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Re-assessing hazard recognition ability in occupational environment with microvascular function in the brain

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ABSTRACT

Hazard recognition (HR) is a critical process for safety management in the complex and dynamic occupational environment. Although previous studies have attempted to quantify hazard recognition ability (HRA), the results are potentially optimistic because of limitations in their experimental settings and/or single data collection channels. This study aims to re-develop a compound HRA index that incorporates microvascular function in the brain. First, the authors identify critical indicators of HR and design an experiment to be conducted in a real scene. Data are then collected through questionnaires (experience and risk tolerance), eye-tracking devices (eye movement), and near-infrared spectroscopy. Finally, discriminant analysis is applied to develop an HRA index. The prediction accuracy of the proposed HRA index is shown to outperform previous approaches. Theoretically, this research signals a new perspective (changes in hemodynamic properties of the prefrontal cortex) in the assessment of HRA. The proposed HRA index can be used for onboard assessment of workers or safety inspectors, reducing human errors and undetected occupational hazards.

1. Introduction

Generally, complex and dynamic workplaces form a hazardous occupational environment. Hazard recognition (HR) provides an opportunity for risk elimination in workplace safety (Bahn, 2013; Perlman et al., 2014). However, up to 57% of hazards may remain unrecognized on construction sites (Carter and Smith, 2006; Bahn, 2013; Albert et al., 2014; Perlman et al., 2014; Albert et al., 2018). Recently, human factors have received considerable attention as a means of addressing poor HR performance, with researchers finding that more than 70% of jobsite accidents were attributable to unsafe behavior. According to Tixier et al. (2013), rather than deliberate violations, these unsafe behaviors result from insufficient hazard recognition ability (HRA). Hence, as a proactive management method, HR is regarded as a necessary ability for both managers and employees (Quinlan and Bohle, 1991; Bahn, 2013).

Despite considerable efforts to improve workplace safety, the process of HR remains the main barrier to safety management. In other words, deficient knowledge about HR restricts the effect of a multitude of safety measurements. Previous research has demonstrated that a large number of the proposed interventions, e.g., safety training and safety checklists, were designed without appropriate comprehension of the HR process (Rozenfeld et al., 2010; Albert et al., 2018). To be specific, managers are confronted with a predicament in that the way in which risks are perceived affects how they are managed, which ultimately affects the organizational safety performance (Fung et al., 2010). It has been suggested that training has become routine and is no longer fit for purpose because of the training methods (Kushiro et al., 2017). Referring to previous training methods, Namian et al. (2016) disagreed with the assumption that workers have the ability to visualize future tasks and predict expected hazards. They emphasized the difficulty of applying knowledge to basic HR. The most important reason why current training practices are ineffective is the inferior conjunction of the safety training design and workers' inability to recognize hazard prompts (Jeelani et al., 2016; Albert et al., 2018). Moreover, Chen et al. (2016) noted that risk assessment through task complexity and individual proficiency is not cogent because of individual differences. They considered a quantitative method essential to identify vulnerable workers rather than merely serious hazards.

This dilemma implies the necessity of identifying the factors that impact HRA and how their effects are transferred. With an effective HRA index, the mechanism delineating the cognitive process of HR could be explicitly illustrated.

In fact, many researchers have attempted to address poor HRA from a cognitive perspective, and numerous studies have been conducted to explore the indicators that are prominently correlated with HR. For

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instance, the most compared groups are novices and veterans (Kushiro et al., 2017), and several researchers have proposed prediction methods to identify workers subjected to ineffectual HRA. Hasanzadeh et al. (2017b) used three eye-movement metrics for HRA prediction, namely the dwell percentage, fixation count, and run time. The discriminant function derived in their study can provide HRA prediction accuracy of up to 66.7%. Albert et al. (2018) undertook a similar task using eight visual search metrics (e.g., search duration, fixation count), and established eight linear regression models. Although the results of these studies certified the predictive power of the eye-movement metrics, there is substantial vulnerability in current methods. Firstly, image-based hazard detection experiments overlooked a large amount information released from the jobsite environment. Secondly, the onefold utilization of eye-movement metrics reveals amphibolous and labile illustrations of the decision-making phase of HR. Finally, the hazard classification methods used to distinguish different search strategies are either vulnerably related to the intrinsic cognitive process or have low robustness and lack a quantitative standard. Details of these defects are provided in the next section. All these deficiencies connote a redesign of the HRA index and a potent experimental arrangement.

Accordingly, this study addresses the need to establish an effective HRA index and predict the jobsite HRA. To conquer the aforementioned deficiencies in previous research, the authors designed an experiment based on a real-world inspection of the civil laboratory of Tsinghua University, as a simulated construction site, in which participants searched for hazards spontaneously. During the inspection, a portable near-infrared spectroscopy (NIRS) device and an eye tracker were employed to record the cognitive features of the visual search process. This is the very first attempt to engage this state-of-the-art instrument, i.e., the NIRS device, into safety management research. Reassuringly, the results demonstrate the necessity of this approach. Moreover, the authors classified the search tasks according to the visual clutter of the scene containing the hazard, which proved to be a valid classifier regarding the cognitive load (Liao et al., 2017; Sun et al., 2018). The results of the subsequent multivariate analysis of variance (MANOVA) verify the correlation between the indicators and HRA. The follow-up discriminant analysis shows that the proposed HRA index is suitable for HRA prediction, achieving an accuracy of up to 74.1%. Conclusively, the HRA index contributes to effective HRA prediction. Furthermore, for a detailed interpretation, this study reveals the different search strategies used across the visual clutter levels and among the HRA groups. Such conclusions could serve as a reference for the future design of safety interventions.

2. Literature review

2.1. Research gaps in real-time monitoring

2.1.1. Nonconformity of image-based experiments with real-time HR tasks

The first defect in previous experiments concerns the image-based simulation of HR tasks. Numerous researchers have conducted simulation experiments to explore the cognitive process of HR, with some creating a digital construction site to replicate hazards. Dzeng et al. (2016) implemented an experiment based on a site model using the Google Sketchup software to compare hazard search patterns between experienced and novice workers. Nevertheless, many studies have used planar stimuli to display jobsite scenarios for the HR task, such as images and videos. For instance, to detect at-risk workers, Hasanzadeh et al. (2017b) selected 35 images as experimental stimuli from a scenario image pool. Similarly, Pandit et al. (2019) used 16 case images depicting diverse construction operations to explore the impact of the safety climate on HR. Additionally, Kushiro et al. (2017) asked participants to detect risks while watching site videos and examined the effectiveness of a video-based training tool. Two-dimensional materials have many merits, such as a controllable inspection process, fixed visual angle, and unified view of the horizon. These features make subsequent data analysis very convenient. However, image-based tasks are substantially different from how the hazards are perceived on construction sites (Borys, 2012). Some differences are inevitable regarding the expression of dynamic and intricate scenarios and surroundings such as weather, noise, diverse tasks, and equipment (Rowlinson et al., 2014; Kushiro et al., 2017). This might induce different search strategies from practical HR. For instance, Perlman et al. (2014) found that risk recognition and perception can be improved using a virtual construction site rather than pictures. The associated dimensionality reduction would lead to information shrinkage and changes in the cognitive process. Thus, it will inevitably induce disparity for the comprehension of HR.

Therefore, seeking an authentically simulated site is vital for experiments toward an HRA index. This study strives to imitate a construction site in a civil laboratory, which is extensively consistent with the jobsite concerning potential hazards. Moreover, the laboratory is rather static, with a constant situation maintained as the holistic experiment continues for several days. This guaranteed that the experimental settings were the same for each participant.

