Impact of Construction Workers' Hazard Identification Skills on Their Visual Attention

Article *in* Journal of Construction Engineering and Management · October 2017

DOI: 10.1061/(ASCE)CO.1943-7862.0001373

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Impact of Construction Workers' Hazard Identification Skills on Their Visual Attention

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Abstract: Eye-movement metrics have been shown to correlate with attention and, therefore, represent a means of identifying and analyzing an individual's cognitive processes. Human errors—such as failure to identify a hazard—are often attributed to a worker's lack of attention. Piecemeal attempts have been made to investigate the potential of harnessing eye movements as predictors of human error (e.g., failure to identify a hazard) in the construction industry, although more attempts have investigated human error via subjective measurements. To address this knowledge gap, the present study harnessed eye-tracking technology to evaluate the impacts of workers' hazard-identification skills on their attentional distributions and visual search strategies. To achieve this objective, an experiment was designed in which the eye movements of 31 construction workers were tracked while they searched for hazards in 35 randomly ordered construction scenario images. Workers were then divided into three groups on the basis of their hazard identification performance. Three fixation-related metrics—fixation count, dwell-time percentage, and run count—were analyzed during the eye-tracking experiment for each group (low, medium, and high hazard-identification skills) across various types of hazards. Then, multivariate ANOVA (MANOVA) was used to evaluate the impact of workers' hazard-identification skills on their visual attention. To further investigate the effect of hazard identification skills on the dependent variables (eye movement metrics), two distinct processes followed: separate ANOVAs on each of the dependent variables, and a discriminant function analysis. The analyses indicated that hazard identification skills significantly impact workers' visual search strategies: workers with higher hazard-identification skills had lower dwell-time percentages on ladder-related hazards; higher fixation counts on fall-to-lower-level hazards; and higher fixation counts and run counts on fall-protection systems, struck-by, housekeeping, and all hazardous areas combined. Among the eye-movement metrics studied, fixation count had the largest standardized coefficient in all canonical discriminant functions, which implies that this eye-movement metric uniquely discriminates workers with high hazard-identification skills and at-risk workers. Because discriminant function analysis is similar to regression, discriminant function (linear combinations of eye-movement metrics) can be used to predict workers' hazard-identification capabilities. In conclusion, this study provides a proof of concept that certain eye-movement metrics are predictive indicators of human error due to attentional failure. These outcomes stemmed from a laboratory setting, and, foreseeably, safety managers in the future will be able to use these findings to identify at-risk construction workers, pinpoint required safety training, measure training effectiveness, and eventually improve future personal protective equipment to measure construction workers' situation awareness in real time. **DOI: 10.1061/(ASCE)CO.1943-7862.0001373.**

Author keywords: Construction safety; Hazard identification skill; Eye-tracking technology; Human error; Multivariate ANOVA (MANOVA); Labor and personnel issues.

Introduction

The construction industry is one of the most hazardous industries worldwide (Fung et al. 2005; Esmaeili and Hallowell 2012; Zhang and Fang 2013). Although statistics have shown a slight improvement in accident rates in the United States, this sector accounted for 19% of all domestic workplace fatalities in 2014 (U.S. Bureau of Labor Statistics 2016). It is well known that unsafe acts caused by human error are the main reason for up to 80% of accidents across various industries (Garrett and Teizer 2009), and previous studies (e.g., Shappel and Wiegmann 2000; Garrett and Teizer 2009; Lopez et al. 2010) have identified skill-based (e.g., attention failure) and perceptual-based (e.g., failure to identify and misperceptions) errors as the main contributors to accidents. Thus, one of the core activities in any construction safety program meant to prevent accidents is identifying and controlling hazards (Goetsch 1996; Holt and Lampl 2006). However, hazard identification levels are considerably lower than ideal for construction projects (Carter and Smith 2006). Because a failure to identify hazards exposes workers to injury (Wilson 1989), developing innovative methods to track and improve workers' hazard-identification skills is essential.

Identifying hazardous situations is a complex and multidimensional cognitive process. Individuals' failure to identify potential risks and the resulting unsafe actions they take in hazardous situations are often caused by their failure to attend to the hazard. Because behavioral data on eye movements represent the most direct manifestation of visual attention, such data can provide valuable information about an observer's attention and the course of his or her behavior in hazardous situations (Huestegge et al. 2010; Cheng et al. 2011; Borowsky et al. 2012; Bhoir et al. 2015; Dzeng et al. 2016; Hasanzadeh et al. 2016a, 2017b, a).

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Note. This manuscript was submitted on October 3, 2016; approved on April 10, 2017; published online on July 21, 2017. Discussion period open until December 21, 2017; separate discussions must be submitted for individual papers. This paper is part of the ***Journal of Construction Engineering and Management***, © ASCE, ISSN 0733-9364.

Eye-tracking technology is one of the most commonly used techniques for measuring oculomotor behavior and, by extension, visual attention (Popa et al. 2015). This type of technology helps researchers investigate the impact of various stimuli (independent variables) on the observer's eye movements (dependent variable) (Duchowski 2007). Because the accuracy and accessibility of eye-tracking systems have been improved through the years, the technology's application has gained traction in a wide variety of disciplines (Jie and Clark 2008). Although several studies have pointed out the importance of studying attention to reduce accidents and improve safety performance in construction projects (e.g., Teizer 2016; Garrett and Teizer 2009; Artman 2000), to date, there have been limited investigations into the visual attention of construction workers and, as such, limited investigation into the link among attention, hazard identification skills, and safety performance.

To address this knowledge gap and improve construction safety, this study empirically examines the relationship between workers' hazard-identification skills and the eye movements that indicate their attentional distributions. Given that where one looks highly correlates with where that person is focusing his or her attention (Hoffman and Subramaniam 1995), this study used eye-tracking technology to decipher whether hazard identification skills manifest as specific eye-movement patterns. Accordingly, this study evaluated the impacts of workers' hazard-identification skills (independent variables) on their attentional distributions and visual search strategies by measuring three fixation-related eye-movement metrics (dependent variables) across various types of hazards (e.g., fall, struck-by, housekeeping hazards). The proposed predictive models built based on the combination of eye-movement metrics will enable safety managers to identify workers with lower hazard-identification skills, and will have the immediate benefit of pinpointing opportunities to provide proactive training, and develop guidelines that reduce human errors and accidents on construction sites.

Literature Review

Hazard identification studies and eye-tracking applications are two arenas that underpin this research. To better establish the concepts of this paper, the authors conducted a literature review on previous hazard-identification studies, the relationship between eye movements and attention, the relationship between eye movements and hazard identification, and the eye-tracking studies in construction safety. The following review is a representative sampling from these areas.

Hazard Identification

One of the major causes of accidents in the construction industry is the unsafe acts of workers—or human errors—as opposed to unsafe working conditions (Abdelhamid and Everett 2000; Garavan and O'brien 2001; Garrett and Teizer 2009). Workers on the construction site are tasked with identifying hazards and responding properly to them in order to prevent undesirable outcomes and uncontrolled risks (Rozenfeld et al. 2010). One of the main causes of human error that may lead to accidents and injuries on a construction site is workers' lack of attention when detecting potential or active hazards, which often leads to improper reactions.

Considering hazard identification's significant role in reducing injuries, a great deal of research has been directed toward various hazard-identification strategies to improve safety management, such as the accident root cause tracing model (Abdelhamid and Everett 2000), failure mode and effect analysis (Stamatis 2003), fault tree analysis (Brooke and Paige 2003), the information retrieval framework and case-based reasoning (Goh and Chua 2009), and job hazard analyses (Rozenfeld et al. 2010). However, some of these strategies are not effective for construction because of the dynamic and complex nature of the construction industry and the lack of standardization in construction processes (Abdelgawad and Fayek 2012). Therefore, a substantial number of hazards remain unidentified, which leads to uncontrollable situations and raises unmanaged risks. This, in turn, can significantly affect project safety (Sneddon et al. 2004; Carter and Smith 2006; Bahn 2013).

The majority of current hazard-identification strategies fall into two categories: retrospective and predictive approaches (Shorrock and Kirwan 2002). The retrospective approach relies on learning from past reported incidents to come up with a framework for future learning (Goh and Chua 2009; Mitropoulos and Namboodiri 2011). The predictive approach, on the other hand, identifies hazards in the preconstruction phase using different kinds of modeling tools and brainstorming techniques (Hola 2010; Esmaeili et al. 2015a, b). Both retrospective and predictive approaches have some limitations that need to be mentioned. Retrospective approaches usually rely on databases that are often incomplete and cannot be used in the preconstruction phase of a project (Dong et al. 2011). Moreover, most of the predictive approaches fall short in accurately identifying hazards in a real construction project (Borys 2012) because the dynamic nature of construction sites creates a large number of confounding factors that are difficult to incorporate into a statistical model. Finally, and most importantly, both approaches substantially ignore the role of human factors and the cognitive processes at play when workers engage in hazard identification. These approaches assume that all workers have a similar ability to identify hazards when exposed to a risky situation (Fleming 2009). Identifying new techniques that can assess both the human factors and cognitive processes at play in hazard identification, as well as which factors/processes can be applied during the construction phase of the project, is vital to reduce injury rates and improve safety on construction sites.

Eye Movements and Attention

Attention, an important element in many cognitive tasks, has been studied for over a century in numerous domains. Attention is defined as the focus of consciousness on a particular stimulus while ignoring other distracting objects in the environment (James 1913). A growing number of psychological and neuropsychological studies have demonstrated the close relationship between attention and eye movements (Yarbus 1967; Sun et al. 2008). Specifically, there is considerable evidence that people often look directly at the stimuli they are currently attending to (Duchowski 2007). If a worker attends to a hazard, it is very likely that he or she will identify and perceive the hazard and consider protective actions. Owing to the limited capacity of human information processing as well as the hazard identification skills at play, this study examines construction workers' visual attention to determine how they choose to attend to or ignore different types of hazards when viewing images of real construction scenarios.

