out for potential hazards), workers are apt to allocate their limited attentional resources according to their priorities [28].

Recent studies in construction safety have also found that construction workers' risk perception is highly related to their attention allocation to workplace hazards [21,25]. When workers' perceived risk is low, workers are likely to allocate less attentional resources to hazards and tend to engage in inattentive behaviors that can result in workplace fatalities and injuries [29–31]. The tendency of workers to be inattentive to workplace hazards is actually exacerbated when workers are frequently exposed to the same hazard [11]. After long-term and frequent exposure to hazards, workers become habituated to the hazard and begin to underrate its risk [15,32,33]. Researchers have defined this phenomenon as *risk habituation* and tried to examine its influence on workers' engagement in inattentive behaviors [1,34]. For instance, previous studies found that lift truck operators who were exposed to regular hazards tended to show a low level of perceived risk while driving a lift truck in hazardous situations [13,35,36].

Other studies have demonstrated that workers' sensitivity to workplace risks decreases with repeated exposure to the same hazard [8,20]. Accident investigation reports also confirmed that one of the significant causal factors of struck-by accidents is workers' inattention to approaching equipment [37,38]. In many cases of struck-by accidents, construction equipment was moving at a low speed, and proximity warning alarms were sounded, but pedestrian workers failed to avoid accidents because they were focused on their task and did not heed the approaching equipment [16,37,38]. Providing auditory warning alarms is a common and simple method used to shift workers' attention from their tasks to approaching hazards [39]. However, as seen in the accident cases mentioned above, its effectiveness in reducing workers' habituated inattentiveness is questionable [1]. Therefore, there is a critical need to assess workers' inattentiveness to workplace hazards to prevent struck-by and other accidents in construction sites.

2.2. Biosignals and attentiveness

Researchers in psychology and cognitive science have generated evidence indicating that workers' attentiveness can be assessed by monitoring reactivities in various biosignals [40–43]. This section reviews previous studies that examined measures of various biosignals in relation to assessments of attentiveness to hazards.

EDA, which indicates changes in the electrical current of the skin in response to adverse or threatening stimuli [44–46], has been widely adopted to objectively measure individuals' sustained attention [19,47–49]. EDA signals usually are sorted into two indices: skin conductance level (SCL) and skin conductance response (SCR) [50]. SCL measures slow changes in average skin conductance, and SCR represents the rapid phasic transient related external stimuli [46,51]. Previous studies have used EDA to identify an individual's mental status changes in various circumstances (e.g., ambulatory settings, occupational settings, etc.) [6,52]. Studies in construction safety [17,53,54] have investigated the applicability of EDA to monitor construction workers' attention to workplace hazards. The results indicated that there were significant short-term changes in EDA when participants were exposed to a hazardous working environment [17].

To monitor workers' inattentiveness during exposure to workplace hazards, researchers also have focused on pupil size measurement and saccadic eye movement (e.g., saccadic velocity, saccadic duration). Pupillometry is a technique that measures changes in pupil size [55]. Pupil dilation reflects the intensity of cognitive load and responses to external stimuli [56]. Increases in cognitive processing of information, or cognitive load, are indicated by increases in pupil size. Thus, changes in pupil size can be used for continuous measurement of mental workload [57]. Kimble et al. [58] demonstrated the association between pupil size and exposure to threatening stimuli. Results showed that larger pupil dilation was demonstrated when participants were exposed to high-risk situations. Specifically, Liao et al. [59] measured pupil dilation to examine its usefulness for assessing construction workers' attentiveness. The results revealed that participants' pupils were differently dilated according to the different types of risks associated with workplace hazards. In addition to pupil dilation, saccadic eye movements have also been considered as useful indicators of mental attention [56]. Saccadic velocity and duration have proved to be related to attentiveness [60]. Saccadic eye movements tell the speed and angle of eye movement, which indicate participants' attention to a presented stimulus [55]. Costela and Castro-Torres [60] found that exposure to hazardous situations is significantly associated with larger saccadic eye movements. Saccadic velocity has been adopted in applied psychology studies to measure participants' emotional arousal [55,61–63]. Since saccadic velocity is not vulnerable to participants' voluntary control, it may indicate underlying mental activity more clearly than other saccade metrics [62,64]. Saccadic duration is another metric that indicates the level of risk perception and attentiveness to exposed hazards [65]. Stasi et al. [66] found that people who engaged in risky-behaviors more frequently showed shorter saccadic duration than people who showed less engagement in risky-behaviors. Based on this evidence, this study examines the usefulness of biosignals (e.g., EDA, pupil dilation, saccadic velocity,