2.1.2. Eye-tracking metrics: limited power for explanation

Another research gap lies in the monotonous utilization of eye trackers. Eye-tracking devices, which are excellent at measuring eye position and movement, are attracting increasing attention in state-of-the-art studies on HR. This is because HR is believed to be a visual search task, and the oculomotor features are known to correlate with the allocation and shift of visual attention (Dzeng et al., 2016; Albert et al., 2018). In these studies, fixations and saccades are the two primary eye-movement events employed to illustrate the visual search patterns (Crundall and Underwood, 2011). Saccade and fixation location indicate the focal orientation of the eye and the allocation of attention. Additionally, fixation duration demonstrates cognitive interest as well as difficulty. A long fixation duration demonstrates that the observer is either attracted to or confronted by an obstruction in a certain area. This would undoubtedly lead to an inconclusive correlation between the HRA and fixation measurement. Precisely, Hasanzadeh et al. (2016) reported a shorter dwell time in the areas of interest (AOIs) for workers with high levels of situation awareness. In contrast, Albert et al. (2018) asserted that those who recognized more hazards spent more time examining the workplace as well as the hazard itself. Albert et al. (2018) illustrated that personalized training could elevate HRA scores for a relatively constant fixation duration. Additionally, Indrarathne and Kormos (2017) found that the relationship between fixation duration and working memory factor score differed significantly in various memory conditions. Liao et al. (2017) reported no significant relationship between HR accuracy and fixation duration. These paradoxical conflicts suggest that the mere employment of eye-movement metrics is deficient for predicting HRA. A metric that is strongly related to the cognition performance is a requirement for the HRA index.

2.1.3. Insufficient hazard classification methods

For the subsequent analysis, researchers believe that diverse visual strategies should be employed when searching for various types of hazards. Accordingly, they have classified hazards into several groups. Many prefer to classify hazards according to injury type. For instance, Dzeng et al. (2016) mimicked hazards regarding accidents such as falls, collapses, and electric shocks in the Sketchup model. Such classification methods were also used by Hasanzadeh et al. (2017b) and Perlman et al. (2014). Simultaneously, the underlying causes of the hazards were widely used to classify the hazards. Namian et al. (2016) classified hazards into radiation, gravity, chemical, pressure, temperature, and so on, and Pandit et al. (2019) displayed hazards in the same way. Although there are differences between the HR strategies observed across the hazard groups, the classification methods show a weak association with the HR process. For hazards associated with a certain injury, the scenes may differ so much that the various levels of detection complexity would involve disparate visual search processes. In contrast, some researchers used classification methods pertaining to the difficulty of detection. The typology of hazards used by Bahn (2013) consists of several categories, including obvious and hidden. A similar scheme was used by Dzeng et al. (2016). Despite efforts to address the connection between the typology and cognitive process, such classification methods are qualitative and difficult to reproduce. The task difficulty varies according to the knowledge, experience, and other individual factors of the judge.

On the basis of the above, this study utilized visual clutter for hazard classification. Visual clutter quantifies the distractors in the scene that cause visual interference. Several studies have determined that visual clutter negatively affects visual search ability (Schmieder and Weathersby, 1983; Ji et al., 2010; Doyon-Poulin et al., 2014). As for HRA, Liao et al. (2017) and Sun et al. (2018) reported cognitive discrepancies in HR under different visual clutter levels. Thus, it is important to take visual clutter into account for hazard typology.

2.2. Index development

2.2.1. Visual search performance from a cognitive view

To establish the HRA index, it is important to identify the indicators that help to predict HRA. To probe the indicators affecting HRA, the authors reviewed the literature on the indicators demonstrating visual search ability. HR is well acknowledged as a visual search task (Jeelani, 2016; Liao et al., 2017; Sun et al., 2018), and previous research has shown the interrelationship between visual search strategies and HRA (Geoffrey et al., 2010; Hasanzadeh et al., 2017b). Thus, it is feasible and valid to analyze the HRA indicators associated with visual search.

Generally, the process of visual search is separated into search and decision stages (Drury, 1975; Spitz and Drury, 1978; Liao et al., 2017). In the search phase, the observer seeks a suspected item of potential hazard. The observer then turns to the next phase to determine whether the item is the target or not. The current study identifies hazard indicators based on this search–decision model.

2.2.2. Indicators for the search phase

As mentioned above, eye-tracking devices are typically used to monitor oculomotor behavior. When introduced to an unacquainted situation, the observer has to glance and scan the scene and find the potential target. The saccade-related metrics recorded by the eye tracker can determine the efficiency of the search phase. As for the specific metric employed, some researches have used the fixation percentage to measure the attention allocation for the search and decision phases. Liao et al. (2017) reported the significant influence of fixation time percentage on the detection accuracy. However, Albert et al. (2018) found no significant changes in either fixation count percentage or fixation time percentage. Explaining this result, they argued that the magnitude of both fixation count and fixation time in AOIs increased, although the total amounts of fixation count and fixation time also increased accordingly. Therefore, this study employs the time to first fixation in AOIs to represent the search efficiency. Time to first fixation is the time spent on the distractors before the participant first perceives the target hazard. Hasanzadeh et al. (2017a) found that experienced workers spent less time on the distractors before they initially fixed on the target hazard. Time to first fixation is also monitored to verify its capacity to predict HRA.

2.2.3. Indicators for the decision-making phase

Regarding the decision-making phase, researchers typically consider fixation metrics in AOIs. However, as mentioned above, the results of the fixation metrics differ significantly because of their complexity. Efforts have been made to develop other methods for measuring the cognitive performance in the decision phase. It is noteworthy that Chen et al. (2016) equipped participants with wearable electroencephalography (EEG) safety helmets to collect neural information while executing HR tasks. They found a significant correlation between hazard perception and mental workload. This inspires us to focus on the vital signs as a proxy for the decision phase. Even so, methodologies such as EEG and functional magnetic resonance imaging (fMRI) constrain the body movements. In turn, although new EEG instruments are portable, the setup time and susceptibility to motion artifacts lead to discrepancies and unstable results (Ayaz et al., 2012). In contrast, the cerebral oxygen metabolic activities recorded by NIRS devices have recently attracted interest in the discipline of driving behaviors (Derosiere et al., 2014; Liu, 2014; Orino et al., 2015; Bruno et al., 2018). As the cognitive process of HR is analogous in part to driving behavior, NIRS has the potential capacity for measuring the decision process. Here, a brief introduction about the NIRS tool as a potential method for HRA prediction is provided.

NIRS is a noninvasive brain imaging technology that quantifies changes in hemodynamic properties such as oxygenated hemoglobin (Oxy-Hb), deoxygenated hemoglobin (Deoxy-Hb), and total hemoglobin (T-Hb) in the brain. Specifically, an increase in Oxy-Hb and a concomitant decrease in Deoxy-Hb are indicators of neural activity (Hoshi, 2010). The NIRS device has high temporal resolution of up to 10 ms, is portable, and can tolerate certain motion artifacts (Liu et al., 2016). Similar to EEG, it can concentrate on certain regions of the brain through laser emitters and probes, and enables an exploration of cerebral activity (see Liu et al. (2016) for the detailed mechanism). In terms of driving safety, the prefrontal cortex (PFC) was the most active region, as indicated by concentration changes of Oxy-Hb (Tomioka et al., 2009; Tsunashima and Yanagisawa, 2015). Other encephalic regions, such as the parietal lobule (PL), were also found to be essential, but partially labile (Schall et al., 2007). Accordingly, driving research regards PFC as the vital region for cognitive safety processes. In additional, Oxy-Hb is often assessed because it is highly sensitive to regional cerebral blood flow, and thus illustrates cortex activity.

