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Eye-Tracking Experimental Study to Investigating the Influence Factors of Construction Safety Hazard Recognition

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Abstract

Construction site accidents could be reduced if hazards leading to accidents are correctly and promptly detected by employees. The proactive safety measures such as safety perceptions and safety detection capability of employees play an important role in improving the safety performance. This study was initiated by three research questions related to: (1) the measurement indicators of employees' cognitive load in recognizing safety hazards; (2) site condition factors (e.g., brightness) that could affect subjects' cognitive load; and (3) the quantification of the effects of these site factors on cognitive load. An eye-tracking experimental approach was adopted by recruiting a total of *55* students from construction management or other civil engineering disciplines to visually search hazards in *20* given site scenes. These site scenes were defined by a combination of three different categories, namely distinctiveness of hazards, site brightness, and tidiness. Quantitative measurements of experimental participants' visual search patterns were obtained from data captured by the

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eye-tracking apparatus. Based on metrics related to experimental participants' fixation, visual search track, and attention map, these measurements were computed to evaluate participants' cognitive load in detecting hazards. Descriptive statistical comparisons were performed to analyze these metrics under pre-defined categories of site conditions, i.e., distinctness versus obscurity/blur, brightness versus darkness, and tidiness versus mess. The findings revealed that: distinct site conditions reduced participants' time in saccades to search hazards but did not improve the accuracy rate of first fixation; messy sites with dis-organized items increased participants' cognitive load in detecting hazards in terms of all five measurement items (i.e., accuracy rate of first fixation, fixation count, intersection coefficient, fixation duration, and fixation count in the attention center); the effect of increased brightness on-site was a double-edged sword which needed further studies on the optimal balance of brightness level and allocation. Recommendations based on the findings were provided to enhance safety education in terms of site hazard distinctiveness, brightness, and housekeeping best practice. This study extended a few prior studies in adopting the eye-tracking technology for safety monitoring by evaluating the impacts of site conditions on participants' cognitive load which was linked to their hazard detection performance. The current study provided insights for evaluating construction employees' hazard detection capabilities to enhance safety education. Future work was proposed in evaluating employees' safety hazard detection pattern under dynamic construction scenarios.

Keywords: eye-tracking; construction safety; safety education; hazard detection; cognitive load

Introduction

Human errors are the main causal factor that contributes to up to *80%* of all accidents across industries (Garrett and Teizer, 2009). In the construction industry, one of the major human factors affecting employees' safety performance is the failure to perceive critical factors in a given environment in order to make correct predictions or decisions (Endsley, 1995). Construction is recognized as one of the most risky industries with high injuries or accidents (Sunindijo and Zou, 2012). Safety education is critical to promote safe and healthy construction work environments (Pedro et al., 2016). A better understanding of human factors' effects in construction safety performance could enhance existing safety education, and further improve site safety performance. Failure to detect hazards, or attention failure is one of the major causes of construction accidents (Li et al., 2019). Prevention of construction employees' attention failure plays an important role to enhance site safety. Existing measurements of construction employees' hazard detection performance or other safety accountability using the questionnaire survey approach (e.g., Han et al., 2019b) could be prone to subjectivity. So far, limited investigation has been conducted using a more objective approach to test employees' hazard detection performance, as well as relevant influence factors, e.g., the site condition, and the mental fatigue of site employees (Li et al., 2019), etc. The mental fatigue is correlated to employees' cognitive load, which should not exceed the working memory (Paas et al., 2003) for learners (e.g., construction employees) to effectively capture and process site information.

The emerging digital or computer vision technologies (e.g., virtual reality) have displayed their positive impacts on safety training or monitoring (Skibniewski, 2014; Seo et al., 2015). One of the visualization technologies that have been adopted in evaluating employees' safety hazard detection is eye-tracking. A limited number of existing studies (e.g., Jeelani et al., 2018; Li et al., 2019) captured the eye-tracking data from experimental participants' visual search track, and analyzed the effects of personal traits (e.g., mental state) on employees' hazard detection performance. As utilizing eye-tracking technology for safety education or cognitive training is still in the early stage, various factors that affect employees' safety detection performance remain unexplored, such as different site conditions (e.g., lighting condition, site tidiness, etc). As indicated by Toole (2007), observing and understanding site conditions that pose hazards to workers is one main criterion for civil engineers to address construction safety issues in their design and engineering management.

Construction employees recognizes potential site hazards through their visual search. Site under varied conditions (e.g., bright or dark condition) could trigger different attention resources for employees to detect potential hazards. Investigation on search pattern and attention resource allocation of employees under different site conditions is important for providing the best practice guides on construction site housekeeping, meanwhile, improving the work efficiency of employees by reducing their cognitive loads in identifying safety hazards. Cognitive load herein refers to employees' mental effort required to allocate their attention resources to search and identify site hazards. Sweller (1998) stated that human beings' working memory, the part of the mind that processes what people are currently performing, can only deal with a limited amount of information at one time. It is theoretically implied that the more mental efforts that construction employees have to deal with site hazards, the less working memory they would have to handle other site activities related to site productivity.