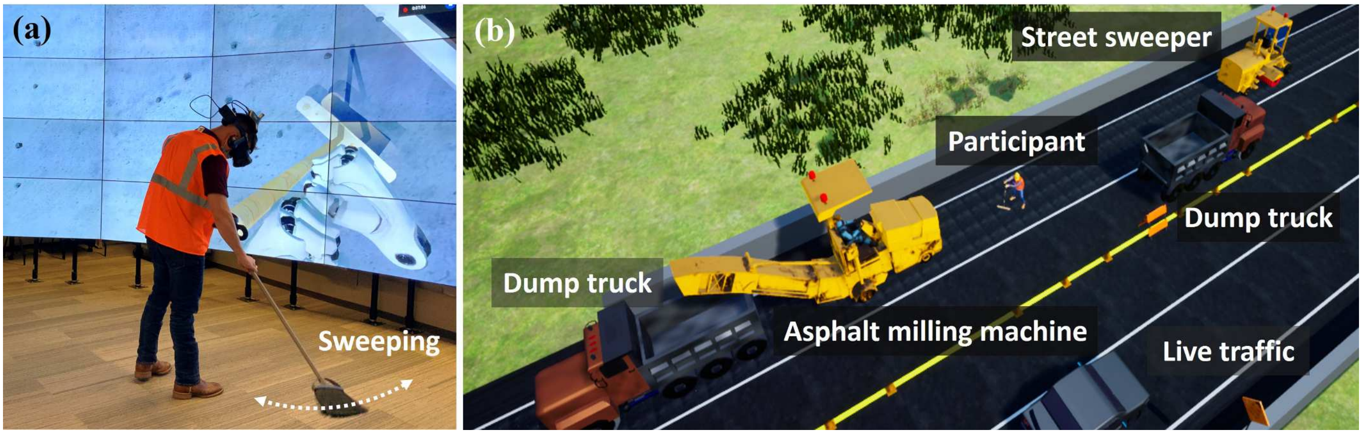

Fig. 1. Construction task in the VR environment: (a) Virtual sweeping task using a broom. Motion controllers were attached to the broomstick; (b) Overview scene of the virtual road construction environment.

and saccadic duration) in predicting inattentive behaviors of construction workers.

2.3. Biosignal analysis and behavior prediction

In various fields of study (e.g., human-robot interaction research, consumer behavior analysis, and driving behavior analysis), researchers have become increasingly interested in the prediction of human behaviors through the analysis of biosignal reactivity [55,67–69]. For example, several studies [68,69] in analyses of driving behavior focused on the utility of assessing drivers' biosignals to predict risky driving behaviors. Liang and Lin [68] found distinctively different reactivities in EEG and EDA signals from risky and safety drivers when they encountered road hazards. Murphey et al. [69] used ECG and EDA to predict drivers' intention to change lanes and illustrated the value of biosignal assessment in predicting human behaviors. Researchers in the field of behavioral and neurophysiological science also have explored biosignal analysis methods to predict participants' decision making during decision-reward uncertainty tasks [70–72]. Cavanagh et al. [70], for example, revealed the association between greater pupil dilation and an increase in decision threshold in difficult decision-making circumstances. Studies in consumer science have investigated the analysis of biosignals that allows the prediction of subsequent purchasing behaviors [55,71]. Guerreiro et al. [71] attempted to predict consumer choice by assessing EDA signals. The results demonstrated that heightened reactivities in EDA signals are correlated with participants' selection behaviors. However, in contrast to other research domains there has been little discussion about assessing biosignals to predict construction workers' inattentive behaviors in hazardous working environments. To this end, this study examines whether construction workers' inattentive behaviors can be predicted by assessing biosignal reactivities when workers encounter workplace hazards.

3. Data collection

In a construction context, it is excessively difficult to observe workers' inattentive behaviors during a construction task [72]. Furthermore, workers cannot be exposed to a hazardous situation for research purposes. On the other hand, a virtual reality (VR) environment can provide a close-to-reality simulation and evoke with high validity an individual's behavioral and physiological responses to exposed hazards [73–76], thereby enabling researchers to analyze relationships between the biosignal reactivity and physical behaviors when a participant encounters simulated hazardous contexts. To this end, the experiment was conducted using a VR environment. Specifically, in order to expose participants to repeated struck-by hazards and monitor their biosignal reactivity, a virtual road construction and maintenance operation was simulated. The following sections describe the VR environment development process, experimental settings, and the data collection process.

3.1. Immersive virtual road construction environment

The experimental scenario focused on repeated exposure of participants to potential struck-by hazards associated with construction vehicles continuously operating around participants and sounding associated auditory warning alarms. In order to build a near-reality virtual environment, ambient sounds of a road maintenance work zone were carefully designed and embedded in the VR environment. For instance, operation sounds from heavy construction vehicles (e.g., milling machine, street sweeper, and asphalt paver) and traffic sounds from passing cars were played during the experiment. Furthermore, to enhance participants' sense of presence, the volume of ambient sounds attenuated as a participant moved away from a source of the sound. A virtual construction task was designed to be able to observe participants' responses to a hazard while they were performing a construction task. In the VR environment, a participant was asked to perform a cleaning crew's task, removing all debris from the surface of the road by sweeping, using a broom. The motion controllers, attached to a real broomstick, captured the physical sweeping movements of a participant, and simulated the participant's movements in the VR environment with a virtual broom and virtual debris [Fig. 1-(a)].

In the virtual road construction environment, construction vehicles move in response to participants' behaviors. One of the construction vehicles behind a participant (i.e., a sweeper) moves back and forth to expose a participant repeatedly to a struck-by hazard. The movement of the sweeper was deliberately designed to evoke participants' behavioral and physiological responses to the exposed hazard without interrupting or stopping a participant's task. During the experiment, the sweeper repeatedly approaches in close proximity to a participant and then moves away. A proximity warning alarm is presented only while the sweeper is moving forward and is turned off while the sweeper is moving backwards [Fig. 1-(b)]. In this scenario, a participant is repeatedly exposed to the potential struck-by hazard without interfering with the road cleaning task. One reciprocal movement of the sweeper is considered as one exposure to the struck-by hazard, and a participant's response to the hazard was measured for each exposure. Furthermore, to build a realistic hazardous working environment, a virtual accident with the sweeper was also designed. In a VR environment, the simulated accident was triggered by a participant's frequent inattentive behaviors. When a participant ignored and did not look back to check the approaching hazard more than 11 times, the sweeper moved toward the participant until it collided with the participant, and the VR accident was triggered.