Eye Movements and Hazard Identification

The literature on hazard detection and eye-movement behavior has often focused on driving and driving skills. These studies involve participants either viewing pictures or scenarios (e.g., Underwood et al. 2005), using movie-based simulators (e.g., Borowsky et al. 2012; Mackenzie and Harris 2015; Underwood et al. 2011), or participating in real-time experiments (e.g., Sun et al. 2016). To automatically detect whether the participants identified the hazards, the researchers had to reliably track participants' eyes to determine whether they fixated on or pursued hazardous sources. In static experiments, participants had to press a button when they identified a hazard, and the researchers simultaneously tracked the participants' eye movements (e.g., Borowsky et al. 2012). In real-world experiments, the researchers used mobile eye trackers and conducted their experiments in dynamic environments while the subjects drove real cars (e.g., Sun et al. 2016). The results of these previous studies have shown that participants' performance in hazard detection tasks serve as predictors of accident involvement (Horswill and McKenna 2004; Wallis and Horswill 2007). These experiments have also revealed participants' knowledge about types of hazards and their associated risks (Browsky and Oron-Gilad 2013). Moreover, examining observers' attentional allocation and visual search strategies as they watch videos of hazardous situations further illustrated their hazard detection skills (Underwood et al. 2011).

Generally, when an individual identifies an imminent hazard, he or she processes information about the scene in an in-depth manner and monitors the location for further potential hazards. However, there is potential danger in overfocusing attention on one region in a scene, which may prevent the observer from detecting and processing other active or potential hazards elsewhere (Underwood et al. 2011). Workers with high hazard-identification skills distribute their attention in balanced ways to identify concurrent risks and respond appropriately. Driving-related studies into this behavior have helped identify oculomotor strategies used by observers with differing hazard-identification skills (Mackenzie and Harris 2015), with some of these studies leading to the development of a training process to better enable the broad distribution of attention and to improve hazard identification skills. These studies then evaluated their training effectiveness using eye-tracking technology (e.g., Pradhan et al. 2009; Underwood 2007).

Eye-Tracking Studies in Construction Safety

Because eye tracking has immense potential to provide deeper insights into construction workers' hazard-identification patterns, in 2015, in one of the earliest studies to apply eye-tracking technology to improve construction workers' safety, Bhoir et al. (2015) investigated construction workers' hazard-identification skills and visual attention by examining participants' eye movements and attentional distribution when they were shown hazardous situations in construction site images. Using a head-mounted *EyeLink II* system, the authors calculated fixation-/gaze-related and saccade-related metrics and generated absolute duration heat maps for each area of interest. The results of the analysis revealed that some people failed to fixate on hidden hazards or even a danger sign. Building on the success of Bhoir et al. (2015), Habibnezhad et al. (2016a) tested the hypothesis that workers' risk perception impacts their visual search strategies when identifying hazards. To test this hypothesis, the authors recruited 31 construction workers and conducted an eye-tracking experiment while also measuring workers' risk perception. After dividing workers into different clusters according to their risk perception, the authors statistically investigated differences in participants' eye-movement metrics. They found that (1) people with high risk perception have a lower mean dwell-time percentage for all types of hazards compared with people with low risk perception, (2) people with high risk perception have a lower mean dwell-time percentage for ladder-included hazards compared with people with low risk perception, and (3) people with higher risk perception have higher first-fixation duration for struck-by-material hazards compared with those with lower risk perception. This study establishes the relationship between risk perception and eye movements.

To assess construction workers' real-time situation awareness, Hasanzadeh et al. (2016a) used a mobile eye tracker to measure workers' situation awareness in different scenarios within a real-world construction site. Using direct measures of situation awareness (eye movements) in parallel with subjective situation-awareness measures, they found a strong association between these two types of situation awareness measurements. They also found that workers' situation awareness and visual attention allocation varies significantly as a function of the scenario's workload and the workers' level of experience. The results from this study may help to identify workers who have lower situation awareness, and therefore pinpoint opportunities to provide proactive training and develop guidelines for workers, which will reduce human errors and accidents on construction sites. Additionally, this approach can measure the same workers' situation awareness after training to determine whether they have improved. This was the first study to use a mobile eye tracker on a construction site to measure construction workers' situation awareness.

In another study, Dzeng et al. (2016) investigated the impact of working experience on worker attention by creating virtual images of hypothetical scenarios that involved multiple hazards. They found that although experienced workers were faster in identifying both obvious and unobvious hazards, their ability to accurately identify hazards was not significantly different from novice workers. Despite the significant contributions of this study, there are some limitations worth noting. First, viewing time was not controlled in Dzeng et al.'s (2016) study, which is problematic for a few reasons. In an actual workplace, workers are required to process information quickly, not in the absence of time constraints. More importantly, many of the critical eye-movement metrics that Dzeng et al. used (e.g., number of fixations, fixation frequency) are impacted by viewing time, but this was not taken into account in the analysis. For instance, number of fixations can be influenced by viewing duration, so comparing the number of fixations of one subject who focused on the area of interest for 15 s with another subject who looked at the same area for 50 s does not permit an equivalent comparison. Without correcting for actual trial time, these data are uninterpretable. Furthermore, the longer the trial goes, the less likely it is that each subsequent eye movement will be directed toward the intended task (i.e., hazard identification), so with an extended viewing time, it is unclear whether the visual behavior was solely directed toward hazard identification, thus further confounding matters. Second, the stimuli in Dzeng et al.'s (2016) work consisted of virtual images of a limited number of hypothetical construction scenarios, not real images taken from real constructions sites—a choice that could confound the outcomes of the study.

In a related study, Hasanzadeh et al. (2017b) addressed some of the limitations related to Dzeng et al.'s (2016) study. With the fundamental objective of measuring the impacts of safety knowledge—specifically, training, working experience, and injury exposure—on construction workers' attentional allocation, Hasanzadeh et al. (2017b) designed a laboratory experiment in which participants identified safety hazards presented in 35 construction site images ordered randomly, each of which showed multiple hazards varying in safety risk. During the experiment, the eye movements of 27 construction workers were recorded using a head-mounted *EyeLink II* system. The impact of worker safety knowledge in terms of training, working experience, and injury exposure (independent variables) on eye-movement metrics (dependent variables) were then assessed by implementing numerous permutation simulations. The authors found that tacit safety knowledge acquired from working experience and injury exposure can significantly improve construction workers' hazard detection and visual search strategies. Other notable findings include the following: (1) there is minimal difference with or without the Occupational Safety and Health Administration (OSHA) 10-h certificate in workers' visual search strategies and attentional allocation when they are exposed to or seeing hazardous situations; (2) relative to less-experienced workers (<5 years), more-experienced workers (>10 years) need less processing time and deploy more frequent short fixations on hazardous areas to maintain situational awareness of the environment; and (3) injury exposure significantly impacts a worker's visual search strategy and attentional allocation. The overall conclusion that can be made from Hasanzadeh et al.'s (2017b) study is that obtaining sufficient safety knowledge on a jobsite and improving safety awareness require the interaction of both tacit and explicit knowledge gained through work experience, injury exposure, and interactive safety training. Although these studies manifest the promise of applying eye tracking to construction safety, there are still gaps in knowledge about the possibility of using eye-movement metrics to identify at-risk workers.

Points of Departure

The majority of workers' safety errors and subsequent unsafe behaviors are rooted either in their inability to identify a hazard or in their misperception of the associated risk. Previous studies have shown that visual attention is closely related to the sequence of eye movements used to search, and that fixations and their related metrics are reliable indicators of ongoing cognitive processes (e.g., Wickens et al. 2015; Duchowski 2007). Although previous studies in the field of cognitive psychology have used the search task to examine subjects' visual information processing and perceptual representation (e.g., Treisman and Gelade 1980; Wolfe 2007), limited attempts have been made to investigate the potential of harnessing eye movements as predictors of workers' hazard-identification skills in the construction industry.

One of the major barriers to studying the impact of hazard identification skills on workers' visual attention relates to the lack of reliable tools for measuring variation in those processes. However, recent advances in eye-tracking technology have provided an easy-to-use and readily available tool for measuring variation in cognitive processes using eye-movement patterns. The use of eye-tracking technology is novel, and it provides a largely direct measure of attention, thereby offering immense potential for investigating, understanding, and improving construction workers' attention.

Thus, the present study explores the links among eye movements, hazard identification skills, and attentional allocation. To achieve this goal, the research team followed these steps: (1) evaluate the impact of workers' hazard-identification skills on their visual attention across different types of hazards (e.g., fall, struck-by, housekeeping hazards) and (2) develop a mathematical models based on eye-movement metrics as predictors of workers' hazard-identification skills to identify at-risk workers by tracking their performance in recognizing active and potential hazards. By focusing on the connection between attention and eye movements, this research will enable the identification of at-risk workers through mathematical models. Accordingly, this study will challenge the traditional reactionary paradigm of construction hazard management by proposing a method to detect at-risk workers and predict their possible safety errors using measurable indicators of attention, namely eye-movement patterns and fixations.

Methodology

As described subsequently, the objectives of the study were accomplished by conducting five main tasks. First, images of construction sites with different types of hazards were collected and screened for the experiment. In the second step, the research team recruited construction workers to participate in the study using various strategies (discussed subsequently). Third, the eye-tracking experiment was designed to track workers' attentional allocation via their visual search strategies as they view randomly ordered scenario images. This eye-tracking technique helped establish where and how workers distribute their attention when viewing a scene to identify active and potential hazards. Moreover, this technique helped reveal the types of hazards at-risk workers missed or perceived as less significant. Fourth, the research team determined workers' hazard-identification skills on the basis of the number of hazards each participant identified in each image scenario; workers were then grouped on the basis of their hazard identification skills. Lastly, multiple statistical analyses, including multivariate ANOVA (MANOVA) and discriminant function analysis, were conducted using the results of the last two steps in order to determine the impact of workers' hazard-identification skills on their eye-movement patterns and visual attention. The results from the statistical analyses were used to propose mathematical models that can classify workers on the basis of their hazard identification skills for different types of hazards. All procedures in this study were approved by the University of Nebraska–Lincoln Institutional Review Board. The following sections elaborate on the research protocol that was undertaken to accomplish the steps. The research framework is provided in Fig. 1.