Besides physiological indicators demonstrating cognitive strategies, there is another individual factor that significantly affects decision-making, namely risk tolerance. In Woodcock's (2014) safety inspection model, it is critical for an inspector to decide whether to report the recognized hazard by asking him/herself "Is the hazard tolerable?" Woodcock found that experienced inspectors were more tolerable to risks, and would thus mark the hazard as "accept but monitor." Lichtenstein et al. (1978) pointed out that overconfidence in the ability to control accidents leads to an underestimation of hazards. Wang et al. (2016) noted that risk tolerance is one of the main reasons for unsafe behaviors. Hence, it is necessary to take risk tolerance into account for HRA prediction.

2.2.4. Experience affecting both phases

Experience is a potential indicator for HRA that affects both the search and decision phases (Schuster et al., 2013; Hout and Goldinger, 2015). Numerous studies have reported that experienced workers performed differently from novices in various aspects of visual search tasks, such as flexible visual scanning patterns (Hosking et al., 2010), reduced search time (Nodine et al., 2002), comprehension of auditory cues (Duffy, 2003), risk perception levels (Shin et al., 2014), and dealing with uncertainties (Woodcock, 2014). Therefore, experience is a potential predictor of HRA. Woodcock (2014) concluded that experienced inspectors could take advantage of knowledge derived from training, documented reports, and discussions with other inspectors. Similarly, Ericsson (2017) explained that experience is accumulated through training and deliberate practice. In addition, research has shown that familiarity with a task would induce degradation in risk perception ability (Zimolong and Elke, 2006). Previous studies on the acquisition of experience serve as references for the experience metric used in this study.

In summary, previous studies fall short in certain aspects, and thus, a broad range of measures is needed. This requires consideration of

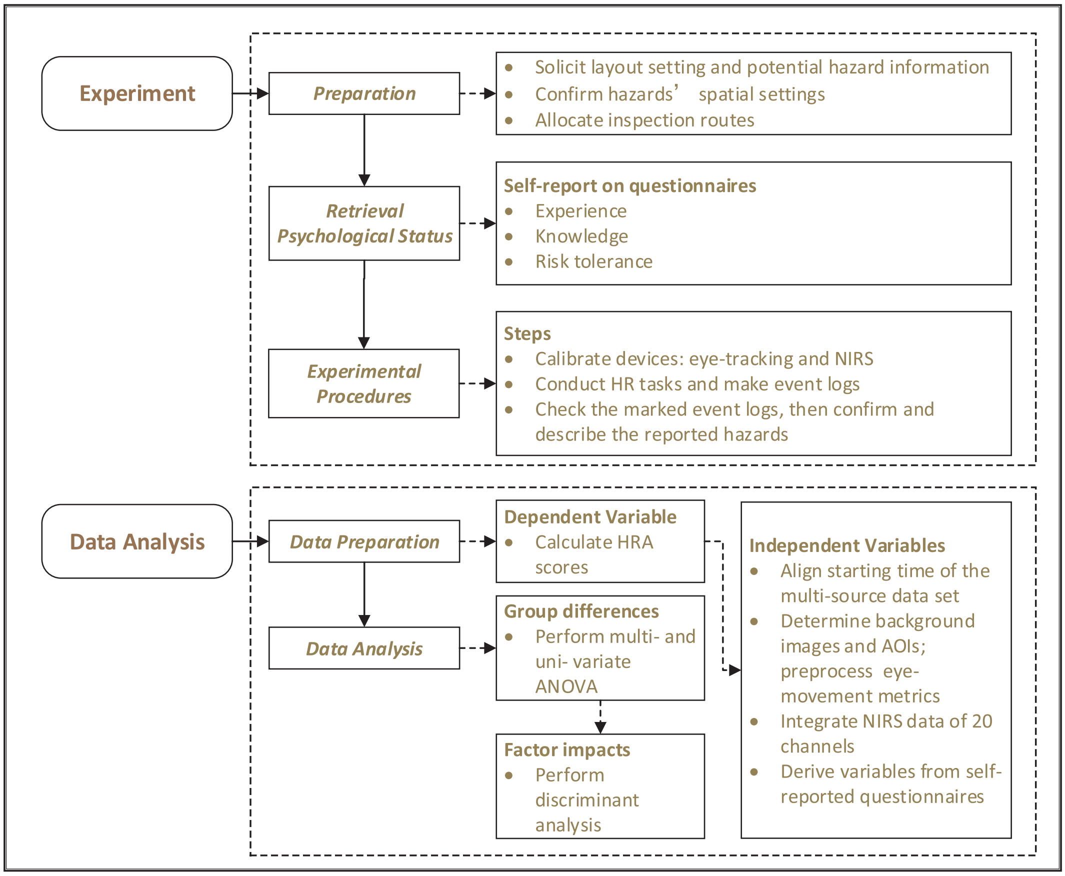

Fig. 1. Research framework.

both the search and decision phases, involving a hybrid system based on multimodal indicators for more robust performance (Yang et al., 2010; Dong and Hu, 2011). Concurrently, the literature review suggests an experiment based on real-world inspection tasks and a hazard classifier directly associated with the cognitive process. Based on these requirements, this study establishes an HRA index including metrics for both eye-tracking and NIRS devices, as well as a self-reported questionnaire.

3. Methodology

3.1. Research framework

As shown in the research framework in Fig. 1, this study was performed in two sections. First, an experiment based on a real-world HR task was designed and conducted using portable eye-tracking equipment and NIRS devices. Subsequently, MANOVA and discriminant analysis were employed to determine the impact of each indicator on the HRA.

3.2. Participants

Forty-eight civil engineering students were invited to participate in this experiment. This sample size is considered sufficient for eye-tracking and NIRS studies (Bonetti et al., 2019; Pernice and Nielsen, 2009). The sampling scale was constrained to civil engineering students to ensure that all subjects possessed a general perception of construction safety risks. Overall, their uncorrected or corrected visual acuities were normal, and they were all in good neurological and cardiovascular health. Additionally, each had acquired safety training about the civil laboratory on his or her entrance to the college. No participants reported relevant injury experience in the laboratory.

The participants were fully informed about the experimental protocol, and informed consent was obtained before participation. They received some financial compensation for taking part in the study.

3.3. Experimental conditions: simulated jobsite settings

Approved by the department of civil engineering, the experiment was conducted in the civil engineering laboratory during a holiday period, when no one was working in the laboratory. The laboratory was chosen for several reasons. First, the hazards on the jobsite should be consistent with those on a construction site. Second, stationarity of the site condition is necessary for the experiment. Thus, an actual construction site is not appropriate because of the ongoing work and variability. The civil laboratory, however, can be kept in a consistent condition on weekends. Additionally, it can act as an imitation construction site with similar instruments and analogous hazards. The primary sources of hazard in the laboratory are the massive instruments, combustible materials, fall protection systems, and electrical equipment, which are similar to those on a real construction site.

The core of the jobsite arrangement is to certificate the hazards on the site and determine the route of the HR task to standardize the observation perspective. The authors invited two experts in charge of laboratory safety to participate in a pre-experiment. With high sensitivity of hazards and over 30 years' experience in the laboratory, the experts were asked to identify as many hazards as possible. Moreover, the risk checklist issued by the department and the university were applied to ensure that all potential hazards had been identified. Finally, nine hazards pertaining to various risk sources were confirmed as the experimental targets. Table 1 presents a description of the hazards.