3.2. Measurement of physical inattentive behaviors and biosignals

In this study, participants' hazard-checking behavior—an eye and/or head movement a participant makes in order to observe approaching hazards—is considered as *attentive behavior*. The manifestation of participants' physical attentive behaviors was determined by an eye movement tracking system integrated into the developed VR environment. During the experiment, when a participant looked back to check the sweeper's proximity, it was labeled as an attentive behavior (i.e., hazard-checking behavior) and documented as such. If a participant did not check the proximity of the sweeper during one exposure cycle, that was labeled as an inattentive behavior (i.e., non-hazard-checking behavior). Participants' behavioral and physiological responses to the exposed hazard were collected as follows. While a participant was performing the virtual road cleaning task, his/her responses in EDA were collected from the wrist-mounted, wearable EDA sensor and were sampled at 4 Hz, and pupil dilation and saccadic eye movements were measured using eye-tracking sensors embedded in the head-mounted display (HMD) at 45 Hz.

3.3. Experimental procedure

A total of 32 participants (26 males, 6 females; $M_{age} = 21.09$, $SD_{age} = 3.04$) participated in the experiment. All participants were undergraduate and graduate students at Texas A&M University (TAMU) majoring in construction/engineering. The experiment was implemented in the Building Information Modeling-Computer Aided Virtual Environment (BIM-CAVE) at TAMU with the approval of the Institutional Review Board.

Before commencing the experiment, all participants were required to watch a safety training video for road maintenance work [77] and were trained on how to perform the virtual road-cleaning task. Then, participants undertook a practice session to become familiarized with the VR task. The struck-by hazard and the simulated accident were not presented in the practice session. During the actual experiment, a participant was asked to alert him/herself to approaching equipment and auditory warning signals for safety purposes. When the VR-simulated accident occurred because of a participant's inattentive behaviors, the experiment was aborted immediately. Otherwise, the experiment was discontinued 20 min after starting the experiment. The validity of the collected physiological and behavioral responses was examined by testing the effect of VR familiarization on participants' behavioral and physiological responses. At construction sites, workers' behavioral/physiological responses to encountered hazards might vary from one day to the next because individual factors—emotional stability, safety experience, and safety awareness—can affect unsafe behaviors [78]. To this end, this study investigates whether the proposed approach can predict inattentive behaviors using biosignal data collected on different days. For this reason, all participants participated in two sessions, separated by a week's interval. Subsequently, the data from both sessions were used to predict inattentive behaviors.

4. Methods

The inattentive behavior prediction method that employs extracted features was designed by applying machine learning algorithms. The prediction process consisted of five steps: data preprocessing and base feature extraction; application of contextual features; feature selection for the classification; statistical analysis; and classification between hazard-checking behaviors (i.e., attentive behaviors) and non-hazard checking behaviors (i.e., inattentive behaviors).

4.1. Data processing and base feature extraction of biosignals

Collected biosignals typically include motion artifacts and noises [17,52]. To identify those noises and artifacts, visual inspection and preprocessing were performed. Eye movement data collected from five participants showed a large number of noises or no fluctuation. For these reasons, the data from those five participants were not included in the analysis. Data from a total of 27 participants were used for this study.

Motion artifacts and noises in EDA signals—such as an excessively abrupt decrease after reaching an absolute maximum peak—were removed using a smoothing filter while preserving the typical EDA fluctuation [44,79,80]. In this study, the Blackman window filter of twelve data points per block was applied to smooth EDA signals [51,81,82]. After the smoothing, a signal segmentation was implemented in order to identify underlying state changes in EDA signals, which result from the external stimulus (i.e., exposure to the struck-by hazard) [50]. Each EDA signal from each participant was segmented into smaller segments using bottom-up segmentation because of its superior performance as compared to other segmentation methods [82,83]. A Python package *Ruptures* was used for the segmentation [84]. After the segmentation, base features from each segment were calculated. The values related to SCR (e.g., amplitude and frequency within the time segment) were extracted using *Ledalab* software [44,85]. The calculated SCR values of each segment were rearranged to synchronize with the time of raw data. To determine a length of each segment that best explains the differences in SCR values corresponding to physical inattentive behaviors, we performed statistical analyses using SCR values with different window period lengths (e.g., the entire period of each exposure, 20 s, 10 s, and 5 s). There was a distinct difference in biosignal reactivities only when a 10-second window period was applied. Thus, 10 s of SCR values before and after the warning alarm occurrence in each hazard exposure were extracted. Statistical features such as maximum, minimum, mean, and standard deviation were calculated from the SCR values. Through this process, 12 base features were extracted from EDA and normalized at the individual level.

In processing pupil and saccadic eye movement data, de-blinking is important to the process of removing artifacts [86]. According to the previous studies' recommendations [86,87], pupil and saccadic eye movement data were eliminated during the blink, 100 ms before and after the blink, and interpolation was implemented for the period of the removed data. After the elimination of blinking, base feature extraction was conducted on pupil data and saccadic eye movement data, respectively. Pupil dilation relative to a baseline size indicates an individuals' extra listening effort in response to external auditory stimuli [88]. Thus, in order to analyze changes in pupil size in response to exposure to the struck-by hazard and auditory warning alarms, the baseline correction was performed. To set the baseline pupil size of each subject, this study applied the 1,000 ms of baseline duration, which is the preferred measurement of human mental perception [89]. Based on the extracted baseline, the pupil dilation was calculated at each data point (calculated pupil dilation = measured pupil size – baseline).