Image Selection

The research team downselected 35 images from a pool of 150 images that were obtained from the safety managers of companies that are members of the Construction Industry Institute. These scenario images were taken from different private residential and commercial construction sites across the United States, and included different types of hazards that are among the most typical safety risks leading to accidents, such as falls to lower level, fall-protection systems, ladders, struck-by hazards, and housekeeping hazards. Safety managers used these images to document existing hazards on a site and communicate improvement strategies to mitigate potential hazards. The selected images were of high quality, and each had at least one hazard that could be identified.

Participants

Construction workers were solicited to participate in this study via (1) invitation flyers posted at construction sites in Lincoln and Omaha, Nebraska; (2) invitations extended directly via stopping by construction companies' main offices and contacting facility managers at the University of Nebraska–Lincoln; and (3) flyers with a one-page summary of the research project sent to Associated Builders and Contractors (ABC) members and department advisory boards. As a result, a total of 31 construction laborers (30 males, 1 female) participated in this study. Given that empirical research of this nature affords the opportunity to collect multiple data points per individual for each trial, a smaller sample size is appropriate relative to larger survey-style studies. However, this study met the sample size requirement discussed by Pernice and Nielsen (2009), who stipulated that sample sizes vary greatly in eye-tracking studies, ranging from 6 for qualitative studies to 30 for quantitative studies.

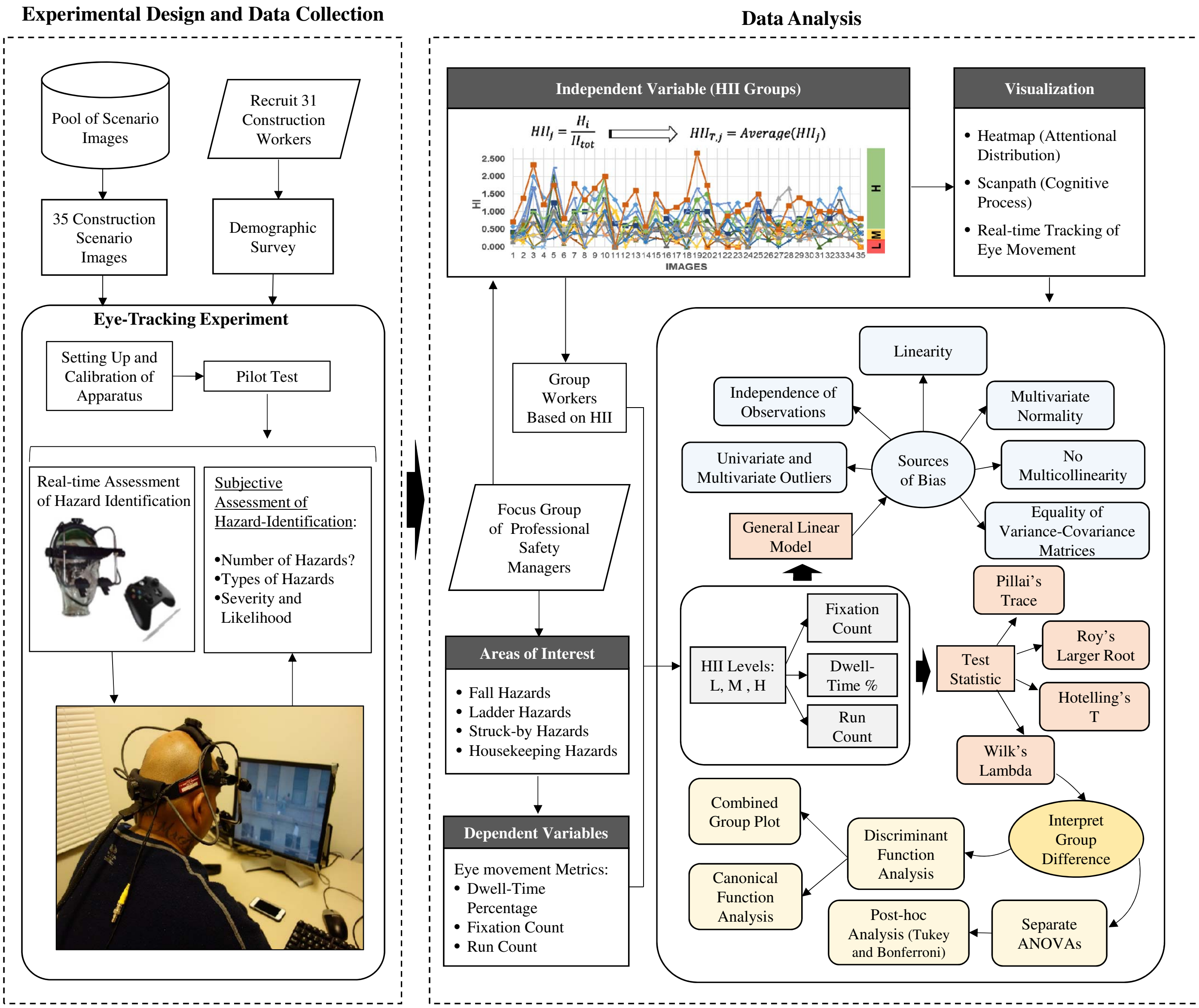

Fig. 1. Research framework (image by Sogand Hasanzadeh)

The participants were mostly young to middle aged (93% were between the ages of 20 and 55 years). All participants had normal or corrected-to-normal vision. The experiment was conducted in a single 30-min session for each worker. The data for four participants was omitted from the analysis because acceptable levels of calibration on the eye tracker could not be achieved. Six participants were also omitted because they were the univariate outliers in the hazard identification calculation (three out of six) and because of interruptions during the eye-tracking experiment (three out of six). The final analyses were based on the data from the remaining 21 workers. All participants received gift cards as compensation.

Experimental Design

The eye-tracking experiment was designed to present 35 randomly ordered construction scenario images, each of which displayed multiple hazards varying in safety risk. Each image appeared on the screen for a maximum of 20 s. Workers were asked to wear an *EyeLink II* with a high spatial resolution and a sampling rate of 500 Hz in order to track and record their eye movements. The *EyeLink II* is a head-mounted eye-tracking system that uses cameras to track the movement of the pupil. Participants were asked to scan each picture and look for potential or active hazards; they then reported the results of their exploration as to whether they found any hazards by pushing button A for "Yes" or B for "No" on a response pad. At the conclusion of each trial, subjects were asked about the number, types, likelihood, and severity of the safety issues they found in each scenario's image. In addition to the eye-tracking experiment, workers took a short survey asking about their demographic information, including age, gender, race, nationality, years of experience, obtained certifications, and training. This protocol was followed while asking for the number of hazards and while conducting the eye-tracking experiment to ensure that the results were comparable.

Hazard Identification Index

To evaluate the hazard identification skills of workers, the hazard identification index (HII_{ij}) was calculated for each worker (j)

(adopted from Carter and Smith 2006). The hazard identification index is defined as $\mathrm{HII}_{ij} = \mathrm{H}_i/\mathrm{H}_{\mathrm{tot}}$, where $\mathrm{H}_{\mathrm{tot}}$ represents the total number of identifiable (potential and active) hazards in image i based on the professional safety mangers' opinions, and H_i indicates the number of hazards identified by the worker j in image i. To compute the total hazard identification index for worker j ($\mathrm{HII}_{T,ij}$), the mean of HII_{ij} was calculated across all 35 images: $\mathrm{HII}_{T,ij} = \mathrm{Average}(\mathrm{HII}_{ij})$. Then, based on the workers' average performance in identifying hazards across 35 images, they were divided into three HII groups, namely low ($\mathrm{HII}_{T,ij} < 0.3$), medium ($0.3 \leq \mathrm{HII}_{T,ij} \leq 0.6$), and high ($\mathrm{HII}_{T,ij} > 0.6$) HII groups.

Eye-Tracking Data Analysis

The first step in extracting eye-movement metrics and establishing dependent measures is to define areas of interest (AOI) in each image. Areas of interest are visual environments of interest the research team defined (Jacob and Karn 2003). To identify the AOIs, an initial focus group consisting of five safety managers with more than 10 years of experience independently reviewed and discussed the hazardous situations depicted in the pictures. Then, the focus group qualitatively studied participants' search strategies and scanpaths to decipher hazardous areas the workers identified. Lastly, by overlaying and comparing the results of both of the previous steps, the AOIs were defined according to the different types of hazards that existed in the construction scenario images. The AOIs included fall to lower level (i.e., a worker is in the proximity of an unprotected building edge or roof, unguarded roof, floor openings, scaffolding, or skylights), fall-protection systems (i.e., misuse of a lanyard or other fall-protection systems), ladder (i.e., improper use of a ladder, such as using an inappropriate type or length of ladder, ignoring ladder-extension rules, using an unstabilized ladder or an unsecured straight ladder, and behaving in an unsafe manner when working on the ladder), struck-by (i.e., probability of being struck by heavy equipment or falling objects like tools, collapsing masonry, or concrete walls), housekeeping hazards (i.e., slippery working and walking surface conditions, unsafe material storage, and unsanitary work environment conditions), and all hazard types (i.e., combined eye-tracking metrics for ladder-, fall-, struck-by–, and housekeeping-related hazardous areas within scenario images).

The *EyeLink Data Viewer* was used to gather and analyze the two-dimensional eye-movement patterns of construction workers. This software provides a large database of metrics, including those needed to analyze eye-movement behavior within the respective AOIs. To explore the determinants of oculomotor behavior, previous eye-tracking studies have incorporated several metrics derived from the fixation measure (defined as a relatively stationary eye position over a minimum duration, such as 100–200 ms, although much longer fixations can also be observed as a function of an individual's processing goals) as dependent variables.