Mental integration requires cognitive resources (i.e., human-beings' cognitive efforts) to find the solution to a given problem (Sweller, 1994), such as to detect safety hazards under a certain construction site scene. Based on the cognitive load theory described by Sweller (1994), this study adopts an eye-tracking experimental approach to test and evaluate the impacts of several pre-defined site conditions on subjects' safety detection performance, which is directly related to subjects' cognitive load. Research questions were initiated as: (1) how to measure subjects' safety recognition performance? (2) what site condition factors (e.g., brightness) would affect the safety recognition performance? and (3) what are the effects of these pre-defined site factors on the recognition performance? Correspondingly, the objectives of the study include: (1) devising a comprehensive set of evaluation indicators to extend existing metrics of cognitive load in searching construction safety hazards; (2) evaluating the impacts of different site scene features (e.g., bright versus dark conditions) on subjects' cognitive load; and (3) providing guides on improving existing construction safety performance through enhanced site conditions. Students from construction management (CM) and other civil engineering (CE) disciplines were recruited for the eye-tracking experimental tests to detect a total of *20* site scenes representing a combination of different site categories (i.e., ease of detection, brightness, and tidiness). This research serves as one of the initial studies to investigate the impacts of site conditions on subjects' cognitive load, which is measured by a variety of metrics related to the information of first fixation, visual search track, and the attention map. The findings from the current study lead to recommendations in enhancing site conditions for better construction safety climate and crew safety performance. The eye-tracking method can be implemented in future's site safety education to evaluate subjects' visual search pattern.

Literature review

Proactive safety performance

Existing measurements of safety performance can be divided into proactive and reactive indicators (Cooper and Phillips, 2004; Choudhry et al., 2007). The reactive measurements included occurrence rates of accidents/incidents (Chen and Jin, 2012). The proactive measurements include safety culture and safety climate (Chen and Jin, 2013). Safety culture reflects the attitudes, beliefs, perceptions, and values that are shared among employees related to safety (Cox and Cox, 1991). Safety climate targets employees' perceptions of the role of safety in the workplace and their attitudes towards safety (Cox and Flin, 1998). Workplace safety perceptions, as studied by Goh and Chua (2010), Hallowell and Gambatese (2010), and Gangolells, et al. (2013), include site hazard identification and risk measurement to prevent occurrences of accidents/incidents. Safety perceptions form part of safety climate, which further constitutes safety culture (Marquardt et al., 2012).

Measurements of safety perceptions of site hazards

Employees' perceptions of safety hazards are part of safety climate (Han et al., 2019c). Existing studies of safety climate related indicators have been largely based on the subjective measurement approach, such as questionnaire survey (Liao et al., 2015; Li et al., 2017) to capture construction employees' self-reflection or perception. Potential drawbacks of the questionnaire survey approach include questions being misunderstood, and being unsuitable for investigation of complex research questions (Evalued toolkit, 2006). The subjectivity nature of the questionnaire survey approach should be considered in generating research findings (Bertrand and Mullainathan, 2001). The technological evolvement has created more alternative measurement methods to gauge employees' perceptions of site hazards or other site issues in the construction industry. As one of the technological advancements, the eye-tracking technology, with test devices to monitor and record human beings' eye movement when facing a virtual or real site scenario, has been implemented in the construction management or education-related activities (e.g., Bhoir et al., 2015; Hasanzadeh et al., 2016).

Eye tracking technology as the research platform for construction safety

Virtual or computer vision technologies (Seo et al., 2015; Zuluaga and Albert, 2018; Shi et al., 2019) are gaining the momentum to support construction safety research. Eye-tracking devices or apparatus have been adopted in several recent studies (Dzeng et al., 2016; Jeelani et al., 2018; Li et al., 2019) to evaluate employees' safety hazard detection or recognition performance. Eye-tracking provides an objective measurement of stimuli when subjects receive attention during visual search activities (Jeelani et al., 2018). In these studies, safety detection or recognition performance was found with significant correlations to other variables, such as construction employees' experience level (Dzeng et al., 2016), and their mental state (Li et al., 2019). In these studies (Bhoir et al., 2015; Hasanzadeh et al., 2016; Jeelani et al., 2017b), either university students or construction site employees in a relatively small sample (i.e., *10* to *20* participants) was recruited to conduct eye-tracking experimental tests. The small sample size was identified as one limitation from the existing studies (Jeelani et al., 2018).

Methodology

Safety hazard detection on construction sites is subject to interventions under a dynamic working environment. This detection process is not easy to capture or measure. As using the eye-tracking technology for the evaluation of construction safety hazard detection or recognition is still in the infancy stage, this study utilizes a variety of photos taken from real jobsites. The research steps in this study are illustrated in Fig.1.