Using the collected saccadic eye movement data, saccadic velocity and duration were calculated by adopting the microsaccades detection method. Microsaccades are rapid events that happen between fixational eye movements [90] and are affected by attentional allocation during task execution [91]. Specifically, the presentation of background noises causes higher velocity and longer duration of microsaccades when a participant is performing a task [92]. Thus, in this study, the features related to the velocity and duration of microsaccades are used as indicators of inattentive behaviors. Using recorded eye positions (i.e., x and y coordinates) the eye movement velocity was calculated. Based on the velocity of each data point, the occurrence of microsaccades was detected, and the microsaccade velocity (i.e., saccadic velocity) and the microsaccades duration (i.e., saccadic duration) were calculated. The 10 s of fixed length window—10 s before and after the warning alarm occurrence in each exposure—was applied to extract pupil dilation and saccadic eye movement values corresponding to hazard exposure.

Then, like EDA base features, the statistical features such as maximum, minimum, mean, and standard deviation were calculated from pupil dilation and microsaccades. A total of 24 base features from

Table 1
Selected features for the prediction of inattentive behaviors.

Modality			Selected features	ID
Electrodermal activity (EDA)		Skin Conductance Response (SCR)	- Difference in the mean SCR amplitude between before and after the warning alarm	E1
			- Maximum SCR amplitude after the warning alarm	E2
			- Mean SCR amplitude after the warning alarm	E3
			- Mean SCR frequency after the warning alarm	E4
Eye	Pupillometry	Pupil dilation	- Mean pupil dilation before the warning alarm	P1
			- Mean pupil dilation after the warning alarm	P2
	Saccadic movement	Saccadic velocity	- Difference in the mean saccadic velocity between before and after the warning alarm	S1
			- Mean saccadic velocity after the warning alarm	S2
			- Peak saccadic velocity after the warning alarm	S3
		Saccadic duration	- Mean saccadic duration after the warning alarm	S4
Context		Number of exposures	- The number of exposures to the approaching hazard	C1
		VR familiarity	- Participants' familiarity with VR technology	C2

Table 2
The number of subjects who experienced VR-accident during the experiment.

Session	Non-accident group (NAG)	Accident group (AG)	Total
First	5	22	27
Second	16	11	27

Table 3
Two-way ANOVA results of mean SCR amplitude: main and interaction effects of inattentive behaviors and accident occurrences.

Measure	Sum of squares	*df*	*F*	*p* -value
Checking	1.76	1	1.894	0.169
Accident	2.51	1	2.705	0.100
Checking*Accident	3.59	1	3.866	0.054

* Significant at the $p = .05$ level.

pupil dilation and microsaccades were extracted and normalized at the individual level. Consequently, from these base feature extractions, a total of 36 features were derived.

4.2. Contextual features

In predicting human behaviors, adding contextual information about the situation in which the behaviors occur plays an important role [93–95]. The use of contextual features could enhance the prediction performance of machine learning models [96,97]. Thus, to provide additional information about when participants were exposed to struck-by hazards, the number of exposures to the hazard is used as a contextual feature. Since this study aims to examine the presence of inattentive behaviors in response to the repeatedly exposed struck-by hazard, we expect that the adopted machine learning method will learn the interaction between the number of exposures to the hazard and selected features. Furthermore, participants' familiarity with VR (i.e., prior experience using VR devices) was measured using a 5-point Likert scale (where 1 = not at all familiar, and 5 = extremely familiar) and used as additional contextual feature, with the underlying assumption that familiarity with a virtual environment may affect participants' responses to stimuli presented in the VR environment [96,98,99].

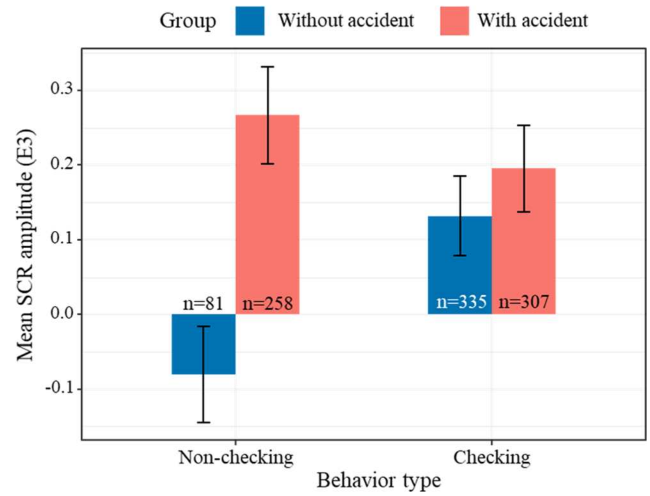

Fig. 2. Depiction of mean SCR amplitude after warning alarm occurrence (E3) by non-checking behaviors vs. checking behaviors. Standard error bars are included.

Table 4
Simple effect of the accident occurrence at the level of mean SCR amplitude.