The selection of eye movement metrics depends on the cognitive processes investigated in each study. In this study, three fixation-related metrics per AOI were chosen: fixation count (i.e., the number of times the observer fixated on the specific area), the dwell-time percentage (i.e., relative to the duration of the trial, what proportion of time was spent fixating on each AOI), and run count (i.e., the average number of times each participant returned their gaze to a specific AOI). These metrics have been used frequently in previous eye-tracking work as dependent variables (e.g., Bhoir et al. 2015; Hasanzadeh et al. 2017b) to determine which information in a scene workers attended to.

Statistical Analyses

Eye-movement metrics were also calculated for each group (low, medium, and high HII) across the various types of hazards (AOIs). To measure whether workers' hazard-identification skills (the independent variable) impact their visual search strategy, the dependent variables described previously were collected during each experiment and were used for the analysis. Because there are multiple dependent variables, MANOVA was selected as the statistical method. Multivariate ANOVA is an extension version of ANOVA that not only illustrates the predictive power of the independent variables, but can also provide insights about the interrelationships and differences in a set of dependent variables (Hair et al. 2010). Multivariate ANOVA tests a set of dependent variables simultaneously rather than one at a time, which helps prevent the inflating alpha (Type I error) problem (Spicer 2005). This method helps identify a combination of dependent variables (eye-movement metrics) that determine the visual search strategies of workers with different hazard identification skills. In the present data set, because eye-movement metrics are correlated, using separate analyses of their determinants may well be confounded. Thus, the research team also examined the effects of workers' hazard-identification skills on two sets of eye-movement variables (canonical functions) that can jointly be mapped onto the complex content of workers' unsafe behaviors.

As far as power is concerned, having fewer than five dependent variables helped improve the power of the MANOVA test, which exceeds what can be obtained with a single ANOVA (Hair et al. 2010). Although having a larger sample size would be better, the only limit required by the test is that the number of participants in each group needs to be more than the number of dependent variables.

Before conducting any multivariate test, it is important to determine whether any critical assumptions have been violated. If the results of these tests are satisfactory, then multivariate test statistics are appropriate (Hair et al. 2010). The first assumption in this test deals with the independence of observations. Having different participants in each group without any extraneous or unmeasured effects enabled the research team to meet the first assumption.

Second, MANOVA is especially sensitive to univariate and multivariate outliers. To check this assumption, boxplots were studied (examples are provided in Fig. 2), and Mahalanobis distances were calculated to identify univariate and multivariate outliers. The boxplot uses the interquartile range (IQR) rule, and values of more than 1.5 IQR and less than 3 IQR are labeled as univariate outliers. Additionally, the Mahalanobis distance of each participant was compared with the chi-square distribution for the same degree of freedom. If the probability of Mahalanobis distance was less than 0.001 (critical value), the subject was considered a multivariate outlier and was removed from the analysis. Using the boxplots and Mahalanobis distance tests, no univariate or multivariate outlier was observed (probability of Mahalanobis distance > 0.001).

A third assumption recommends having multivariate normality among dependent variables across groups. Unfortunately, there is no direct test available for multivariate normality. However, if the univariate normality of all dependent variables is met, then the departures from multivariate normality are inconsequential. Therefore, the univariate normality of each eye-movement metric was tested using a Shapiro-Wilk test. If $-1.96 < z$ score $< +1.96$, or Shapiro $p > 0.05$, the test shows that the dependent variable for that group is approximately normally distributed. To meet the normality assumption of MANOVA, the fixation count and run count for ladder-related hazards were transformed using Log10. The results of the Shapiro-Wilk tests showed no violation in univariate

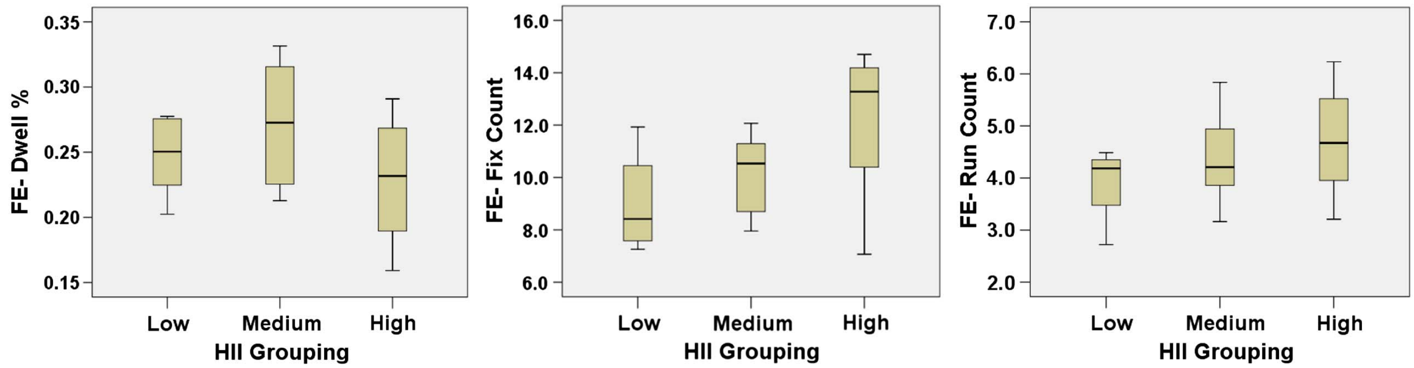

Fig. 2. Example of using boxplots to check for the existence of univariate outliers in HII groups for all eye-movement variables in all fall-to-lower-level (FE) hazardous areas

normality across different groups (Shapiro $p > 0.05$), so any departures from multivariate normality are inconsequential.

Fourth, conducting MANOVA requires linear relationships between each pair of dependent variables—that is, the eye-movement metrics. To satisfy this assumption, the scatterplot matrix of the dependent variables was plotted to determine whether they are linearly related. Examining complex scatterplots showed that there are linear relationships between each pair of eye-movement metrics.

Fifth, to measure the amount of multicollinearity that exists among the variables across groups, the variance inflation factor (VIF) was calculated using linear regression analysis. If the VIF is lower than 3, one can assume that there is minimal multicollinearity among variables across groups (Neter et al. 1996; Hair et al. 2010). Conducting linear regression showed there is no multicollinearity among dependent variables across groups (VIF < 3).

The last assumption for MANOVA is to meet the "equality of variance-covariance matrices across the groups." To test this assumption, the Box's M test was used to determine the "equality of covariance." If the Box's M test was significant ($p < 0.05$), Levene's test would have been used to test for variance homogeneity, and to determine where the problem may lie. However, the Box's M tests of equality of covariance was not significant for any of the eye-movement metrics ($p > 0.05$), and the assumption of homogeneity was also met (Table 1). The results of these tests illustrated that the assumptions of multivariate test statistics were met and that MANOVA will provide robust test statistics for this case.

There are several different multivariate tests that can be used to measure the significance of group differences in MANOVA. These multivariate tests vary on the basis of their associated F ratio. The four most common multivariate test statistics are Pillai-Bartlett trace, Wilks' Lambda, Hotelling's T^2, and Roy's largest root. The authors chose the Pillai's trace as the test statistic for this study because the HII groups (low, medium, and high) differed along two (more than one) variates. In addition, the Pillai's trace is the most robust to violations of assumptions when sample sizes across groups are equal, as in this study (Bray and Maxwell 1985). If the F statistic is significant ($p < 0.1$), one can conclude that the levels of workers' hazard-identification skills had significant impact on their eye movements—and, consequently, on their visual search strategies and visual attention—when they were exposed to different types of hazards.

Table 1. Box's M Test of Equality of Covariance Matrices

Source of hazard	Box's M	F	Df_1	Df_2	p-value
Ladder	19.282	1.208	12	1570.154	0.272
Fall to lower level	10.093	0.632	12	1570.154	0.816
Fall-protection system	9.019	0.565	12	1570.154	0.871
Struck-by	7.754	0.486	12	1570.154	0.924
Housekeeping	17.732	1.111	12	1570.154	0.347
All hazard types	26.052	1.632	12	1570.154	0.077

To follow up on the MANOVA test and further investigate the nature of hazard identification skills' effect on the dependent variables, two approaches were identified from the literature. The first—and most traditional—approach is to conduct separate ANOVAs on each of the dependent variables, and then conduct a post hoc test on significant relationships. However, as mentioned previously, using univariate ANOVA does not consider the linear relationship between dependent variables. Considering this limitation, statisticians have suggested to follow up MANOVA with the second approach, which is called discriminant function analysis.

In this paper, discriminant function analysis takes into account the correlation between eye-movement metrics (the dependent variables) and, because the analysis is conducted based on the variables' interactions, has more power to detect HII group differences. When discriminant function analysis is implemented, the eye-movement variables are transformed into new variables, called canonical variables. The quantity of canonical variables equals the number of original variables minus one. Some optimal combinations of variables are automatically determined [using Statistical Package for the Social Sciences (*SPSS*) software]. The first function provides the most overall discrimination between HII groups, and the second provides second most discrimination between groups. Moreover, these functions are independent or orthogonal, and their contributions to the discrimination between HII groups will not overlap. This analysis looks for an appropriate set of weights (the discriminant function) to be applied to the dependent variables (i.e., eye-movement metrics) and provides as much separation as possible among the grouped independent variables (workers with different hazard identification skills). Accordingly, in the current study, these two canonical variables combine three eye-movement metrics, appropriately weighted by the software, into a new variate (discriminant function), which maximizes the discrimination between the HII groups (low, medium, high) in terms of their hazard identification skills. The discriminant scores—which are developed for each canonical variable (function)—can be used to predict HII group membership on the basis of the maximum likelihood technique.