<Insert Fig.1 here>

It is seen from Fig.1 that this study started from site visits and photo-takings of different site scenes. Afterwards, these photos were screened and categorized into different features (i.e., distinctness versus obscurity/blur, brightness versus darkness, and tidiness versus mess). A total of *20* finalized photos were adopted for the eye-tracking experimental study in the laboratory of Jiangsu University. The research team then analyzed the experimental data capturing participants' eye movement according to pre-defined metrics, which measured their cognitive load to identify site hazards in each photo. Finally, recommendations were proposed based on how different site conditions could affect participants' safety hazard recognition.

Site visits, photo-taking, and photo screening

As the start of the research according to Fig.1, a large amount of site photos were taken from the same type of camera by the research team. The camera was pre-set to maintain the original condition (e.g., brightness) of sites. All site photos taken from site visits were strictly prohibited from any automatic or human editing (e.g., adjustment of brightness). It was ensured that all photos maintained the original site conditions without any adjustments (e.g, color, brightness, etc.). These photos taken from jobsites were then categorized with different features defined in Table 1.

<Insert Table 1 here>

The three different site condition factors related to distinctness, brightness, and tidiness were defined according to researchers' earlier work (e.g., Han et al., 2019a; 2019b) and existing literature beyond the construction industry. Han et al., (2019a) found that the distinctness of a safety hazard affected construction employees' perceptions towards the hazard. Choi et al. (2014) stated that the physical environment, including how the physical items are laid out or organized on-site, would affect participants' cognitive load. Other physical site conditions, such as lighting condition, and the location of the target, would also impact the cognitive load (Amadieu et al., 2009). Choi et al. (2018) further confirmed that the physical environment, including lighting condition and site layout, would contribute to the cognitive load of subjects. Unevenly distributed lighting, low lighting condition, disorganized site, and less distinct objects would increase subjects' cognitive load (Choi et al., 2018).

This study served as the initial work of adopting eye-tracking techniques to evaluate the effects of site features on subjects' hazard recognition capability. Site scenes adopted for follow-up experimental studies would contain one of the two opposite features (e.g., bright versus dark condition). Each scene's feature could be easily identified by employees or experimental participants. There have been limited quantitative measurements of site scenes (e.g., tidiness or distinctness) under the context of construction jobsites for safety hazard recognition. As the initial stage of studying employees' hazard recognition performance, a more descriptive measurements of site scenes meet the current research needs.

The three different site factors, although seemingly interconnected, are actually separated from each other with different emphases on the feature of the site condition or the site hazards. Specifically, ease of detection describes the distinctness of a safety hazard. For example, a worker without wearing hardhat on-site can be easily detected. This is considered a distinct scene. In comparison, a nail laid on the floor is not easily detected, and is hence considered blurry. Brightness differs from ease of detection in that it focuses on the lighting condition of the environment rather than the hazard itself. Instead, ease of detection is affected by the participants' safety knowledge and the hazard feature (Han et al., 2019c). A blurry scene or hazard may still not be easily detected even under bright conditions. Tidiness refers to how well that site miscellaneous items are organized. For example, a site is generally tidy right before pouring concrete to the floor. But the floor is more likely to be messed at the interior finish stage. Site employees may need to spend more attention resources on the disorganized miscellaneous items.

Initially *558* site photos were collected from construction sites in China, covering these typical safety hazards such as fall, caught-in-between, struck-by, and electrocution defined by OSHA (2011). The research team in this study ran a first-round screening of these photos by removing those with low quality or not containing hazardous zones. A total of *297* photos were kept following the first-round screening. The second round screening by the research team aimed to determine the final photos for experimental tests using the eye-tracking apparatus. Finally, totally *20* site photos representing different combinations of scene features defined in Table 1 were selected for the later eye-tracking experiment. Fig.2 displays these *20* photos. According to Fig.2, there were more than one photo representing the same combination of scene features (e.g., blurry, dark, tidy). That was because researchers aimed to display different construction scenarios, e.g., material storage, site vehicles moving, scaffolding work, indoor electrical and plumbing work, and construction of structural members, etc.

<Insert Fig.2 here>

Before these *20* photos were displayed in the monitoring screen of the eye-tracking apparatus shown in Fig.3, they were reviewed by an expert panel to confirm the quality and the categories of scene features. The expert panel consisted of three faculty members with more than five years' academic or industry experience in construction safety management, two site safety officers, and three workers with more than *25* years' site experience. Following the definitions described in Table 1, all members in the expert panel agreed with the combination of site features for each of the *20* photos shown in Fig.2. For example, photo (16) was defined as being distinct, bright, and messy. The hazardous areas in each scene were also agreed by the research team and all the panel members.