Accident occurrence	Comparison	Estimated difference	*df*	*F*	*p* -value
Without accident	(Checking) – (Non-checking)	0.212	977	3.056	0.080
With accident	(Checking) – (Non-checking)	0.071	977	0.739	0.390

* Significant at the $p = .05$ level.

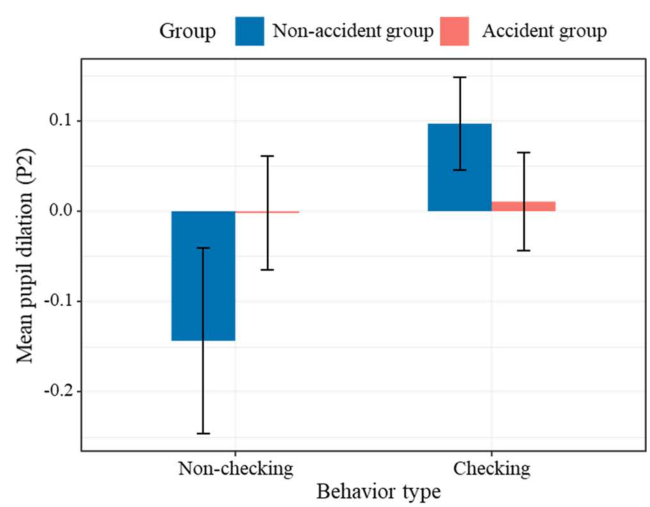

Fig. 3. Depiction of mean pupil dilation after the warning alarm (P2) by non-checking behaviors vs. checking behaviors. Standard error bars are included.

Table 5
Two-way ANOVA results of mean saccadic velocity after the warning alarm: main and interaction effects of inattentive behaviors and accident occurrences.

Measure	Sum of squares	*df*	*F*	*p* -value
Checking	4.68	1	5.011	0.025*
Accident	0.10	1	0.105	0.746*
Checking*Accident	0.18	1	0.196	0.658*

* Significant at the $p = .05$ level

Table 6
Mann-Whitney *U* test results of mean saccadic duration.

Accident occurrence	Behaviors (*Median*)		*U*	*Z*	*p* -value
	Checking	Non-checking			
Without accident	– 0.034	– 0.196	11,816	– 2.101	0.036*
With accident	0.125	– 0.299	39,142	– 4.732	< 0.001*

* Significant at the $p = .05$ level

Immersiveness has been used to refer to the degree of realism achieved by a virtual environment [100]. The level of perceived immersiveness in a VR environment is another important factor that influences participants' behaviors during an experiment [101]. Thus, to measure participants' perceived immersiveness in the VR environment, a survey using the Igroup Presence Questionnaire (IPQ) that employed a 5-point Likert scale, was conducted after the experiment [102,103], and the survey result was employed for the contextual feature. A total of 3 contextual features were used as base features.

4.3. Feature selection for the classification of inattentive behaviors

To find features that best explain the differences between reactivities in biosignals when a participant showed attentive behaviors (i.e., hazard-checking behaviors) and inattentive behaviors (i.e., non-hazard- checking behaviors), feature selection was implemented. The stepwise regression method outperforms other feature selection methods, such as forward selection and backward selection [104–106]. Thus, through the stepwise regression analysis, less significant base features among all 39 features were eliminated, and 12 features were ultimately selected (Table 1). From EDA data, the difference in the mean SCR amplitude between before and after the warning alarm occurrence (E1), the maximum amplitude after the warning alarm occurrence (E2), the mean SCR amplitude after the warning alarm (E3), and the mean SCR frequency after the warning alarm (E4) were selected as significant features for the prediction of inattentive behaviors. Mean pupil dilation before (P1) and after the waring alarm occurrences (P2) were selected as important features of pupil data. The difference in the mean saccadic velocity between before and after the warning alarm occurrence (S1), the mean saccadic velocity after the warning alarm (S2), the peak saccadic velocity after the warning alarm (S3), and the mean saccadic duration after the warning alarm (S4) were selected from saccadic eye movement data. Lastly, the number of exposures to the approaching hazard (C1), and participants' familiarity with VR technology (C2) were selected from among the contextual features.

4.4. Statistical analysis

Prior to conducting the behavior prediction, statistical analyses with all selected features were performed to evaluate the significance of differences in biosignals between two types of behaviors. The magnitude of reactivities in biosignals when participants showed inattentive behaviors was compared to that when they exhibited attentive behaviors. For further analysis of the effect of accident occurrence during the experiment on reactivities in biosignals, the data from all participants were separated into two groups according to the occurrence of the VR-simulated accident: (1) the Non-accident group (NAG)—participants who did not engage in the accident, and (2) the Accident group (AG)—participants who engaged in the accident during the experiment. A two-way Analysis of Variance (ANOVA) was performed to examine the main and interaction effects of participants' inattentive behaviors and accident occurrences on biosignal reactivities. Post hoc analyses were conducted with Bonferroni corrections for multiple comparisons. The equality of variances was checked with Levene's test [107,108]. Since pupil dilation data and saccadic duration data did not meet the assumption of the normal distribution, a non-parametric test, the Mann–Whitney *U* test, was performed to examine the significant difference in pupil dilation and saccadic duration between two types of behavioral responses (i.e., non-checking and checking behaviors) at $\alpha = 0.05$.

Table 7
Prediction performance depending on the modality of biosignals.