In terms of assessing the accuracy of these designations, three approaches can be used to calculate classification accuracy based on discriminant scores: resubstitution, cross-validation, and

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Cohen's Kappa. In the first approach, resubstitution, all data points are treated as training data to develop the discriminant functions, and then the accuracy of the classifications are calculated by dividing the number of cases that were classified correctly by the total number of observations. In the second approach, the "leave-one-out classification" as a cross-validation method is used to determine how well a discriminant score can predict HII group membership. In this technique, training data are treated as the test data while excluding one case from the analysis. The removed case is then classified on the basis of the new model to verify whether the original classification was correct. This process is repeated n (number of subjects) times, and then the percent of subjects classified correctly is calculated for each type of hazard.

Although these two approaches offer benefits, arguably the resubstitution value for classification accuracy could be affected by chance agreement (i.e., accuracy rate may appear better than it actually is). To address this issue, in the third approach, Kappa statistics serve as an index to correct for chance agreement. Kappa computes the accuracy in prediction of group membership [Eq. (1)] where $Pr(o)$ is the probability of observed agreement and $Pr(e)$ is the probability of random agreement:

$$\text{Kappa} = \frac{Pr(o) - Pr(e)}{1 - Pr(e)} \tag{1}$$

The Kappa coefficient value ranges from -1 to $+1$, wherein $+1$ indicates the perfect condition, 0 indicates the chance-level prediction, and any value greater than 0 indicates better than chance-level prediction. There are no established interpretations of Kappa coefficient values in eye-tracking studies, but based on the guidelines adapted from Landis and Koch (1977) and Altman (1991), a Kappa of 0.0 to 0.2 is interpreted as slight agreement; 0.21 to 0.4 equates to fair agreement; 0.41 to 0.6 signifies moderate agreement; 0.61 to 0.8 represents substantial agreement; and 0.81 to 1.0 demonstrates almost perfect agreement.

In this study, the research team adopted both follow-up approaches (separate ANOVAs and discriminant function analysis). First, separate ANOVAs were conducted on each independent variable, and then a discriminant function analysis was used to see how the different combinations of eye-movement metrics differentiate the workers in terms of their level of hazard identification skills. The following section illustrates the outcomes of all these analyses.

Results and Analysis

First, MANOVAs were performed to determine whether fixation count, run count, or dwell-time percentage differed on the basis of workers' hazard-identification skills across different types of hazards, namely, ladder, fall to lower level, fall-protection system, struck-by, housekeeping, and all hazard types combined. The results of the MANOVAs are summarized in Table 2. If the Pillai's trace's significance value is less than 0.05, this means that hazard identification skills have a significant impact on workers' eye-movement metrics for specific types of hazards (p-values less than 0.1 are considered moderately significant). Using Pillai's trace, this study found a significant effect of hazard identification skills on the visual search strategies (eye movements) of workers as they identified different types of hazards (see p-values less than 0.05 in Table 2). Although promising, this test cannot clarify which groups differed from which, or whether the effect of hazard identification skills was on dwell-time percentage, fixation count, run count, or a combination of these eye-movement metrics. Accordingly, two approaches were selected to follow up the MANOVAs: separate ANOVAs and discriminant analysis. The results for each of these follow-up approaches are described next.

Table 2. Multivariate Pillai's Trace Tests among HII Groups across Different Types of Hazards

Source of hazard	Value	F	Hypothesis df	Error df	Significance
Ladder	0.633	2.622	6	34	0.034[a]
Fall to lower level	0.651	2.738	6	34	0.028[a]
Fall-protection system	0.714	3.149	6	34	0.015[a]
Struck-by	0.732	3.268	6	34	0.012[a]
Housekeeping	0.642	2.682	6	34	0.031[a]
All hazard types	0.622	2.559	6	34	0.037[a]

[a]$p \leq 0.05$.

Separate ANOVAs

Separate ANOVA tests were conducted on each dependent variable, and the results of the tests of between-subject effects are summarized in Table 3. For example, for ladder-related hazards, hazard identification skill has a significant effect on dwell-time percentage: $F(2, 18) = 3.638$, $p = 0.047 < 0.05$ (Table 3).

Whenever there was a significant difference between the HII groups in terms of the eye-movement metrics, post hoc (Tukey HSD—honest significant difference—and Bonferroni) analyses were conducted to further investigate the relationships and understand which HII groups had a significant impact on which eye-movement measure. The results of the post hoc analyses (Tukey HSD and Bonferroni) for each AOI is provided here:

- Ladder-related hazards: The low HII group dwelt significantly more on ladder-related hazards than the high HII group ($p_{\text{TukeyHSD}} = 0.037 < 0.1$, $p_{\text{Bonferroni}} = 0.044 < 0.1$).
- Fall-to-lower-level–related hazards: The high HII group tended to fixate their gaze more on fall-to-lower-level hazards than the low HII group ($p_{\text{Tukey HSD}} = 0.059 < 0.1$, $p_{\text{Bonferroni}} = 0.072 < 0.1$).
- Fall-protection-system–related hazards: Workers with low or medium HII had significantly lower fixation counts on hazards related to fall-protection systems than workers with high HII ($p_{\text{TukeyHSD-low\&high}} = 0.007 < 0.1$; $p_{\text{TukeyHSD-medium\&high}} = 0.019 < 0.1$; $p_{\text{Bonferroni-low\&high}} = 0.008 < 0.1$; $p_{\text{Bonferroni-medium\&high}} = 0.022 < 0.1$). Moreover, workers with high HII tended to have a higher run count—that is, they returned their attention more frequently—to fall-protection-system–related hazards than workers with low HII ($p_{\text{Tukey HSD}} = 0.058 < 0.1$, $p_{\text{Bonferroni}} = 0.070 < 0.1$).
- Struck-by hazards: Workers with low or medium HII had significantly lower fixation counts on struck-by hazards than workers with high HII ($p_{\text{Tukey HSD-low\&high}} = 0.017 < 0.1$; $p_{\text{TukeyHSD-medium\&high}} = 0.017 < 0.1$; $p_{\text{Bonferroni-low\&high}} = 0.019 < 0.1$; $p_{\text{Bonferroni-medium\&high}} = 0.020 < 0.1$).
- Housekeeping hazards: Workers with low or medium HII had significantly lower fixation counts on housekeeping hazards than workers with high HII ($p_{\text{Turkey HSD-low\&high}} = 0.001 < 0.1$; $p_{\text{Turkey HSD-medium\&high}} = 0.001 < 0.1$; $p_{\text{Bonferroni-low\&high}} = 0.001 < 0.1$; $p_{\text{Bonferroni-medium\&high}} = 0.001 < 0.1$). Moreover, workers with high HII tended to have a higher run count of housekeeping hazards than workers with low and medium HII ($p_{\text{TurkeyHSD-low\&high}} = 0.002 < 0.1$; $p_{\text{TurkeyHSD-medium\&high}} = 0.003 < 0.1$; $p_{\text{Bonferroni-low\&high}} = 0.002 < 0.1$; $p_{\text{Bonferroni-medium\&high}} = 0.004 < 0.1$).
- All hazard types: Workers with low and medium HII had significantly lower fixation counts and run counts than workers with high HII ($p_{\text{Turkey HSD low\&high}} = 0.007 < 0.1$;

Table 3. Tests of between-Subject Effects on HII Groups across Various Types of Hazards

Source of hazard	Eye-movement metrics	HII groups	Mean	Standard error	Sum of squares	df	Mean square	F	p-value
Ladder	Dwell %	Low	0.119	0.007	0.002	2	0.001	3.638	0.047[a]
		Medium	0.107	—	—	—	—	—	—
		High	0.094	—	—	—	—	—	—
	Fix count	Low	2.096	0.098	0.051	2	0.025	2.301	0.129
		Medium	1.996	—	—	—	—	—	—
		High	2.283	—	—	—	—	—	—
	Run count	Low	1.543	0.080	0.025	2	0.013	0.879	0.432
		Medium	1.530	—	—	—	—	—	—
		High	1.659	—	—	—	—	—	—
Fall to lower level	Dwell %	Low	0.247	0.017	0.007	2	0.003	1.549	0.240
		Medium	0.271	—	—	—	—	—	—
		High	0.228	—	—	—	—	—	—
	Fix count	Low	9.096	0.841	31.226	2	15.613	3.152	0.067[b]
		Medium	10.076	—	—	—	—	—	—
		High	12.030	—	—	—	—	—	—
	Run count	Low	3.864	0.355	2.646	2	1.323	1.499	0.250
		Medium	4.402	—	—	—	—	—	—
		High	4.724	—	—	—	—	—	—
Fall-protection system	Dwell %	Low	0.082	0.003	2.948×10^{-5}	2	1.474×10^{-5}	0.181	0.836
		Medium	0.084	—	—	—	—	—	—
		High	0.084	—	—	—	—	—	—
	Fix count	Low	2.942	0.313	9.893	2	4.947	7.198	0.005[a]
		Medium	3.146	—	—	—	—	—	—
		High	4.489	—	—	—	—	—	—
	Run count	Low	1.675	0.155	1.030	2	0.515	3.079	0.071[b]
		Medium	1.912	—	—	—	—	—	—
		High	2.216	—	—	—	—	—	—
Struck-by	Dwell %	Low	0.068	0.006	0.000	2	.000	0.730	0.496
		Medium	0.060	—	—	—	—	—	—
		High	0.070	—	—	—	—	—	—
	Fix count	Low	2.615	0.293	7.616	2	3.808	6.338	0.008[a]
		Medium	2.621	—	—	—	—	—	—
		High	3.896	—	—	—	—	—	—
	Run count	Low	1.412	0.184	1.081	2	0.540	2.272	0.132
		Medium	1.665	—	—	—	—	—	—
		High	1.967	—	—	—	—	—	—
Housekeeping	Dwell %	Low	0.074	0.007	0.002	2	0.001	2.431	0.116
		Medium	0.068	—	—	—	—	—	—
		High	0.088	—	—	—	—	—	—
	Fix count	Low	2.838	0.400	28.207	2	14.103	12.565	0.000[a]
		Medium	2.743	—	—	—	—	—	—
		High	5.248	—	—	—	—	—	—
	Run count	Low	1.571	0.142	2.921	2	1.461	10.377	0.001[a]
		Medium	1.610	—	—	—	—	—	—
		High	2.381	—	—	—	—	—	—
All hazard types	Dwell %	Low	0.102	0.004	0.000	2	7.884×10^{-5}	0.843	0.447
		Medium	0.104	—	—	—	—	—	—
		High	0.097	—	—	—	—	—	—
	Fix count	Low	3.835	0.288	0.918	2	0.459	2.922	0.080[b]
		Medium	4.012	—	—	—	—	—	—
		High	5.266	—	—	—	—	—	—
	Run count	Low	1.940	0.150	8.527	2	4.264	7.350	0.005[a]
		Medium	2.127	—	—	—	—	—	—
		High	2.447	—	—	—	—	—	—

[a] $p \leq 0.05$.
[b] $p \leq 0.1$.