It is seen in Fig.2 that among all possible eight combinations of site scene features, the combinations of "blurry, dark, and messy" and "distinct, dark, and messy" were not included in the finalized *20* photos. Although these two missing combinations were available from the initial *558* site photos collected, the focus of the study was not to have site scenes with all the eight different combinations. Instead, this research aimed to conduct the paired comparison within each site scene category (e.g., brightness versus darkness) on the given category's effect on subjects' cognitive load. Researchers emphasized more on how the scenes represented typical site scenarios, and omitting the two combinations did not affect the analysis of a given site category's effect on safety hazard recognition.

Measurements of participants' eye movement in hazard detection

The eye movement related metrics were found with correlations to human beings' psychological state and cognitive load (Djamasbi et al., 2010). Fixations and saccades are two typical types of eye movements when human beings view the stimuli (Jeelani et al., 2018). A fixation is a time interval or period when the eyes are not moving and the gaze is targeting a single point in a given visual scene; in contrast, a saccade shows rapid movements between fixations and the eyes are moving from one point of interest to the next (Jeelani et al., 2018). The visual information for cognitive analysis of a given scene can be acquired from fixations (Yarbus, 1967). Instead, no valuable information is obtained during saccades (Jeelani et al., 2018). The visual search track of an individual completing the visual search in a given site scene consists of fixations connected with saccades. Several measurements and metrics in evaluating individuals' visual search pattern associated with cognitive load have been adopted in existing studies (e.g., Bhoir et al., 2015; Dzeng et al., 2016; Jeelani et al., 2017a) conducting eye-tracking experiments, such as fixation duration, fixation count (i.e., number of fixations), and correct detection rate of hazards. More definitions of these metrics of cognitive loads measured by eye movement related indicators can be found in Rayner (1998), Djamasbi et al. (2010), and Tsai et al. (2012). In this study, the main measurements and metrics of the experimental participants' viewing pattern are defined in Table 2.

<Insert Table 2 here>

AOI (i.e., Area of Interest) in eye-tracking experiments refer to visual environments of interest (Jacob and Karn, 2003). In the visual search of construction site hazards, AOI has been defined by several recent studies (e.g, Bhoir et al., 2015; Jeelani et al., 2018) as the annotated hazardous zone(s). The center of focus or the attention center is defined by the annotated zone with the highest fixation count. It is considered that a participant has correctly identified the hazard if the center of focus merges the AOI. The hazardous zones (i.e., AOIs) were defined for each of the *20* selected site photos through the early-stage expert panel discussion. The correct location, size, and the number of hazardous zones in each site scene were agreed by the expert panel members.

In this current study, descriptive statistics was adopted instead of inferential statistics based on both theoretical and empirical reasons. Theoretically, descriptive statistics is suitable for the circumstance that focuses on a certain population but not for generalization to a wider population (Taylor, 2019). In this study, the CM student population at Jiangsu University was selected as experimental participants. The current population could not be generalized to the larger population of construction employees in China based on the findings from Han et al. (2019a, 2019b) that site employees' hazard recognition and perception would be affected by employees' personal traits (e.g., experience). Empirically, these metrics described in Table 2 are by nature more descriptive or qualitative. The researchers believe descriptive statistics would fit better for presenting the data analysis following the eye-tracking experimental tests.

Eye-tracking experimental apparatus

The Tobii T60 XL eye-tracker supplied by Tobii Pro (2019) was integrated into a high-resolution *24''* wide screen monitor as seen in Fig.3 for large stimuli display. The eye-tracker adopted in this study had maximum gaze angles at *42* degrees with built-in camera, embedded eye-tracking server, and connectors (e.g., VGA, power, user camera, and audio). It allowed the researchers to accurately and unobtrusively measure human beings' gaze over any points or areas of an image displayed in the screen, for example, a person's fixation time focusing on a point of interest. This eye-tracker could be applied in a variety of areas including psychological studies, visual perception research, and eye-based computer interaction. Detailed features and functionality can be found from the supplier (i.e., Tobii Pro, 2019).

<Insert Fig.3 here>

According to the instruction manual provided by the eye-tracker supplier (Tobii Pro, 2019), a fixation is defined as when eye pupils are staying by gazing at a fixed point for not less than 0.1 second. The first fixation point is determined automatically by the Tobii T60 XL eye-tracker when the participant's pupils are not moving for over 0.1 second. The eye-tracker also records other experimental data, such as the fixation count (Tobii Pro, 2019).