The origin, terminus, and route were determined according to the experts' suggestions. The final route was shaped like an upside-down "U," with hazards distributed evenly on both sides of the passageway.

Table 1
Hazard types and descriptions.

No.	Type	Description
1	Fire prevention and control	Erroneous storage and preservation process of acetone
2	Electrical safety	Multiple electrical sockets connected in series
3	Fall protection	Obstacles in the passageway
4	Heavy equipment	Massive loading devices with sharp angles
5	Fall protection	Uncovered grooves on the ground threatening a fall
6	Electrical safety	Unprotected and unclosed electrical compartment
7	Fire prevention and control	Inaccessible fire hydrant covered with sundry objects
8	Struck-by	Vertical and unstable rebar without protection
9	Struck-by	Perilous pre-stressed component without protection and warnings

Additionally, participants were kept distant from some hazards and other hazards were either inactivated or protected, only used for display, to eliminate any potential injuries to the participants.

3.4. Devices

3.4.1. Eye-tracking device

The wearable eye-tracking devices utilized in this experiment were Tobii Glasses II, made in Sweden. These have a gaze sampling frequency of 100 Hz and scene camera recording angles, i.e., visual angle, of 82° (horizontal) and 52° (vertical). Wireless data transmission allows subjects to observe and move without restriction.

3.4.2. NIRS device

A 20-channel NIRS instrument (NirSmart, Huichuang Co., China) that generates near-infrared light at wavelengths of 760 nm and 850 nm was utilized to monitor the changes in optical density at a sampling rate of 12 Hz. This was subsequently converted into Oxy-Hb and Deoxy-Hb concentration changes. Six probes and ten emitters were placed side by side at intervals of 3 cm. They were configured evenly over the PFC regions of the subjects, as shown in Fig. 2. During the placement of the probes, the real-time signal intensity of each channel connecting the light source to the receiver was assessed and displayed by the software. When the signal quality was acceptable, a zero baseline was set, and the experimental protocol was executed.

3.5. Experimental design

The experiment was conducted in four steps. The time of each step was constrained, although the actual time consumption was subject-dependent. Generally, the experiment was completed in 25 min. The detailed time course of the four steps is presented in Fig. 3. To mark the time and place where a hazard was detected, the subjects were equipped with a laser pointer. They were asked to mark the hazards with the laser pointer only after they had completed the searching, confirming, and judging stages, and had decided to report the hazard. The time logs were marked once the subject used the laser pointer. After the HR task, the event logs of the recognized hazards recorded by the eye-tracking glasses were displayed and the subjects were asked to name the hazard for subsequent evaluation.

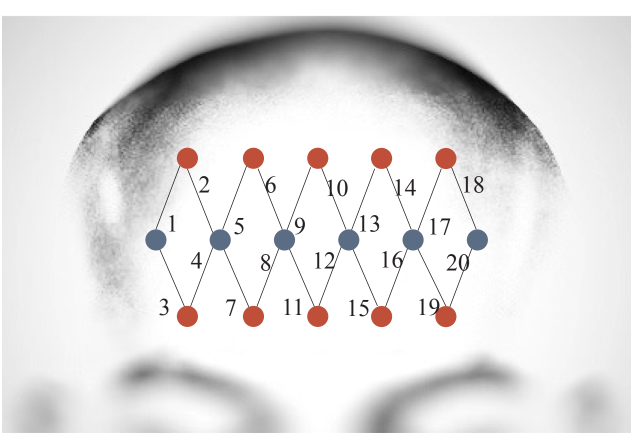

Fig.2. Probe and emitter arrangement. Note: Red points denote emitters; blue points denote probes. The full color version of this figure is available online. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

3.6. Measurements

3.6.1. Eye-movement data

The AOI metrics derived from the oculomotor data were analyzed to identify the cognitive features in the search phase. The crucial matter of data processing normalized the AOIs and determined the beginning and end of the event.

The Tobii Pro Lab software was employed to derive the eye-movement metrics, which automatically matches the gazes in the recorded video with a background photo. Further analysis of AOI metrics based on that photo can then be conducted. For a constant standard background photo, the authors selected the most common one from the video snapshots of each participant. The AOIs were defined according to the outlines of the recognized hazards drawn by each participant.

The beginning of the recognition process for a specific hazard was set when the item was first recorded by the camera. That is, the hazard was assumed to be ready for recognition when it appeared in the video. The end of the event was the time when the participant began to point out the hazard using the laser pointer.

3.6.2. NIRS data

The optical signals were filtered using a fourth-order digital low-pass Butterworth filter with a cutoff frequency of 0.1 Hz to remove the heart rate and respiration responses. Subsequently, movement noise was removed using the moving standard deviation and spline interpolation routines in Matlab 2017a. The oxyhemoglobin concentrations recorded over the 20 channels were then formed, and the average level for the search process of each hazard was calculated. As this study aims to explore the relationship between HRA and a series of physiological and psychological indicators, rather than focusing on the specified cortical regions activated during the process, the average level of the 20 channels was utilized to represent brain activity in the whole forehead area. The process of normalization was performed in the subsequent discriminant analysis.

3.6.3. Risk tolerance

To measure risk tolerance, researchers often use a self-reported assessment method based on questionnaires (Hunter, 2002; Wang et al., 2016). The eight-question scale is popular and is known to have good reliability (Wang et al., 2016). Specifically, eight hazard scenes were provided pertaining to common construction injuries, e.g., fall protection and electronic safety. The participants were asked “To what extent are you willing to accept the risk scenario?” and assigned a rating from

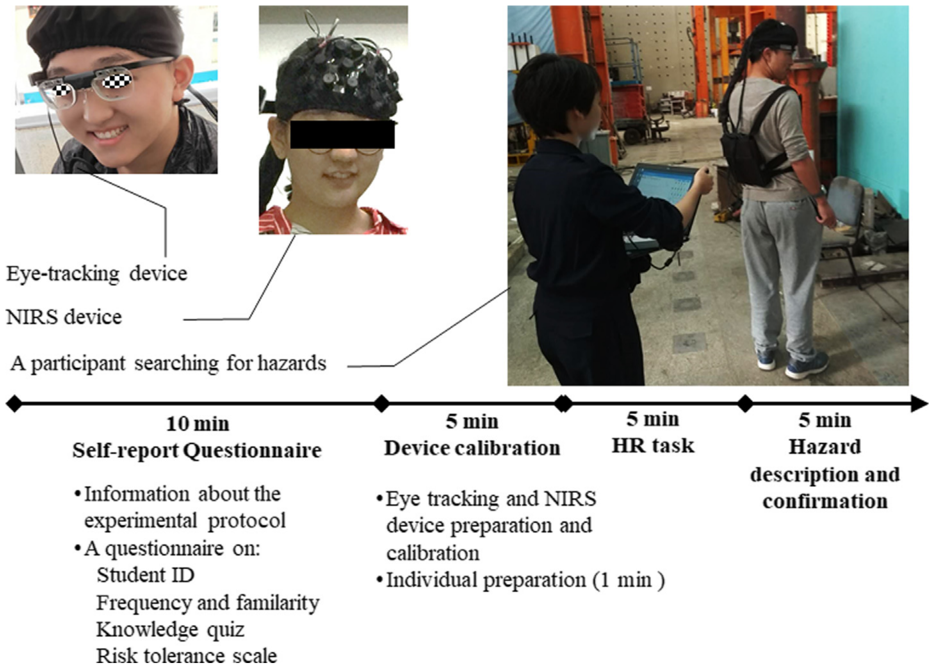

Fig. 3. Experimental protocol.