$p_{\text{Turkey HSD-medium\&high}} = 0.017 < 0.1$; $p_{\text{Bonferroni-low\&high}} = 0.007 < 0.1$; $p_{\text{Bonferroni-medium\&high}} = 0.019 < 0.1$). Moreover, workers with low HII had significantly lower run counts—that is, returned their attention less frequently—to all types of hazards than workers with high HII ($p_{\text{Turkey HSD-low\&high}} = 0.069 < 0.1$, $p_{\text{Bonferroni-low\&high}} = 0.084 < 0.1$).

The results of the univariate ANOVAs are informative; however, conducting separate ANOVAs does not consider the linear

Table 4. Eigenvalues for Proposed Functions

Source of hazard	Function	Eigenvalue	Percentage of variance	Cumulative variance (%)	Canonical correlation
Ladder	1	1.185	92.3	92.3	0.736
	2	0.099	7.7	100.0	0.301
Fall to lower level	1	1.278	92.8	92.8	0.749
	2	0.099	7.2	100.0	0.301
Fall-protection system	1	1.449	91.2	91.2	0.769
	2	0.140	8.8	100.0	0.350
Struck-by	1	1.139	82.1	82.1	0.730
	2	0.249	17.9	100.0	0.446
Housekeeping	1	1.571	98.0	98.0	0.782
	2	0.032	2.0	100.0	0.177
All hazard types	1	1.166	92.7	92.7	0.734
	2	0.091	7.3	100.0	0.290

relationship between dependent variables. Thus, statisticians have recommended following up MANOVAs with discriminant analysis.

Discriminant Analysis

Discriminant analysis attempts to predict the total amount of variation among HII groups using one or more different weighted combinations of eye-movement metrics (dwell-time percentages, fixation count, run count), called canonical variables. The results of the discriminant analysis revealed two canonical functions for each type of hazard (Table 4). The number of functions is one less than the number of groups of independent variables. These canonical linear discriminant functions project the data onto a dimension that maximizes discrimination between the groups—that is, between levels of hazard identification skills. The functions are orthogonal; the first function maximizes the differences between the groups in terms of the dependent variable, and the second function does the same thing by controlling for the first function. The eigenvalue and percentage of variance explained by each canonical function are also shown in Table 4. Eigenvalues, the third column, are related to the canonical correlations and represent the ratio between the explained and unexplained variation in a model. Higher eigenvalues indicate that a function has higher discriminative ability. The fourth column, percentage of variance, demonstrates the discriminative ability of the eye-movement variables included in the function. The fifth column shows the cumulative proportion of discriminative ability of functions. The last column of Table 4 includes the canonical correlations of predictor variables (i.e., dwell-time percentage, fixation count, and run count) and the groupings in HII (i.e., low, medium, and high).

The results of the significance tests for the canonical functions are shown in Table 5. The null hypothesis is that the canonical correlations associated with the functions are all equal to zero, or the means of the functions are equal across groups—that is, the functions have no discriminative ability. Because there are two discriminant functions for each type of hazard, the first test presented in this table tests combination of both canonical correlations (Functions 1–2), and the second test presented tests the second canonical correlation alone. As one can see, only Functions 1–2 was significant for all sources of hazards. Moreover, Wilks' Lambda is a measure of how well each function separates workers into groups. The Wilks' Lambda values in Table 5 can be interpreted as the unexplained variance among HII groups while using a combination of both possible canonical functions. Smaller Wilks' Lambda values indicate that the function has greater discriminative ability. To demonstrate how the results provided in Table 5 can be interpreted, an example is provided for ladder-related hazards: in combination, Discriminant Functions 1 and 2 significantly differentiated the

Table 5. Wilks' Lambda for Discriminant Functions

Source of hazard	Test of function(s)	Wilks' Lambda	Chi-square	df	p-value
Ladder	1–2	0.416	14.897	6	0.021[a]
	2	0.910	1.610	2	0.447
Fall to lower level	1–2	0.399	15.608	6	0.016[a]
	2	0.910	1.612	2	0.447
Fall-protection system	1–2	0.358	17.453	6	0.008[a]
	2	0.877	2.228	2	0.328
Struck-by	1–2	0.374	16.700	6	0.010[a]
	2	0.801	3.774	2	0.151
Housekeeping	1–2	0.377	16.594	6	0.011[a]
	2	0.969	0.543	2	0.762
All hazard types	1–2	0.423	14.627	6	0.023[a]
	2	0.916	1.488	2	0.475

[a]$p \leq 0.05$.

HII groups—$\Lambda(\text{Wilks' Lambda}) = 0.42$, $\chi2(6) = 14.90$, $p = 0.02 < 0.1$—but removing the first function showed that the second function cannot significantly discriminate between the HII groups—$\Lambda(\text{Wilks' Lambda}) = 0.91$, $\chi2(2) = 1.61$, $p = 0.45 > 0.1$ (Table 5). The results for the other types of hazards can be interpreted in a similar fashion.

The standard coefficients of the canonical functions are shown in Table 6. The distribution of the scores from each function is standardized to have a mean of 0 and a standard deviation of 1. Comparing coefficient weights across variates illuminates the relative importance of each eye-movement metric in explaining "group separation" (differences in levels of hazard identification skills) while statistically controlling for correlations among all the dependent variables. For different types of hazards (i.e., AOIs), the standardized coefficient for fixation count ($Z_{\text{Fixation Count}}$) in the first function is greater in magnitude than the coefficients for the two other variables. Thus, fixation count will have the greatest impact of the three variables on the first discriminant score for different types of hazards. However, for the second function, fixation count has the greatest magnitude in ladder-related hazards only. Run count is the dominant eye-tracking metric in the second function for fall to lower level, fall-protection system, struck-by, and all hazard types, and dwell-time percentage has the largest magnitude in the second function for housekeeping hazards.

The discriminant score equation for each function can be formed on the basis of the standardized coefficients from Table 6. These discriminant functions can be used to calculate the discriminant score—as a predictor of hazard identification skills—for a given worker to predict HII group membership. The discriminant score equations for the different types of hazards are presented here.

- Ladder-related hazards:

$$\text{Discriminant score}_1 = 1.133 \times Z_{L-\text{Dwell\%}} + 1.142 \times Z_{L-\text{Run Count}} - 1.722 \times Z_{L-\text{Fixation Count}}$$

$$\text{Discriminant score}_2 = 0.491 \times Z_{L-\text{Dwell\%}} - 0.587 \times Z_{L-\text{Run Count}} + 1.017 \times Z_{L-\text{Fixation Count}}$$

Table 6. Standardized Canonical Discriminant Function Coefficients

Source of hazard	Eye-movement metrics	Function 1	Function 2
Ladder	Dwell %	1.133	0.491
	Fixation count	−1.722	1.017
	Run count	1.142	−0.587
Fall to lower level	Dwell %	1.140	0.471
	Fixation count	−1.823	−0.187
	Run count	0.905	0.953
Fall-protection system	Dwell %	−0.115	0.030
	Fixation count	2.413	−1.036
	Run count	−1.800	1.867
Struck-by	Dwell %	−0.285	−0.795
	Fixation count	1.931	−0.464
	Run count	−1.156	1.416
Housekeeping	Dwell %	−0.152	1.004
	Fixation count	0.771	0.040
	Run count	0.390	−0.507
All hazard types	Dwell%	−0.475	0.583
	Fixation count	1.634	−0.695
	Run count	−0.998	1.542

- Fall-to-lower-level–related hazards:

$$\text{Discriminant score}_1 = 1.140 \times Z_{FL-\text{Dwell\%}} + 0.905 \times Z_{FL-\text{RunCount}} - 1.823 \times Z_{FL-\text{FixationCount}}$$

$$\text{Discriminant score}_2 = 0.471 \times Z_{FL-\text{Dwell\%}} + 0.953 \times Z_{FL-\text{RunCount}} - 0.187 \times Z_{FL-\text{FixationCount}}$$

- Fall-protection-system–related hazards:

$$\text{Discriminant score}_1 = -0.115 \times Z_{FP-\text{Dwell\%}} - 1.800 \times Z_{FP-\text{RunCount}} + 2.413 \times Z_{FP-\text{FixationCount}}$$

$$\text{Discriminant score}_2 = 0.030 \times Z_{FP-\text{Dwell\%}} + 1.867 \times Z_{FP-\text{RunCount}} - 1.036 \times Z_{FP-\text{FixationCount}}$$

- Struck-by hazards:

$$\text{Discriminant score}_1 = -0.285 \times Z_{ST-\text{Dwell\%}} - 1.156 \times Z_{ST-\text{RunCount}} + 1.931 \times Z_{ST-\text{FixationCount}}$$

$$\text{Discriminant score}_2 = -0.795 \times Z_{ST-\text{Dwell\%}} + 1.416 \times Z_{ST-\text{RunCount}} - 0.464 \times Z_{ST-\text{FixationCount}}$$

- Housekeeping hazards:

$$\text{Discriminant score}_1 = -0.152 \times Z_{H-\text{Dwell\%}} + 0.390 \times Z_{H-\text{RunCount}} + 0.771 \times Z_{H-\text{FixationCount}}$$

$$\text{Discriminant score}_2 = 1.004 \times Z_{H-\text{Dwell\%}} - 0.507 \times Z_{H-\text{RunCount}} + 0.040 \times Z_{H-\text{FixationCount}}$$

- All hazard types:

$$\text{Discriminant score}_1 = -0.475 \times Z_{A-\text{Dwell\%}} - 0.998 \times Z_{A-\text{RunCount}} + 1.634 \times Z_{A-\text{FixationCount}}$$

$$\text{Discriminant score}_2 = 0.583 \times Z_{A-\text{Dwell\%}} + 1.542 \times Z_{A-\text{RunCount}} - 0.695 \times Z_{A-\text{FixationCount}}$$

By inserting the actual value of workers' eye movements into canonical functions, one can calculate the mean score (centroid) for each HII group (low, medium, and high). The resulting centroids for each HII group are shown in Table 7. Centroids are the mean of the discriminant scores for each HII group and can be used to establish the cutoff points for classifying construction workers on the basis of their hazard identification skills. To better comprehend differences, a visual representation of the groups' centroids (vector of means) on the two canonical functions formed by considering discrimination weights are shown in Fig. 3. The first canonical function can discriminate workers with high hazard-identification skills from workers with medium and low hazard-identification skills (probably at-risk workers) across all types of hazards, whereas the second function does not differentiate any HII groups from others.