Modality	With biosignals			
	UAR	Recall for each class		F1 Score
		Non-checking	Checking	
EDA	0.548	0.541	0.552	0.557
Eye	0.637	0.590	0.662	0.646
EDA + Eye	0.679	0.656	0.692	0.677
EDA + Context	0.630	0.652	0.619	0.638
Eye + Context	0.699	0.698	0.700	0.698
EDA + Eye + Context	0.722	0.705	0.731	0.730

Note: EDA = EDA data (E1, E2, E3, and E4); Eye = Pupil data (P1, and P2), and Saccadic eye movement data (S1, S2, S3, and S4); Context = Contextual features (C1, and C2)

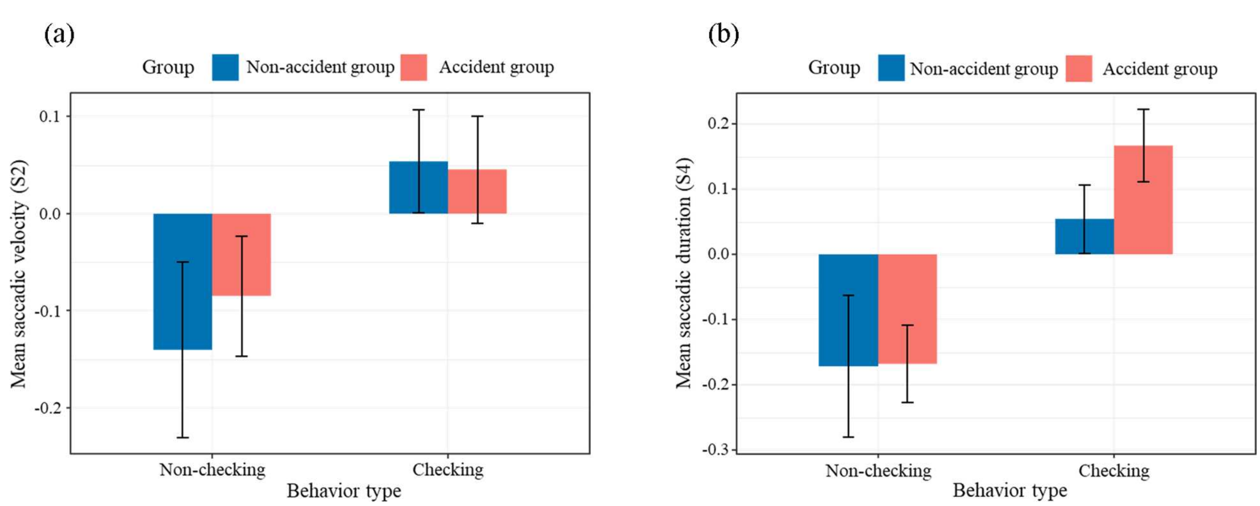

Fig. 4. Analysis of biosignal reactivities in the two types of behavioral responses. Standard error bars are included: (a) Depiction of mean saccadic velocity after the warning alarm (S2) by non-checking behaviors vs. checking behaviors; (b) Depiction of mean saccadic duration after the warning alarm (S4) by non-checking behaviors vs. checking behaviors.

4.5. Classification

A support vector machine (SVM) with linear kernel function was used for the supervised machine learning due to its strength in handling classes of imbalances [109,110]. During the experiment, participants' responses to the approaching hazard were not controlled. Therefore, the number of samples in each behavior class was unevenly distributed. The number of checking behaviors (n = 642) was almost twice the number of non-checking behaviors (n = 339). The number of non-checking behaviors (i.e., inattentive behaviors) was relatively small. The SVM weights minority classes by increasing the penalty for misclassifying minority classes to prevent them from being overwhelmed by the majority class [110]. In particular, the SVM performed better than decision tree and random forest, which are well known for their interpretability and accuracy in the binary classification (see Table A1 in the Appendix). An inattentive behavior prediction was performed using the data from each modality of biosignals. Then, to improve the behaviors' prediction performance, an additional inattentive behavior prediction was performed with classification models, which were trained on the data from multimodal biosignals. Lastly, to boost the classifier's performance, contextual features (including the number of exposures to the hazard [C1] and participants' familiarity with VR [C2]) were included as input features in the prediction model, and the prediction was conducted. The performance of the prediction was scored using the unweighted average recall (UAR) [111]. The presented UARs were averaged over 10 runs with 10-fold cross-validation classification in each combination of biosignals.

5. Results

A total of 981 samples (481 samples from the first session, 515 samples from the second session) were collected through the experiment. Participants were exposed to the struck-by hazard on average 18 times ($M = 17.73, SD = 3.75$) in the first session, and on average 19 times ($M = 19.07, SD = 3.13$) in the second session. Of the 981 samples, 339were labeled as inattentive behavior (i.e., non-checking behavior), and 642 samples were labeled as attentive behavior (i.e., checking behavior). During the experiment, participants who showed frequent inattentive behaviors experienced the VR-simulated struck-by accident (i.e., AG), and other participants, who continuously paid attention to the hazards, did not experience the simulated accident (i.e., NAG) (Table 2).