1 (totally unacceptable) to 5 (totally acceptable). The risk tolerance scale used by Wang et al. (2016) was translated into Chinese for this research. The scale data were demonstrated to meet the requirements of both reliability and validity. Cronbach's alpha was calculated at 0.824 (greater than 0.6) and, for the validity test, the Bartlett test of sphericity scored 173.676 with a significance level of 0.000 and the Kaiser–Mayer–Olkin measure of sampling adequacy was 0.754 (greater than 0.5).

3.6.4. Experience

The experience was measured using a multi-dimensional approach. The participants' major areas of study cover diverse realms. Thus, some of them conduct research in the laboratory quite frequently, whereas others seldom enter the room. Consequently, the comprehension of the lab, especially in terms of the potential hazards, differs among the subjects. Considering the factors influencing experience, the authors measured the subjects in terms of three aspects: (1) working frequency in the laboratory; (2) a self-reported assessment of the comprehension and familiarity with the laboratory hazards; and (3) for an objective evaluation of safety knowledge, a quiz comprising three questions selected from the Experimental Safety Test Library of Tsinghua University. Finally, the working frequency, laboratory familiarity, and knowledge quiz score were integrated into one indicator representative of experience.

3.6.5. HRA score

Initially, the individual HRA scores were calculated according to the number of correctly recognized hazards. Generally, 0–5 hazards were recognized. For discriminant analysis, the participants were divided into three groups according to their HRA scores, namely high, medium, and low groups.

3.6.6. Visual clutter

The visual clutter of the background images was calculated according to four indices (color, size, distinction, and orientation). A detailed illustration of the computation process is provided in the methodology section of Liao et al. (2017). With the exact value of visual clutter, the hazards were divided into three groups: high, medium, and low visual clutter groups (i.e., H, M, L). Subsequent analysis was conducted separately for each group.

3.7. Data analysis

3.7.1. ANOVa

ANOVA was used to determine any macroscopic discrepancies among the personal characteristics, eye movements, and NIRS metrics in different HRA groups. Both multivariate and univariate ANOVA were employed. Although this research is based on a small sample size, the number of samples exceeds the number of dependent variables. Thus, it fulfills the requirements of the method.

3.7.2. Discriminant analysis

Discriminant analysis was conducted to probe the HRA index for two main purposes. First, it was expected that the coefficients would reveal the impact of the indicators on the HRA. Furthermore, as an effective approach for classification and prediction, the derived functions could serve to predict HRA according to the person's characteristics and instrument metrics.

4. Results

4.1. Assumptions check

Several assumptions were checked before applying MANOVA and discriminant analysis, and no violations were found. (1) The samples were independent in each group as each participant only belongs to one HRA group. (2) The outliers were eliminated based on boxplots and Mahalanobis distances. (3) The normality of the data distribution was confirmed by Shapiro–Wilk tests. (4) The bivariate correlation between the dependent variables was significant according to Pearson correlation analysis. (5) No multicollinearity was present, with the variance inflation factor measured at up to 2.600 (< 3). 6) No homogeneous matrices were found by Box's M test, thus confirming the equality of the matrixes of variance and covariance.

4.2. Descriptive statistics

Several descriptive statistics are presented in Table 2. These

Table 2
Descriptive statistics.

Visual clutter groups	Indicators	Mean	Std. deviation	Minimum	Maximum
H	Experience	2.864	1.001	1.000	4.429
	Risk tolerance	1.574	0.464	1.000	3.125
	Time to first fixation	1.705	1.231	0.380	4.918
	Oxy-Hb	−0.058	0.194	−0.544	0.196
M	Experience	2.764	1.013	1.000	4.429
	Risk tolerance	1.528	0.380	1.000	2.625
	Time to first fixation	1.173	0.694	0.393	2.835
	Oxy-Hb	−0.004	0.245	−0.390	0.642
L	Experience	2.825	0.966	1.000	4.429
	Risk tolerance	1.558	0.458	1.000	3.125
	Time to first fixation	1.275	0.785	0.185	3.119
	Oxy-Hb	−0.052	0.267	−0.613	0.467

descriptive statistics are provided across visual clutter groups.

Specifically, the mean values of time to first fixation in the H, M, and L groups were 1.705, 1.173, and 1.275 with standard deviations of 1.231, 0.694, and 1.785, respectively. The corresponding mean values of Oxy-Hb were −0.058, −0.004, and −0.052 with standard deviations of 0.194, 0.245, and 0.267.

4.3. Visible differences between the HRA groups

Overall, the MANOVA results revealed significant differences between the HRA groups according to Wilks' Lambda. Table 3 presents the MANOVA results. In visual clutter groups H, M, and L, the p-values of Wilks' Lambda ranged from 0.002 to 0.041, indicating significant differences in the four HRA index variables under the different visual clutter levels. These results demonstrate the potential of the current four indicators to predict HRA.

4.4. Influence of HRA on different index variables

Although the MANOVA results signify that the values of the four index variables differ in the three HRA groups, it still remains implicit as to which variable was influenced by the HRA. To determine the mechanism of how the HRA impacts the four index variables, univariate ANOVA was conducted.

Table 4 helps to identify the particular variable affected by the HRA. Additionally, the significance level was adjusted using the Bonferroni revision method. At a statistical significance of 0.05, the p-value should be less than 0.0125. According to the results, there are various combinations of index variables that are impacted across the visual clutter groups. In group H, the variables of experience and Oxy-Hb showed a discrepancy in different HRA groups (p = 0.004 and 0.002, respectively). When the visual clutter is low, experience was still impacted by the HRA (p = 0.009), whereas no significant differences appeared for Oxy-Hb (p = 0.024 > 0.0125). However, time to first fixation was more sensitive to HRA under low visual clutter (p = 0.002). Group M had the highest number of variables affected by HRA. In particular, differences existed among three of the four variables (all but risk tolerance), which implies that under medium visual clutter, the variables of experience, time to first fixation, and Oxy-Hb differed significantly across the HRA groups.

Table 3
Multivariate tests based on Wilks' Lambda among the HRA groups across different levels of visual clutter.

Visual clutter groups	Value	F	Hypothesis df	Error df	Sig.
H	0.485	2.400	8.000	44.000	0.030**
M	0.332	3.862	8.000	42.000	0.002***
L	0.488	2.266	8.000	42.000	0.041**

Note: ***: significant at 0.01 level; **: significant at 0.05 level.

Table 4
Tests of between-subject effects on HRA groups across different levels of visual clutter.

Visual clutter groups	Predictors	Sum of squares	df	Mean square	F	Sig.
H	Time to first fixation	23001.663	2	11500.831	2.004	0.156
	Experience	8.905	2	4.453	6.842	0.004*
	Risk tolerance	0.959	2	0.479	2.543	0.099
	Oxy-Hb	0.754	2	0.377	8.005	0.002*
M	Time to first fixation	54704.554	2	27352.277	9.300	0.001*
	Experience	8.613	2	4.307	5.717	0.009*
	Risk tolerance	0.567	2	0.283	2.129	0.141
	Oxy-Hb	0.479	2	0.240	5.327	0.012*
L	Time to first fixation	16251.008	2	81260.504	8.418	0.002*
	Experience	8.410	2	4.205	5.717	0.009*
	Risk tolerance	1.215	2	0.608	3.325	0.053
	Oxy-Hb	0.263	2	0.131	4.386	0.024

Note: *significant at adjusted 0.05 level.