Experimental participants

Students from the CM or other CE programs were recruited as eye-tracking experimental participants to use the eye-tracking apparatus displayed in Fig.3. The reasons for initially selecting students as participants instead of workers from the local construction industry were based on the facts that the objectives of this study were to explore the impacts of site conditions (i.e., blurry versus distinct, bright versus dark, and tidy versus messed) on subjects' hazard recognition performance. These site conditions were set as independent variables for the later statistical analysis. Instead, personal traits (e.g., experience) should be under control rather than being another independent variable. Workers' or other professional employees' safety perception or hazard recognition performance could be affected by their personal traits (e.g., prior experience, and age, etc.) according to some earlier findings (e.g., Hasanzadeh et al., 2016; Han et al., 2019a). Therefore, students recruited for the hazard recognition experiment from the similar background would be more appropriate. Student participants in this study were in the similar age range. They had all taken similar courses in construction engineering and management. They also had similar prior construction experience (i.e., little practical experience). Recruiting students as eye-tracking experimental participants can be found in some earlier studies (e.g., Bhoir et al., 2015; Hasanzadeh et al., 2016). It is not uncommon that universities or other learning institutions, with funding for research studies and data collection, recruit students in the laboratory study (Liu and Gambatese, 2018). Recruiting students for the eye-tracking experimental study could also address the concern of Pedro et al. (2016) that current pedagogical methods and tools at the tertiary level have not sufficiently engaged students or provided practical experience to support the acquisition of safety knowledge. Students selected for the eye-tracking experiment were all without eye prescriptions or weaknesses (e.g., colorless blindness, glaucoma, and amblyopia, etc.). Each participant, before starting the experiment, would be double-checked to confirm that he or she did not have any eye prescription, weakness, or other eye-related problems that would prevent them from participating.

Experimental procedure

Before the formal experimental study, a pilot study was conducted by recruiting ten students from the CE or CM undergraduate and graduate programs at Jiangsu University. Each of them was guided by the research team members to undergo the consistent procedure consisting of: (1) introduction of the experimental study; (2) completing the personal consent form; (3) setup and trial of eye-tracking devices; (3) the participant searching hazard(s) in each photo displayed in the monitor screen shown in Fig.3; (4) automatic generation of eye-tracking data (e.g., fixation duration); and (5) follow-up short interview of the participant. Before signing the consent form, participants' were made aware that no personal information would be recorded or saved. Upon the completion of detecting all hazards in the *20* given scenes, each participant was interviewed to describe their hazard perceptions, such as what hazards they had identified. The pilot study with ten participants aimed to ensure that: (1) all eye-tracking devices were easy to use without difficulties; (2) the time interval for participants to complete the whole experimental process was reasonable and under plan (e.g., it was found that generally each participant was able to complete visual searching in all the *20* scenes within *15* minutes); (3) participants were not allowed to return to prior scenes which they had completed. As part of the experimental procedure, upon the end of the introduction, each individual participant was guided with descriptions of "In the follow-up tests, you will be viewing real construction site photos. Each photo contains one or more safety hazards that may cause accidents. Assuming that you are a construction worker on that site, your task is to search and identify the hazards in each site scene." Using the pre-defined eye-tracking metrics shown in Table 2, the pilot study with the ten participants searching hazards in each of the *20* site scenes also validated the size, location, and number of hazardous zones which were agreed in the earlier-stage expert panel discussion.

Results

Excluding the ten student participants in the pilot study, another *55* students from CE or CM subjects were recruited for the formal experimental study. Compared to the population size of *25* participants in Dzeng et al. (2016) and *47* participants in Xu et al. (2019) for eye-tracking experimental data analysis, *55* participants involved in this study were considered a reasonable population size. The eye-tracking data collected from these *55* students were analyzed based on the three main types of visualization maps, namely fixation map, visual track map, and attention map. Using the three different maps, eye-tracking metrics were acquired to study how the participants' cognitive load was affected by site conditions defined in Table 1. Applying the metrics defined in Table 2, participants' cognitive load level under different site conditions were compared.

Display of visual search metrics from eye-tracking experimental data

The first fixation point of all participants were merged for each scene as displayed in Fig.4. The percentage of participants who had their first fixation falling into the hazardous zone was calculated to measure the accuracy detection rate in each scene. The average detection rate of scenes from each feature defined in Table 1 (e.g., distinct) with hazards being correctly identified by the first fixation is displayed in Fig.5.

<Insert Fig.4 here>

<Insert Fig.5 here>

As seen in Fig.5, the differences were *3.1*%, *2.1*%, and *5.6*% respectively for scenes categorized by ease of detection, brightness, and tidiness. It is seen that the largest difference comes from the category of tidiness, inferring that tidy site scenes could have their hazards more easily detected by participants.

The visual search track was unique for each participant. Combining all participants' tracks would make the track analysis complicated and difficult. Instead, the research team was able to identify typical search track where the majority of participants had spent their attention resources. The typical search track of participants in each scene is displayed in Fig.6. The two metrics (i.e., fixation count and intersection coefficient) are calculated. The comparisons of each metric under different scene categories are presented in Fig.7 and Fig.9 respectively. Fig.8 illustrates how the intersection coefficient is calculated by weighting all *55* participants' visual tracks.