5.1. Statistical analysis: Biosignal reactivities and inattentive behaviors

The two-way ANOVA analysis was performed because the result of *t*-test comparison did not indicate a significant difference in mean SCR amplitude after the warning alarm (E3) between non-checking behaviors and checking behaviors; $t\ (979) = 0.33$, $p = 0.74$. The result of the two-way ANOVA analysis is presented in Table 3 and Fig. 2. While the ANOVA analysis did not reveal any significant main effect, the interactional effect between hazard checking behaviors and accident occurrence approached a significant level ($F(1, 977) = 3.719$, $p = 0.054$). To explore how the accident occurrence affects the participants' behaviors at the level of mean SCR amplitude, a simple effect test was performed (Table 4). The result approached a significant level ($F(1, 977) = 3.056, p = 0.080$). The results of the ANOVA analysis indicate that NAG had higher values of mean SCR amplitude when they engaged in checking behaviors in response to the approaching hazards, compared to when they failed to engage, but AG did not present much difference in SCR amplitude values between attentive and negligent behaviors. This indicates that NAG has demonstrated a relatively higher level of attentiveness towards warning signals and may contribute to the behavioral consequences each group experienced (safe operation versus accident engagement).

The analysis results of mean pupil dilation (Fig. 3) are in accordance with those of mean SCR amplitude. There was no significant difference in pupil dilation between the two types of behavioral responses, $U = 103556$, $p = 0.21$). Thus, the Mann-Whitney U test was performed for each group. The results confirmed that NAG had higher values of pupil dilation for checking behaviors ($Mdn = 0.100$) than for non-checking behaviors ($Mdn = 0.024$), $U = 11989, p = .052$, while AG did not present any significant difference between non-checking (Mdn = -0.012) and checking behaviors (Mdn = 0.050), $U = 39142, p = .405$. This also indicates that NAG may have exercised heightened levels of attentiveness toward warning signals as compared to AG.

The results of the two-way ANOVA analysis on mean saccadic velocity and mean saccadic duration, on the other hand, indicated that AG and NAG shared similar patterns of saccadic movements (Table 5 and 6, and Fig. 4). Both groups had significantly higher values of saccadic velocity and duration when they engaged in checking behaviors, which may be largely because subjects initiated checking behaviors during the time window taken for feature computations (10 s after warning signals). The results of direct comparison analyses (*t*-test) also confirmed that saccadic velocity and duration differed significantly between non-checking behaviors and checking behaviors (p = .013 and p < .001, respectively). On the other hand, the statistical analysis results of features E1, E2, E4, P1, S1, S3, C1, and C2 did not indicate any significant relationship.

5.2. Inattentive behaviors classification

The results from the classification of biosignal data between checking behavior and non-checking behavior classes are provided. The performance of each modality and combinations of biosignals is illustrated in Table 7. The UAR yielding from the EDA data was close to chance accuracy (i.e., 50%). The UAR from the eye data (including pupil dilation and saccadic eye movement features) also exhibited a relatively low performance (i.e., 63.5%) for classifying inattentive behaviors. However, the combination of EDA and eye data yield a statistically meaningful increase in the UAR (i.e., 67.9%). The results indicate the potential of combining multimodal biosignals to enhance prediction performance. Furthermore, a significant increase in UAR is achieved by including context variables. When contextual features are used in combination with all modalities to predict inattentive behaviors, the UAR was 72.2%, the best performance across all settings.

6. Discussion

Recent studies have demonstrated the potential of monitoring biosignal reactivities to predict near-future or subsequent behaviors [112–114]. However, a dynamic and hazardous construction environment poses challenges to objectively monitoring construction workers' biosignals and their physical engagement in inattentive behaviors while performing construction tasks. Therefore, this study examined the potential of using multimodal biosignals in predicting workers' inattentiveness to workplace hazards using a VR environment. Through the statistical analyses, significant differences in biosignals were identified. Several features (E3, P2, S3, and S4) extracted from the biosignals showed higher levels of reactivity when participants engaged in attentive behaviors as compared to inattentive behaviors. In addition, the accuracy (72.2%) of inattentive behavior classification using these features is quite comparable to the accuracy (ranging from 50% to 82%) of previous studies that attempted to predict human intent based on biosignals [42,97,115–118]. Furthermore, the prediction accuracy increased when multimodal biosignals were used compared to when each modality data was used separately. This result indicates that the contextual information about how often construction workers have been exposed to workplace hazards helps increase the prediction performance. Consequently, the outcomes of this study revealed that workers' physical engagement in inattentive behaviors to repeatedly exposed approaching hazards can be predicted by using biosignals collected immediately after warning signals are given.

At a construction site, the ability to predict workers' decreased alertness can greatly benefit construction safety efforts. Specifically, biosignal-based inattentive behavior prediction will enable the closed-loop warning/feedback system that measures human activities (both biosignals and physical movements) and automatically activates an intervention (e.g., warnings or feedback) when workers' inattention is detected. The activated intervention is then terminated when workers exhibit attentive behaviors, thus closing the loop [119,120]. In road construction/maintenance work zones, current warning alarms associated with construction vehicles do not consider workers' perceived risk levels or alertness and thus generate redundant alarms [1]. This can result in alarm fatigue, which distracts workers' attention to hazards and leads to workers' inattentive behaviors and habitual ignorance of surrounding hazards [1]. In this regard, a closed-loop warning/feedback system driven by the assessed inattentiveness of workers (e.g., providing warning alarms or feedback only when a worker shows inattentiveness, and stopping warning alarms when workers' attentiveness is recovered) may help reduce workers' habituated inattention at construction sites, thereby reducing workers' engagement in inattentive behaviors. Consequently, the biosignals-based inattentiveness prediction holds the potential to save human lives, and reduce costs and time needed to monitor workers' inattentive behaviors at construction sites. Furthermore, the patterns of biosignal reactivities to the presented hazard can vary according to an individual's attentional capacity. Thus, the outcomes of this study could be used to identify individual workers' response patterns to workplace hazards. Based on the identified patterns, a personalized prediction model can be developed and deployed for tailored safety interventions. Future studies will examine the feasibility of developing a personalized inattentive behavior prediction model.