In summary, the results illustrate noteworthy discrepancies in experience across different HRA groups, whereas risk tolerance does not appear to differ according to HRA. Additionally, the eye-movement metric of time to first fixation and the neural-activity metric Oxy-Hb were impacted by HRA under certain circumstances. Specifically, the differences in time to first fixation were not significant when visual clutter was high, whereas those in Oxy-Hb were not significant when visual clutter was low.

Post hoc tests were conducted using Tukey's Honest Significant Difference adjustment to reveal information about how the index variables were affected by HRA. The results are as follows.

For high visual clutter, Oxy-Hb was larger in the low HRA group than in both the medium and high HRA groups (p = 0.077 and 0.001, respectively). Moreover, the high HRA group possessed significantly more experience than the medium and low groups.

For medium visual clutter, the high HRA group spent more time conspicuously searching the surroundings (showing larger time to first fixation) than the medium and low HRA groups (p = 0.001 and 0.058, respectively). Similarly, they had more experience than the medium and low HRA groups (p = 0.045 and 0.012, respectively). As for the NIRS metric, Oxy-Hb in the high HRA group was significantly lower than in the low HRA group (p = 0.009).

For low visual clutter, time to first fixation in the high HRA group was greater than in the other two groups (p = 0.005 and 0.006, respectively). The high HRA group also exhibited lower Oxy-Hb and possessed more experience than the low HRA group (p = 0.029, 0.009). In addition, they had a lower risk tolerance than the medium group (p = 0.083).

4.5. Contribution of different indicators to HRA prediction

The previous sections explored how the HRA indicators differ across the various HRA levels. This indeed validates the potential of the HRA index to predict HRA. Thus, discriminant analysis was used to predict HRA through the index, with all index variables inserted into the equation at the same time.

Discriminant analysis provides several functions with which to forecast the classification. Specifically, the number of functions is one

Table 5
Eigenvalues for the discriminant functions.

Visual clutter groups	Function	Eigenvalue	Percentage of variance	Cumulative variance (%)	Canonical correlation
H	1	0.853	88.3	88.3	0.679
	2	0.113	11.7	100.0	0.319
M	1	1.117	72.5	72.5	0.726
	2	0.423	27.5	100.0	0.545
L	1	0.914	92.8	92.8	0.691
	2	0.071	7.2	100.0	0.258

less than the number of categories in the dependent variable. Thus, two discriminant functions were derived to weight the four indicators. Before examining the indicator weights, two tests were applied to assess the effectiveness of the obtained functions. First, the eigenvalue was identified to confirm the association between the determinant scores and those of the groups. This could be revealed by the percentage of the dependent variable exposed by the model. Concurrently, Wilks' Lambda manifests the statistical significance of the discriminatory power of the derived functions.

Tables 5 and 6 present the results of the eigenvalues and the Wilks' Lambda tests under various visual clutter levels. Pertaining to the eigenvalue tests, larger eigenvalues can be interpreted as higher discriminative ability. Moreover, the percentage of variance denotes the variation in the dependent variable explained by the corresponding function. Focusing on the first function, the explained variation is greater than 72.5% in group M and up to 92.8% in group L.

The values of Wilks' Lambda in the three visual clutter groups are 0.485, 0.332, and 0.488 (Table 6). This reflects the unexplained variation among the HRA groups. Additionally, the significance of both canonical correlations (Functions 1 and 2) for H, M, and L is less than 0.05 ($p = 0.030$, 0.002, 0.040, respectively) according to the results from the Wilks' Lambda test. This suggests that the differences between the HRA groups are statistically significant.

From the abovementioned tests, the first function is effective for explaining the relationship between the four indicators and HRA.

For an in-depth analysis, the standardized canonical discriminant function coefficients and the structural matrixes displayed in Tables 7 and 8 were analyzed. The structural matrix reveals the order of magnitude of the simple correlation between the functions and the indicators (time to first fixation, Oxy-Hb, experience, and risk tolerance). The charts reveal that the rank of the relative importance of each indicator differs remarkably.

When visual clutter is high (in group H), the four indicators all contribute to the first function more than the second one. Specifically, Oxy-Hb and experience are the most important indicators for HRA, their absolute correlations being 0.848 and −0.769, respectively. In group M, time to first fixation and Oxy-Hb make the greatest contribution to the discriminant of the HRA, with correlation coefficients of −0.817 and 0.624, respectively. Furthermore, risk tolerance is

Table 6
Wilks' Lambda for the discriminant functions.

Visual clutter groups	Test of functions	Wilks' Lambda	Chi-square	df	Sig.
H	1–2	0.485	17.019	8	0.030**
	2	0.898	2.521	3	0.471
M	1–2	0.332	24.813	8	0.002***
	2	0.703	7.940	3	0.047**
L	1–2	0.488	16.147	8	0.040**
	2	0.934	1.545	3	0.672

Note: ***: significant at 0.01 level; **: significant at 0.05 level.

Table 7
Standardized canonical discriminant function coefficients.

Visual clutter groups	Predictors	Function	
		1	2
H	Time to first fixation	0.026	−0.126
	Experience	−0.592	0.770
	Risk tolerance	−0.078	−0.387
	Oxy-Hb	0.699	0.849
M	Time to first fixation	−0.879	−0.121
	Experience	0.461	1.531
	Risk tolerance	−0.034	0.405
	Oxy-Hb	0.812	0.708
L	Time to first fixation	0.631	−0.734
	Experience	0.244	1.004
	Risk tolerance	−0.327	0.538
	Oxy-Hb	−0.157	−0.371

Table 8
Structural matrix.

Visual clutter groups	Predictors	Function	
		1	2
H	Oxy-Hb	0.848*	0.481
	Experience	−0.769*	0.618
	risk tolerance	0.473*	−0.337
	Time to first fixation	−0.431*	0.120
M	Time to first fixation	−0.817*	0.264
	Oxy-Hb	0.624*	−0.147
	risk tolerance	0.397*	−0.059
	Experience	−0.458	0.757*
L	Time to first fixation	0.875*	−0.173
	Experience	0.700*	0.632
	Oxy-Hb	−0.628*	−0.261
	Risk tolerance	−0.546*	0.264

Note: *: Largest absolute correlation between each variable and any discriminant function

significant in the first function, whereas experience is more important in the second function. Regarding group L, the four indicators are all indispensable for the first function, and time to first fixation again makes the greatest contribution to the discriminant, with the submaximal weights concerning the absolute correlation coming from experience, followed by Oxy-Hb (coefficients of 0.875, 0.700, and −0.628, respectively).

To summarize, time to first fixation makes the greatest contribution to HRA in groups L and M, followed by Oxy-Hb. For group H, however, Oxy-Hb is the primary contributor, and time to first fixation ranks last. As these two indicators represent different cognition processes, this contrast is vital in the subsequent analysis. Additionally, experience shares the submaximal weight under extreme visual clutter, namely in both the L and H groups. Nonetheless, it is not as important in the first function as it is in the second one in group M. Finally, the risk tolerance indicator is also significant in all three visual clutter groups, but always ranks fairly low.