<Insert Fig.6 here>

<Insert Fig.7 here>

The average fixation count is based on the mean value of all scenes falling into the same category (e.g., blurry). There is a marginal difference of average fixation count between distinct and blurry scenes. The largest difference comes from the category of brightness, where the bright scene has 9.3 more fixation points on average compared to the dark scenes. More fixation points are found in messed scenes compared to tidy scenes. It is indicated that bright scenes may not always reduce the cognitive load. Instead, there may be an optimized brightness level to minimize site subjects' cognitive load.

Fig.8 uses one scene as the example to demonstrate the computation steps of intersection coefficient by weighting all participants' search tracks. Basically, for each scene, there would be a typical track where the majority of participants would follow to detect hazardous zones. The remaining participants may have their different search tracks. The weighted method based on the number of participants either in the typical track or other tracks was adopted to calculate the overall intersection number (i.e., intersection coefficient) as shown in Fig.9.

<Insert Fig.8 here>

<Insert Fig.9 here>

It is found in Fig.9 that the largest difference comes from the category of ease of detection, with the value under blurry scenarios nearly three times of the value under distinct scenes. A marginal difference is found between bright and dark scenes. Messed scenes are found with a higher average intersection coefficient value than tidy scenes.

The attention maps for the *20* scenes are displayed in Fig.10. The total fixation duration for each participant under each scene was acquired automatically using the eye-tracking apparatus shown in Fig. 3. Under each scene in Fig.10, the total fixation duration on average for the *55* participants is also displayed. All participants' fixations were merged to identify the attention center visualized in darkest colors shown in Fig.10. The comparisons of the two main metrics (i.e., fixation duration and fixation count defined in Table 1) are summarized in Fig. 11 and Fig.12 respectively.

<Insert Fig.10 here>

<Insert Fig.11 here>

Little difference of average fixation duration is found between distinct and blurry scenes. The largest difference is found in the category of brightness, with the bright scenes causing more fixation time than dark scenes.

<Insert Fig.12 here>

The number of fixation points in the attention center visualized by dark red color in Fig.10 is summarized for each scene feature as seen in Fig.12. The largest difference comes from the category of ease of detection. Distinct scenes are generally found with higher fixation count than blurry scenes. Linked to Fig.11 where the fixation duration between the two scene features are almost the same, it is indicated that distinct scenes could let participants focus more on the hazard or AOI, and reduce the waste of attention resource on other non-relevant areas within the scene. More fixations targeting AOI or the hazardous zones, as indicated by Jeelani et al. (2018), could mean that the given hazard has higher chance of being detected by participants.

The effects of scene features in participants' visual search metrics

The effects of the three different types of measurements (i.e., first fixation, visual search track, and attention map) obtained from the eye-tracking experimental tests are displayed in Figs.13-15. A total of five metrics are compared between each pair of scene features, including the accuracy rate by first fixation, fixation count, intersection coefficient, fixation duration, and the fixation count in the attention center.

<Insert Fig.13 here>

Although the accurate detection of hazard(s) by the first fixation under blurry scenes is slightly higher than that in distinct scenes, the difference is not large (i.e., *82.7*% over *79.6*%). Similar marginal differences can be found in fixation count and the fixation duration between distinct and blurry scenes. The higher intersection coefficient under blurry scenes indicates that participants had to spend more time in saccades to search targets (i.e., hazards). The ratio of fixation count in the attention center to the total fixation count also indicates that distinct scenes generally enable participants to concentrate more on AOI or hazards, with less time wasted in other non-hazardous zones or saccades. Overall, it is suggested that blurry scenes would trigger participants' higher cognitive loads in searching hazards due to the more complex search track measured by intersection coefficient. In comparison, hazards in distinct scenes, although may not be with a higher accuracy rate of being detected by the first fixation, would reduce participants' attention resource on saccades and increase the efficiency of spending the attention resource on AOIs.

<Insert Fig.14 here>

Fig.14. Comparisons of eye-tracking measurements between bright and dark scenes

Compared to dark scenes, bright scenes increase participants' fixation counts and total fixation durations, meaning that participants have to spend more attention resources. On the other hand, the higher brightness also decreases the intersection coefficient and fixation count in the attention center zone. It is further inferred that there are both advantages and disadvantages of working in a brighter scene. Increasing the brightness may not increase the chance for the hazards to be detected by the first fixation. Instead, more fixations may be needed due to the increased search area in the given scene, causing more attention resources to be spent on searching. According to the metrics of total fixation count, a lower portion is allocated to gazes in the attention center under bright scenes. The comparisons shown in Fig.14 imply that there could be an optimized brightness level to minimize site employees' cognitive load in detecting hazards. Increasing the brightness does not necessarily result in better hazard detection performance for employees. How to decide the optimized lighting level under a certain construction scenario needs further research.