The classification results, which include the percent of subjects classified correctly, are summarized in Table 8. As far as classification accuracies for low, medium, and high HII groups are concerned, the resubstitution values show what percentages of the construction workers were correctly classified into HII groups (group membership) by discriminant scores for each hazard

Table 7. Hazard Identification Index Group Centroids for Each Function

Source of hazard	HII groups	Function 1	Function 2
Ladder	Low	0.812	0.339
	Medium	0.609	−0.373
	High	−1.420	0.034
Fall to lower level	Low	0.579	−0.380
	Medium	0.890	0.330
	High	−1.469	0.050
Fall-protection system	Low	−0.536	−0.461
	Medium	−1.015	0.375
	High	1.551	0.086
Struck-by	Low	−0.462	−0.616
	Medium	−0.911	0.495
	High	1.373	0.121
Housekeeping	Low	−0.832	0.203
	Medium	−0.808	−0.205
	High	1.641	0.002
All hazard types	Low	−0.611	−0.357
	Medium	−0.799	0.327
	High	1.410	0.030

type. Fall-to-lower-level and all types of hazards had the smallest classification error, and ladder had the largest classification error (Table 8). As expected, cross-validation reduced the number of grouped cases that were correctly classified. The largest difference between the resubstitution and cross-validated approach related to fall-to-lower-level, and the smallest difference related to fall-protection systems. These classification results demonstrate that the discriminant scores perform better than chance (33.3% of samples in data are expected to be correctly classified by chance, regardless of classification functions) and are useful for classifying workers on the basis of their hazard identification skills. As the Kappa coefficient value shows in Table 8, most of the functions have moderate accuracy (kappa 0.41–0.6), except ladder and fall-protection functions, which showed fair accuracy (kappa 0.21–0.4) in prediction. Such outcomes demonstrate the potential of eye-tracking technology to measure hazard identification skill of workers.

Because one of the main objectives of this study was to use eye-movement metrics to identify at-risk workers who are placed in the low and medium hazard-identification group classification, accuracies for these two groups of workers were also calculated. As Table 8 demonstrates, using the resubstitution approach, the discriminant scores predicted group membership correctly for more than 80% of the individuals in the sample that is much better than chance. Because there are 14 at-risk subjects (out of 21) in the sample, 66.6% of samples in the data are expected to be correctly classified by chance, regardless of classification functions. Using the leave-one-out technique, the functions correctly classified more than 76% of the workers within a new sample. Finally, Kappa was run to determine the proportion of membership accuracy over and above chance agreement. There were moderate accuracies (kappa 0.41–0.6) in prediction of group membership (at-risk group and high HII group) for ladder-, fall-to-lower-level–, and fall protection system–related hazards. However, classification functions of housekeeping, struck-by, and all hazard types indicated substantial accuracy (kappa 0.61–0.8) in detecting at-risk workers. Thus, the

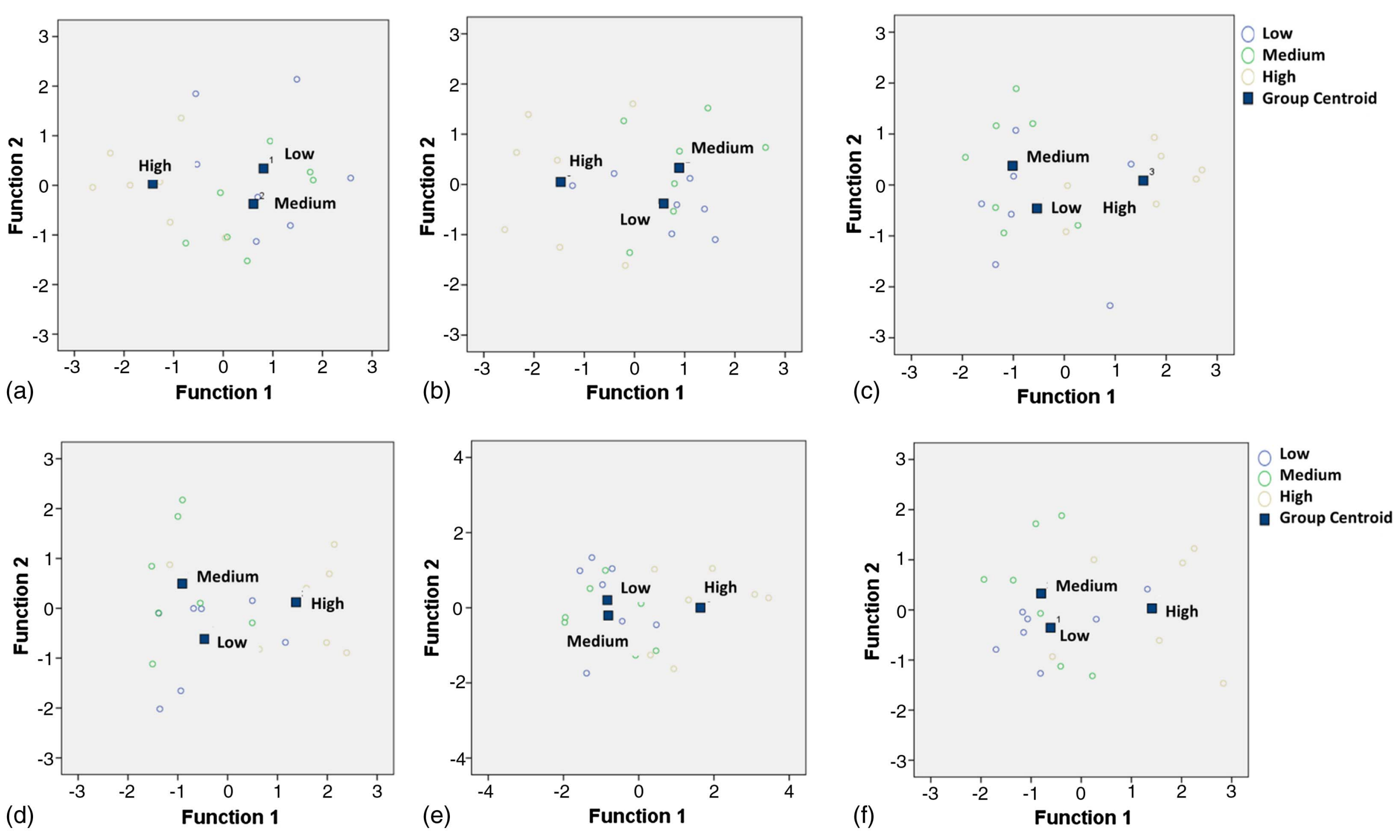

Fig. 3. Combined group plots for canonical discriminant functions: (a) ladder hazards; (b) fall-to-lower-level hazards; (c) fall-protection-system hazards; (d) struck-by hazards; (e) housekeeping hazards; (f) all hazard types

Table 8. Classification Accuracy for Different Type of Hazards

Type of hazard	Low, medium, and high HII groups: Resubstitution	Cross-validated	Kappa coefficient	At-risk (low and medium) and high HII groups: Resubstitution	Cross-validated	Kappa coefficient
Ladder	52.4	42.9	0.29	81.0	81.0	0.60
Fall to lower level	66.7	42.9	0.50	81.0	76.2	0.57
Fall-protection system	57.1	52.4	0.36	81.0	81.0	0.57
Housekeeping	61.9	42.9	0.43	85.7	81.0	0.69
Struck-by	61.9	47.6	0.43	81.0	76.2	0.60
All hazard types	66.7	52.4	0.50	85.7	81.0	0.67

Note: Resubstitution and cross-validated values are shown as percentages.

classification functions (discriminant scores) from this study can be used to accurately detect at-risk workers of additional samples for which their hazard identification is unknown. Furthermore, the results of the classification accuracy assessment demonstrate that discriminant functions are better in classifying workers into two groups of at-risk and high HII, than in classifying them into low, medium, and high HII groups.

Discussion

Impact of Hazard Identification Skills on Visual Attention

As shown previously, the multivariate analyses indicated that hazard identification skills significantly impact workers' visual search strategies when they search for hazards related to ladders, falls to lower levels, fall-protection systems, struck-by situations, and housekeeping. Workers with higher hazard-identification skills had lower dwell-time percentages on ladder-related hazards. Higher dwell-time percentages among workers with low hazard-identification skills may be explained by the fact that they are less confident in determining whether an existing ladder in a scene contains any hazard, so they dwell longer to process the information in the scene. The results showed that workers with low hazard-identification skills spent more time looking at the ladder instead of searching for other hazards in a scene. It can be inferred that by distributing attention throughout the entire scene, skilled workers are able to identify hazards better. Therefore, they are more likely to respond properly and maintain situational awareness in a dynamic construction site.