The results of the canonical discriminant functions were visualized to elaborate the samples distinguished by them (Fig. 4). The figures depict how HRA was classified by the two discriminant functions. Apparently, the first function, i.e., the horizontal axis, could pinpoint high HRA from low and medium. The second function, however, could not identify either case. Moreover, a positive correlation between HRA and the scores derived from the first function in L can be observed. This situation contrasts with that for M and H. Combining the figures with the coefficients in Table 7, it is possible to determine whether the correlation between the indicators and HRA is positive or negative. In

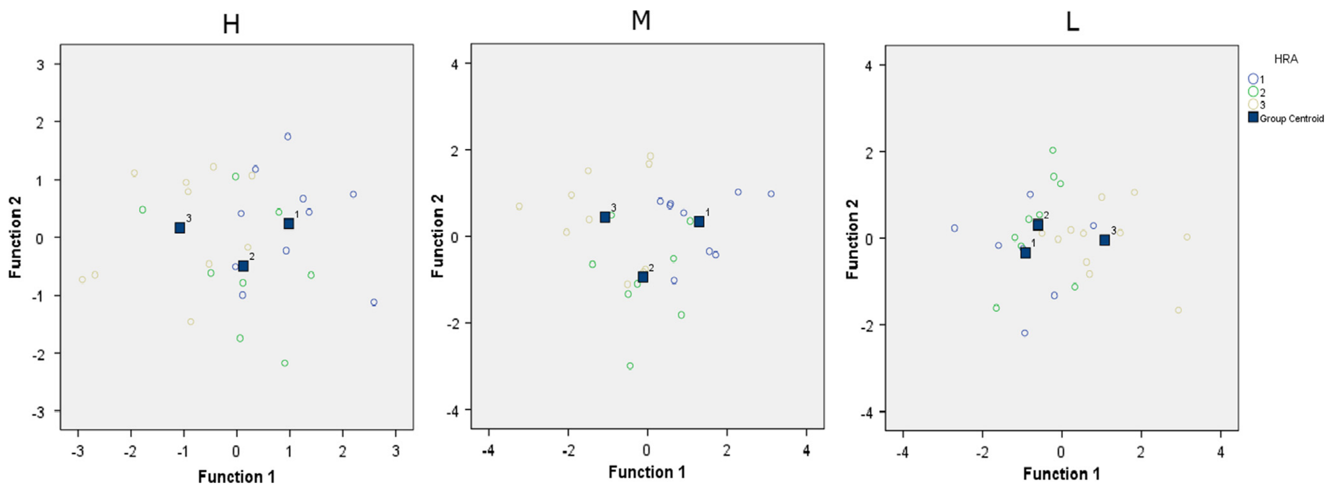

Fig. 4. Canonical discriminant function. Note: 1 = low HRA group; 2 = medium HRA group; 3 = high HRA group. The full color version of this figure is available online.

particular, a negative coefficient in the M and H groups suggests a positive correlation between the indicator and the levels of HRA, as it helps to generate a lower discriminant score. The values of the indicators are consistent across the visual clutter groups. Time to first fixation and experience are always positive with respect to HRA, whereas risk tolerance and Oxy-Hb are always negative.

The classification results are provided in Table 9. The resubstitution values illustrate the percentage of correctly identified samples through the discriminant scores. Cross-validation tests were conducted for verification purposes. According to the resubstitution results, 67.9% (H) and 74.1% (M and L) of the samples were correctly classified by the discriminant functions. As expected, the correct classification rates decreased following the cross-validation test, falling to 48.1%, 55.6%, and 53.6% for L, M, and H, respectively. Considering the complexity of the hazard identification process, a correct classification rate of greater than 33% (the probability of randomly being correctly classified) is acceptable.

5. Discussion

5.1. Relationships between HRA and indicators

5.1.1. Self-reporting indicators

In the three visual clutter groups, the self-reporting indicators of experience and risk tolerance are correlated with HRA, as generally expected. Higher experience implies better HRA. This is because those who work in the laboratory frequently will be better acquainted with the hazards in the lab, attain higher scores in the risk knowledge test, and recognize hazards more accurately in the experiment than those who do not. This conclusion verifies the consensus from previous studies that the accumulation of experience on construction sites enhances hazard perception ability. In contrast, risk tolerance is negatively correlated with HRA. This negative relationship manifests itself as participants with higher risk tolerance identifying fewer hazards than those with lower risk tolerance. The result is consistent with prior studies as well as the definition of the variable: defined as “the number of risks that individuals are willing to accept in the pursuit of some goal” (Hunter, 2002; Roszkowski and Davey, 2010), high risk tolerance implies the inclination to endure a risky working environment.

Table 9
Classification accuracy for HRA.

Visual clutter groups	Resubstitution	Cross-validated
H	67.9%	53.6%
M	74.1%	55.6%
L	74.1%	48.1%

5.1.2. Physiological metrics

The results of this research also show inconsistencies beyond general expectations. The two physiological metrics reveal that a different cognition paradigm from that of the image-based experiments was employed for hazard detection. Specifically, the discrepancies of both the eye-movement metric (time to first fixation) and the NIRS metric (Oxy-Hb) across the HRA groups were incompatible with the results derived by previous studies.

The values of time to first fixation in the AOIs were increased in the high HRA groups. This suggests that participants with higher HRA spent more time scanning the environment before initially allocating their attention to the hazardous areas. In contrast, participants with worse HRA fixated on the hazards faster. Such results are similar to those reported in the study of Hasanzadeh et al (2017a). Many previous studies, however, regarded less time observing “distractions” as better performance in the visual search (Brockmole and Henderson, 2006; Dong et al., 2018). These empirical studies were based on experiments utilizing images as the stimuli. Nonetheless, the processes of visual search and situation awareness differ considerably in real construction environments. The observers spend more time scrutinizing their surroundings and inspecting each object meticulously. Brockmole and Henderson (2006) found that, in real-world scenes, attention allocation is initially driven by scene identity. Subsequently, the shifts of attention are guided by detailed information regarding scene and object layout. Specifically, this effect, called contextual cueing, identifies the prominence of task-relevant information provided by the surroundings around the search target. Through spatial inference of the relationships between the distractors, participants were able to perceive an integral comprehension of the scene and better analyze the potential hazards (Henderson, 2003). Moreover, in the individual interviews following the experiment, several participants reported that they could extract little information from the surroundings, and so guided their attention directly to plausible hazards. This could be explained by the stimulus-based gaze control introduced by Henderson (2003). In stimulus-based gaze control, the uniform regions along some dimension are uninformative, and thus guide the spatial gaze distribution. Although differing in dimensions such as color and intensity, the unfamiliar regions providing insufficient information were uniform for participants with low HRA, who hence obtained fewer fixations.

As for Oxy-Hb, it was found to decrease when HRA was higher. This means that, compared with low HRA participants, the concentration of oxygenated hemoglobin in the PFC of the high HRA participants was lower. Undoubtedly, this finding is important in the cognitive process of hazard perception. Previous studies reported various results across participant groups for various task conditions. Durantin et al. (2014) found that, under a high processing load, Oxy-Hb increased in hard control conditions during a simulated piloting task compared with that in easy control conditions. However, the opposite results were found under a low processing load. Kojima and Suzuki (2010) conducted a visual search experiment and found significant correlations between changes in Oxy-Hb and attention strength. Specifically, the enhancement in Oxy-Hb was greater for subjects who could not find a target under attentional conditions. Generally, lower Oxy-Hb is explained as certain brain regions being less active (Liu et al., 2016). Kojima and Suzuki (2010) inferred that Oxy-Hb increased substantially when the observers could not find the target, and thus kept looking at the visual scene. Once the observers found the target, however, they no longer needed to pay attention to the stimuli, and the Oxy-Hb stopped rising. This offers inspiration for the present study. Regarding the attention effect, participants with high HRA might be more convinced of their judgment regarding hazards. Those with low HRA, however, might hesitate to make a decision, and hence paid more attention to potential hazards. Thus, the constant attention produced a strong activation in the brain.