<Insert Fig.15 here>

Fig.15. Comparisons of eye-tracking measurements between tidy and messed scenes

All the five metrics displayed in Fig.15 consistently show that messed scenes increase the cognitive load of participants. Poor housekeeping or disorganizing items on-site does not only cause higher cognitive load for site employees, but may also lead to more potential safety accidents. In contrast, a well-organized site with proper layout of materials, equipment, and other resources can reduce the intervention of non-relevant items and decrease employees' attention resources to search and detect hazards.

Discussions

This research serves as one of the first studies to investigate the effects of different construction site scenes on employees' safety cognitive load. The findings of the effects from different construction site conditions were generally consistent with the descriptions of how cognitive loads could be affected by the physical environment (e.g., Choi et el., 2014). The implications of this current study can be summarized in the following three aspects related to the distinctiveness of hazard(s), the proper utilization of lighting facilities, and site housekeeping.

The distinctiveness of the hazard

Existing literature (Corbetta and Shulman,2002; Carrasco, 2011; Anderson et al., 2018) have defined two typical visual attention models, namely top-down and bottom-up attention.

The former type refers to voluntary allocation of attention to certain features, objects or regions (Pinto et al., 2013), such as the hazard zone in this study. The top-down approach can implement human beings' longer-term cognitive strategies (Connor et al., 2004), e.g., safety hazard detection or recognition. The bottom-up approach is more stimulus-driven rather than goal-oriented (Pinto et al., 2013). Salient stimuli can attract human beings' attention, even though they do not have the intention to attend to the stimuli (Schreij et al., 2008). The top-down attention is affected by the subjects' experience, knowledge, and capability. For example, the search patterns to safety hazards is strongly related to construction workers' experience (Dzeng et al., 2016). When the subjects have similar knowledge or skill background, the bottom-up approach could display higher impacts on subjects' attention resource allocation and cognitive load. In this study, more distinct objects (i.e., hazard zones) could more easily catch subjects' attention and lead to lower attention resources spent. A recommendation can be provided for site safety management that safety warning signs with different colors should be set to indicate the location and the level of danger of hazards.

Adopting proper lighting condition to minimize site employees' cognitive load

Rods and cones are the two main types of photoreceptors in human retina (RIT CIS, 2019). Rods are responsible for vision at low light levels but can not detect the colors; cones are active in brighter conditions and are capable of color visions (RIT CIS, 2019). Human beings are unable to detect colors in the darkness. Generally, dark environment will cause subjects' decrease or even loss of detecting the objects. A higher cognitive load will be required to detect the objects under a darker environment. In this study, it is found that the dark scenes slightly decrease the detection rate of the hazard and increase the intersection coefficient. However, it is also noticed that increasing the brightness would make subjects exposed to more objects and increase the fixations on more non-relevant objects that become visible due to the increased lighting. As a result, subjects end up spending more attention resources gazing these extra objects. The current study could only imply that the site brightness is a double-edged sword that may cause both positive and negative effects in subjects' cognitive load. For night construction work or construction in a dark environment, it is recommended that contractors should properly allocate the lighting resources to distribute the lighting mainly in the working zone. It would be helpful to add some safety signs that are easily detected to complement the lighting condition.

Housekeeping and proper site layout

The tidiness of jobsites has been found with highly consistent effects in subjects' safety hazard detection. Tidy and well-organized sites could also reduce subjects' cognitive load through reduced efforts spent on other non-relevant objects or saccades. According to Chun (2003), subjects have to spend more attention resources to recognize the more complicated site layout or irregularly organized spatial conditions. Instead, a clearly organized site would make items laid in a more regular and simple manner, and reduce the cognitive load of subjects. Therefore, it is recommended that construction sites should be properly planned with a clear layout. Materials, equipment, and other construction resources should be placed in a regular and disciplined manner in order to make them more easily found by employees. Housekeeping is not only critical to productivity but also to safety performance, the latter of which is linked to employees' cognitive load.

Conclusions

This study investigated the effects of site conditions on subjects' hazard detection performance which was directly linked to human beings' cognitive load. A total of *20* site scenes were selected to represent a combination of scene features (i.e., distinctness versus obscurity/blur, brightness versus darkness, and tidiness versus mess). The cognitive load, which was highly connected to human beings' attention resource allocation, was measured according to participants' fixation, visual search track, and attention map in the eye-tracking experiments. There were different measurements and metrics of participants' cognitive load, such as fixation count and intersection coefficient. The eye-tracking experimental studies revealed that: (1) more distinct hazards or hazard zones on construction sites tended to be more easily noticed by subjects, hence reducing subjects' cognitive loads. Therefore, increasing the distinctiveness of site hazards would generally improve the hazard detection performance. (2) site brightness has both positive and negative effects on subjects' safety recognition performance. The mechanism of how the lighting condition impacts hazard detection performance is more complicated and needs more research; and (3) a tidy site with clear layout would reduce subjects' cognitive loads, leading to better safety recognition performance. This study provided a quantitative and empirical approach addressing three main research questions by contributing to: (1) establishing a comprehensive list of measurement indicator for subjects' cognitive load in detecting construction hazards; (2) defining the three separated site factors (i.e., distinctness, brightness, and tidiness) which could affect subjects' safety hazard recognition; and (3) examinating the effects of the three defined site factors on hazard recognition. Overall, the study contributed to the body of knowledge in safety management by extending qualitative descriptions and theories of cognitive load to the context of construction safety hazard detection. It would lead to more future work in reduction and prevention of safety accidents linked to construction employees' cognitive load.