Some limitations of this study should be noted. First, all of the participants were undergraduate and graduate students. Thus, the biosignal reactivities in response to exposed hazards might differ from those exhibited by experienced construction workers. Second, some sample data may include participant checking behaviors that had already occurred within 10-seconds of the data window period, which may have affected the prediction performance. Third, during the experiment, the participants were divided into two groups depending on the occurrence of the virtual accident that resulted from a participant's frequent engagement in inattentive behaviors: vigilant participants (NAG) and inattentive participants (AG). The 11th time that a participant demonstrated inattentive behavior was used to provoke the virtual struck-by accident and determine participants' inattentiveness. Although the 11 instances of ignorance function as a reference point that is somewhat arbitrary, it exceeds 50 percent of the total number of exposures and is reflective of a participant's frequent inattention to the approaching hazard in the experiment. Therefore, the 11 occurrences of engagement in non-checking behaviors provides a proxy for an individual's inattention to the repeatedly presented hazard. Future studies will be required to determine an optimal reference point that better explains individuals' inattentiveness. Fourth, some participants experienced the accident as a result of their behavioral responses during the experiment. Although experiencing the accident during the first session may have affected participants' behavioral/physiological responses during the second session, that phenomenon was not investigated in this study. During the next phase of this study, an association between the simulated accident experience and a change in participants' inattentiveness to repeatedly exposed hazards will be examined. Lastly, the findings of this study may be somewhat limited by the laboratory conditions: employing a VR environment. In a real environment, it is difficult to observe workers' inattentive behaviors in response to frequently exposed workplace hazards. For this reason, we exposed participants to the repeated struck-by hazard in a virtual environment. Further validation in field experiments is warranted.

With regard to practical application of the proposed approach, a technology or device that senses the occurrence of warning alarms can be integrated with the proposed biosignal-based inattentive behavior prediction. For example, an internet of things (IoT) safety helmet that is equipped with sensors detecting auditory warning alarms and sensing workers' biosignals can be developed. The IoT safety helmet would capture biosignals when a warning alarm is detected and analyze workers' inattentiveness. Then, it would provide feedback only when workers' inattentive behaviors are predicted, thereby mitigating workers' habituation resulting from redundant alarms in a workplace. However, the integration of these technologies and a proposed inattentive behavior prediction method was not considered in this study. It could be investigated in future studies.

7. Conclusion

This study investigates the usefulness of biosignal data collected using wearable biosensors and a VR environment in preventing fatalities and injuries at construction sites. The findings help explain the association between reactivities in multimodal biosignals and inattentive behaviors. A laboratory experiment was conducted using a virtual environment, and a total of 981 behavior and biosignal samples were collected. Using stepwise future selection, 12 features were identified to predict inattentive behaviors. The results of the statistical analysis indicate an association between reactivities in biosignals and inattentive behaviors. When participants demonstrated inattentive behaviors, the reactivities in some biosignals were lower than when participants exhibited attentive behaviors. There was a significant difference in the mean saccadic velocities ($p = .013$). The mean saccadic duration of non-checking behaviors was lower than for checking behaviors ($p < .001$). Specifically, NAG showed higher mean SCR amplitude ($p = 0.08$) and pupil dilation ($p = 0.052$) when workers exhibited checking behaviors than when they engaged in non-checking behaviors. However, there was no significant difference in AG. This implies that NAG revealed larger reactivities in biosignals in response to repeatedly presented warning signals than AG did, and such a high level of attentiveness may associate with more frequent engagement in safe behaviors. The findings also indicate that adopting multimodal biosignals for inattentive behavior prediction can effectively enhance the prediction accuracy to 72.2%, which is quite competitive compared to studies in other domains that used biosignals to predict human behavior. This demonstrates that workers' inattentive behaviors can be predicted by monitoring reactivities in workers' biosignals to repeatedly exposed workplace hazards during a work task. Consequently, the outcomes of this study lay the groundwork for future research on how construction workers' inattentive behavior—the attentional consequences of habituation to repeatedly exposed hazards—can be predicted by monitoring workers' biosignals. The proposed computational approach could potentially change the current strategy for the observation and prevention of workers' unsafe behavior from a manual and direct observation to an automated sensing method using biosignals. Furthermore, the findings of this study, while preliminary, suggest that using VR as an experimental tool can be effective in examining construction workers' behaviors in hazardous working environments.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

(see Table A1)

Table A1
Prediction performance depending on the classifier.

Modality	Classifier	UAR		Recall for each class	
		Avg.	Std.	Non-checking	Checking
EDA + Eye + Context	SVM with linear kernel	0.722	0.001	0.705	0.731
	SVM with gaussian kernel	0.720	0.001	0.698	0.730
	SVM with polynomial kernel	0.718	0.002	0.681	0.737
	Decision Tree	0.648	0.003	0.507	0.726
	Random Forest	0.736	0.002	0.434	0.896

Note: EDA = EDA data (E1, E2, E3, and E4); Eye = Pupil data (P1, and P2), and Saccadic eye movement data (S1, S2, S3, and S4); Context = Contextual features (C1, and C2)

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