5.2. Discrimination power of indicators

The variation and discrimination power of each indicator differed considerably in the three visual clutter groups. According to the univariate ANOVA, experience always showed significant variance across the HRA groups, whereas risk tolerance showed no significant variance. Moreover, significant discrepancies in time to first fixation were observed under relatively low visual clutter, namely the L and M groups. Intriguingly, Oxy-Hb changed in the M and H groups. As for the discrimination power, the results were quite similar. Risk tolerance had a relatively poor power for predicting HRA (ranked in the lower half for all three groups), and experience showed unstable explanation power, with strong performance in groups L and H but poor performance in group M. Taking the physiological indices into account, time to first fixation had a strong power for prediction in groups L and M, whereas Oxy-Hb performed better in the M and H groups. Generally, the discriminant power of the physiological indices was stronger than that of the personal characteristics. This serves as an important signal in acknowledging the priority of the inspection process, namely the physiological indices, for HRA prediction. Many researchers have emphasized the process of hazard identification as a significant barrier to improving hazard detection (Bahn, 2013). Certainly, the low efficiency of training and knowledge absorption leads to a poor correlation between training and work experience and between training and HRA (Perlman et al., 2014).

Additionally, the results reveal that cognitive discrepancies in hazard identification can be attributed to the different search phases according to the level of visual clutter. Disparities in time to first fixation contributed more to HRA prediction when visual clutter was relatively low, while variations in Oxy-Hb were more significant under high visual clutter. Taking the two cognitive phases represented by the two metrics into consideration, this conclusion illustrates that participants with high HRA spent more time looking around the whole environment under low visual clutter than those with poor HRA. When the visual clutter was high, however, the cluttered objects in the visual field caused the participants significant distraction and confusion. Thus, those with low HRA had to concentrate to deconstruct the scene and extract effective information for decision-making, leading to a high level of Oxy-Hb. Discrepancies in the time spent on observing the surroundings were not significant, as the cluttered visual field also demanded attention for those with low HRA.

In conclusion, our analysis reveals that different cognitive strategies were employed to accommodate the change in visual clutter. Under low

Fig. 5a. Hazard 3 in group L.

Fig. 5b. Hazard 9 in group H.

visual clutter (Fig. 5(a), for example), the main variation lies in the saccade phase. Having little knowledge about the site risks, participants with low HRA could attain little information from the surroundings. In contrast, the uncluttered scene was still informative for those who performed better, and thus more time was spent observing the scene. When visual clutter was high (Fig. 5(b), for example), all participants had to analyze the surroundings for some time. However, the participants who performed better encountered little uncertainty in terms of hazard identification. On the contrary, participants with low HRA concentrated more on their judgment, and this caused more active cerebral oxygen metabolism. As for HRA prediction, given the limited representation efficiency for the judgment phase by the eye-movement metrics, the level of Oxy-Hb is an essential measurement for further consideration.

5.3. Overall prediction of the HRA index

The classification results indicated a firm prediction capacity. The discriminant functions derived in this study could identify the workers' HRA with accuracy ranging from 67.9 to 74.1% across the visual clutter groups. Concurrently, the cross-validated accuracy rates ranged from 48.1 to 55.6%. This performance is superior to that reported in other studies (Hasanzadeh et al., 2017b). It has been claimed (Yang et al., 2010; Dong and Hu, 2011) that a hybrid system introducing several multimodal indicators would be fairly robust. The predictive power of the proposed HRA index has demonstrated the effectiveness of hybrid prediction systems by involving multiple monitoring devices and psychological scales. Specifically, the innovative use of NIRS devices proved to be valuable, allowing cognitive discrepancies to be distinguished in the decision phase. Additionally, the psychological (risk tolerance) scale proved to be effective in predicting HRA. Furthermore, the experimental paradigm of a real-world inspection task makes the results authentic and convincing.

6. Conclusions

This research has developed an HRA index engaging both physiological and psychological indicators. For data collection, a real-world task-based experiment was conducted. Portable eye-tracking and NIRS devices were equipped for multimodal monitoring. Subsequently, MANOVA and discriminant analysis were utilized for factor analysis and HRA prediction across different visual clutter groups. The results revealed that different search strategies are employed by people in different HRA groups, and thus verified the prediction efficiency of the proposed HRA index. The theoretical and practical contributions of this study are summarized as follows.

6.1. Theoretical contributions to HRA

First, this study successfully developed an HRA index that was shown to provide accurate HRA predictions from self-reported metrics and vital signs, including eye movement and vascular response. The theoretical basis for the proposed HRA index digs deep into the cognitive process of HR. It reveals the different search strategies employed by observers of various HRA levels and across visual clutter groups. Specifically, observers with high HRA spend more time on the search phase in low visual clutter, and the prefrontal lobe is less activated in high visual clutter cases. Such results are quite different from those of previous studies. The real-world experimental protocol, however, was shown to be credible through a simulated HR task. In addition, according to the index, the predictive power of the vital signs is greater than that of the self-reported metrics. This indicates the importance of embedding monitoring devices such as eye trackers and NIRS devices. By initially introducing the NIRS method, our knowledge of the decision phase was extended and unified. The effectiveness of the multimodal fusion method based on a hybrid monitoring system is expected to inspire researchers to conduct further studies.

6.2. Practical application suggestions

By applying the proposed HRA index, it is possible to predict the HRA of an inspector or worker on site through his/her experience, risk tolerance, eye-movement (namely time to first fixation), and vascular response (namely Oxy-Hb). The prediction method is based on real-time monitoring rather than a comparison with some presupposed task execution. Thus, it is robust and repeatable. A continuous assessment could be conducted without sophisticated preparation to analyze the HRA promotion of the staff. Therefore, the proposed HRA index is valuable for jobsite HRA estimation, which serves as a reference for further occupational environment management (Perlman et al., 2014).

Regarding the practical implications of the HRA index, it provides more information than mere HRA levels. The advantage is that each of the four indicators is associated with one specific aspect of the cognitive process. Therefore, both vulnerable and reliable processes can be identified. For instance, a worker with high HRA is likely to have a relatively long time to first fixation in low visual clutter scenes, according to the discussion in Section 5. Thus, if a worker was ranked as low HRA because of his/her short time to first fixation in low visual clutter, this would be a signal of poor performance in the search phase. For the subsequent training plan, the improvement of perception ability should be the focal point for the worker. In addition, managers can allocate tasks according to worker's HRA performance in different jobsite settings. Such insight regarding HRA helps to improve occupational safety related to the indistinct comprehension of HR failure (Namian et al., 2016).

6.3. Limitations and future research

Despite our best attempts in this pilot study, e.g., the real-world HR task and controlled approach to capture physiological data, certain limitations and challenges still remain to be addressed in future research. First, as a pilot study, civil engineering students were employed rather than workers. Differences between HR processes may exist because civil experiments are different from construction work. Additionally, the number of participants constrains this study to a small sample-based trial. Thus, readers should interpret the results cautiously. Second, unexpected influences from mobile participants may exist, although previous studies praised NIRS devices for their insensitivity to body movement (Liu et al., 2016).

Based on this trial, efforts could be focused on promoting experiments for future research. Researchers could attempt to involve real construction sites and large sample sizes. In addition, NIRS and eye movement data were employed as independent variables. The interaction between the two variables during hazard recognition may be interesting, and researchers could explore this in future studies.

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Declaration of Competing Interest

None.

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