Following the prescriptive data analysis by comparing participants' eye movement metrics, recommendations were provided towards the enhancement of site safety features, specifically: (1) using safety signs with different colors to increase the distinctiveness of hazards; (2) proper allocation of lighting resources to working zones especially for night construction or dark environment; and (3) proper housekeeping to keep sites tidy and well-organized in order to decrease employees' cognitive load. These implications could be adopted to enhance safety education to construction employees, as the cognitive load is directly linked to employees' capability to detect site hazards and further influences their safety performance.

The current study serves as the early-stage research of using digital technologies to evaluate construction employees' cognitive load spent on detecting site hazards. It is limited to static photos by excluding other interventions. In reality, construction sites are dynamic with complex intervening factors such as noise and working with other peers. It is still difficult to capture the real-world cognitive load of construction employees in perceiving hazards. As the follow-up work, researchers will continue utilizing immersing technologies (e.g., Building Information Modeling linked to Virtual Reality) to simulate the dynamic site scenarios. As a step forward from the current study, the eye-tracking data from the virtually simulated scenarios would be captured for analysis under a dynamic environment. Another limitation of the current study is that only student participants with similar educational and practical experience were recruited for the eye-tracking experimental tests. This work excluded the effects of personal traits (e.g., working trade, safety knowledge, and prior scenario of accidents, etc.) on subjects' hazard recognition capability by solely focusing on site conditions. As part of the future research agenda, construction employees would also be recruited to run these virtual eye-tracking experiments.

Data Availability Statement

Data generated or analyzed during the study are available from the corresponding author by request.

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Table 1. Site scene selection and descriptions of each scene

Scene category	Scene feature	Definition
Ease of detection	Distinct	Scenes where hazards are obvious and easy to detect
	Blurry	Scenes where hazard are not easily detected and may require some longer time for employees to detect
Brightness	Bright	Scenes with adequate lighting and little need for additional lighting devices
	Dark	Scenes with insufficient lighting, and need additional lighting device (e.g., artificial lighting) to assist construction work
Tidiness	Tidy	Scenes where working zones are clearly defined with good housekeeping and with items well organized.
	Messed	Scenes without clearly planned working zones, with materials or equipment disorganized.

Table 2. Definitions of measurement and metrics of experimental participants’ viewing pattern

Eye movement measurement	Description	Metrics	Definition	Rationale in the context of cognitive loading
Location of first fixation	The first fixation point	The percentage of participants that could correctly identify the hazard at the first fixation	The ratio of all participants who correctly placed their first fixation in the hazardous zone (i.e., areas of interest or AOIs)	This measurement defines the distinctness a hazard or a search target. A higher percentage of participants with their first fixation falling into the hazardous zone would mean that the hazard can be detected correctly with a higher accuracy rate. It also means that the hazard is more distinct for participants to notice, indicating that participants spend less attention resource with a lower cognitive load.
Visual search track	The visual search track consists of multiple scan paths when a participant is looking for site hazards through fixations and saccades	Fixation count	Number of fixations in the whole search track	This measurement defines the detection complexity in a certain site scene. More fixations and a higher intersection coefficient in the scene mean that hazards are more complex or with a higher degree of variety. Therefore, the difficulty increases for participants to correctly detect the hazards. They would have to spend more attention resource with a higher cognitive load.
		Intersection coefficient in the search track	The level of intersection measured by different scan paths crossing each other during the search process	
Attention map visualized by the cognitive resource allocation in a given site scene	Experimental participants’ attention resource allocation visualized by different colors to show the center of focus	Fixation duration	The summed duration of all fixations in viewing a given scene	This measurement defines the cognitive load to recognize site hazards. The attention map, which is automatically generated upon the end of the eye-tracking experiment, is visualized by different colors representing the allocation of attention resources. The darkest color zone represents where participants have spent most attention resources. Other zones in the given site scene with less attention resources spent are marked by lighter colors. The total fixation duration and fixation count in the attention center zone measure the attention resource needed to correctly detect hazards in a given scene. Higher fixation duration and fixation count in the attention center indicate a more complex scenario for participants, who have to spend more attention resources with a higher cognitive load.
		Fixation count in the attention center zone	The number of fixation (i.e., fixation count) in the center zone where participants have spent most attention resource	