Workers with higher hazard-identification skills had higher fixation counts and less dwell time on fall-to-lower-level hazards and higher fixation counts, less dwell time, and higher run counts on fall-protection systems, struck-by situations, housekeeping hazards, and all hazardous areas. Because higher fixation and run counts are indicators of AOIs' importance and complexity (Holmqvist et al. 2011), these results provide empirical evidence that workers with higher hazard-identification abilities spent less time looking at hazards despite the fact that they fixated on hazards. This means that they scanned scenes more quickly, processed hazards more quickly, and are far better at identifying and perceiving the risk of a hazardous situation. In contrast with previous methods of measuring hazard identification skills using subjective or self-report techniques, this project's outcomes demonstrate that tracking workers' eye movements can be a reliable method of measuring their hazard identification skills.

Eye-Movement Metrics as Predictors of Hazard Identification Skills and Human Error

As mentioned previously, the fundamental concept underlying discriminant function analysis is determining whether a hazard identification group differs with regard to a linear combination of eye-movement metrics, and then the applying those metrics to predict group membership. Therefore, another question that this study addressed was, which eye-movement metrics are the best for predicting workers' hazard-identification capabilities when they search for different kinds of hazards. As shown previously, construction workers' visual search strategy can be better explained in a multivariate construct of fixation count, run count, and dwell-time percentages. Among all eye-movement metrics, fixation count had the largest standardized coefficient for all functions, which implies that it uniquely contributes to discriminating workers with high hazard-identification skills from others. Because discriminant function analysis is similar to regression, these functions can be used to predict workers' hazard-identification capabilities. In other words, by calculating discriminant scores using workers' eye movements, one can classify workers into different groups on the basis of their hazard identification skills. Additionally, because failure to identify hazards and attentional failure are the main contributors to human errors that can cause injury, to improve construction safety, targeted training can be provided to workers with low and medium hazard-identification skills (at-risk workers) to prevent them from committing safety errors.

Practical Applications

Although the methodology of this paper corresponds with a lab test that used a sophisticated piece of technology, the theoretical advancements of this study yield short-term and long-term gains. In the short term, safety managers can use the findings herein to identify at-risk construction workers (with low and medium hazard-identification skills) by conducting experiments of this type, and then provide directed training to target identified errors or measure training effectiveness by evaluating workers' gaze plots. Such eye-tracking experiments—whether conducted using a remote eye-tracker, such as *EyeLink II*, or a mobile eye-tracker, such as the Tobii Pro Glass 2 (Tobii, Stockholm, Sweden)—can be designed to require workers to search for hazards in a limited number of pictures while their eye-movement data is collected. Then, the results can be analyzed using two distinct approaches. In the first and simpler approach, safety managers can develop confidence intervals around the mean of the eye-movement metrics that were significantly different between workers with high and low hazard-identification skills (the result of post hoc analysis). Thereafter, the confidence interval developed can be used as a baseline for classifying workers on the basis of their hazard identification skills. If the eye-tracking metrics are in the confidence interval of low hazard-identification skills, one may conclude that the worker is at higher risk of missing hazards during work. To provide an example, the research team provides confidence intervals for the different eye-movement metrics that this study found to be significantly different between workers with low and high

Table 9. Confidence Interval for Identifying Workers with Low and High Hazard-Identification Skills

Hazard	Eye-movement metric	Grouping	Mean	Standard error	90% confidence interval Lower bound	Upper bound
Ladder	Dwell %	Low	0.119	0.007	0.108	0.131
		High	0.094	0.007	0.083	0.106
Fall to lower level	Fix count	Low	9.096	0.841	7.638	10.555
		High	12.030	0.841	10.571	13.489
Fall-protection system	Fix count	Low	2.942	0.313	2.399	3.486
		High	4.489	0.313	3.946	5.033
	Run count	Low	1.675	0.155	1.407	1.943
		High	2.216	0.155	1.948	2.484
Housekeeping	Fix count	Low	2.838	0.400	2.144	3.532
		High	5.248	0.400	4.553	5.942
	Run count	Low	1.571	0.142	1.326	1.817
		High	2.381	0.142	2.135	2.627
Struck-by	Fix count	Low	2.615	0.293	2.107	3.123
		High	3.896	0.293	3.388	4.404
All hazard types	Fix count	Low	3.835	0.288	3.336	4.334
		High	5.266	0.288	4.767	5.766
	Run count	Low	1.940	0.150	1.680	2.200
		High	2.447	0.150	2.187	2.706

hazard-identification skills (Table 9). Although this approach is simple and straightforward, it does not consider the multivariate nature of eye-movement metrics in determining individuals' visual search strategies. To address this limitation, the second approach is to use the discriminant functions presented previously. These functions represent linear combinations of the eye-movement metrics that can best discriminate the HII groups for each type of hazard. By inserting the value of workers' eye movements in the discriminant function, one can calculate the discriminant score, which represents the degree of membership of each person in the high or low hazard-identification group (cut-off scores for group membership are shown in Table 9). Workers who are placed in the low and medium hazard-identification group can be considered at-risk workers, and they can be assigned to activities that do not include the types of hazards they need further training on.

Furthermore, the results of these eye-tracking experiments can also be used to pinpoint required safety training (Hasanzadeh et al. 2017c). For example, if most of the workers are missing hazards related to fall-protection systems, safety managers can provide training related to these specific hazards. Delivering safety training in this way will save significant amounts of time and costs for contractors. Additionally, because tracking eye movements can provide information regarding construction workers' hazard awareness, it can be used as a method for measuring training effectiveness. Workers can participate in eye-tracking experiments before and after receiving training, and by comparing their eye movements and gaze plots, one can determine whether the training was effective enough to improve their hazard identification and visual search strategies.

As far as long-term applications are concerned, this work will lay the foundation for the improvement of future personal protective equipment (e.g., eye trackers can be installed in safety glasses). As the technology advances and the price of this equipment decreases, construction workers will be able to use these eye trackers on-site. Such a reality will allow researchers and safety managers to measure construction workers' situation awareness in real time, a novel and long-term benefit to construction safety. As one can see, measuring eye movements as an indicator of visual attention provides valuable information about hazard-identification skills and, consequently, the potentially unsafe behavior of construction workers.

Conclusion

Attention has been found to play a significant role in causing human error (Schmidt 1975; Lee et al. 2013; Manchi et al. 2013; Preischl and Hellmich 2013) such that a better understanding of attention as it relates to construction will elucidate the more predictable varieties of human fallibility and allow for the creation of strategies to avoid human errors (Busse 2002; Sun et al. 2012). Whereas previous studies have shown that eye movements and fixations can be reliable indicators of attention, there are few studies that have attempted to empirically understand the role of attention in causing human errors in construction.

To address this gap, this research team designed an eye-tracking experiment to evaluate the impact of workers' hazard-identification skills on their visual attention (illustrated via their eye movements). The results of this study demonstrated that eye movements can be used as precursors of workers' safety errors—especially those that lead to accidents in construction, such as failure to identify a hazard. This study's findings provide a proof of concept that mathematical models of eye-movement metrics can be developed to maximally discriminate workers on the basis of their hazard identification skills. The accurate identification of at-risk workers not only contributes to significant accident reduction by determining the precursors of unsafe behavior, but will also provide a critical validation measure to confirm the effectiveness of training programs in enhancing workers' hazard-identification skills and improving their visual search strategies.

This study's contribution to academia and practice is significant; however, there are some limitations that should be mentioned. First, all participants were from the state of Nebraska, which limits the external validity of the study. To address this limitation, future studies should be conducted in other regions, and should recruit a larger number of workers with diverse backgrounds. Second, using static images of construction sites might not demonstrate the challenges that workers face in identifying hazards in dynamic construction sites. Future studies should be conducted using a mobile eye-tracker in real-world construction sites. Furthermore, among all cognitive processes, this study only focused on attention. However, other cognitive processes, such as working memory, can also impact workers' hazard-identification capabilities. Future studies should be conducted to measure the impact of working memory on hazard identification and the unsafe behavior of construction workers. Nevertheless, this study is unique in utilizing eye-tracking technology to detect at-risk workers, and the results can benefit both academia and practice.

Data Availability Statement

Data generated or analyzed during the study are available from the corresponding author by request. Information about the *Journal*'s data sharing policy can be found here: http://ascelibrary.org/doi/10.1061/%28ASCE%29CO.1943-7862.0001263.

Acknowledgments

Thanks to the University of Nebraska–Lincoln for supporting the research reported in this paper through a Research Council Faculty Seed Grant. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the writers and do not necessarily reflect the views of the University of Nebraska–Lincoln. The authors also would like to thank workers who participated in this study. Appreciation is extended to professional safety managers for their support in this study.

References

Abdelgawad, M., and Fayek, A. (2012). "Comprehensive hybrid framework for risk analysis in the construction industry using combined failure mode and effect analysis, fault trees, event trees, and fuzzy logic." *J. Constr. Eng. Manage.*, 642–651.

Abdelhamid, T., and Everett, J. (2000). "Identifying root causes of construction accidents." *J. Constr. Eng. Manage.*, 52–60.

Altman, D. G. (1991). "Inter-rater agreement." *Practical statistics for medical research*, 5, 403–409.

Artman, H. (2000). "Team situation assessment and information distribution." *Ergonomics*, 43(8), 1111–1128.

Bahn, S. (2013). "Workplace hazard identification and management: The case of an underground mining operation." *Saf. Sci.*, 57(1), 129–137.

Bhoir, S. A., Hasanzadeh, S., Esmaeili, B., Dodd, M. D., and Fardhosseini, M. S. (2015). "Measuring construction workers' attention using eye-tracking technology." *Proc., ICSC15: The Canadian Society for Civil Engineering 5th Int./11th Construction Specialty Conf.*, T. M. Froese, L. Newton, F. Sadeghpour, and D. J. Vanier, eds., Univ. of British Columbia, Vancouver, Canada.

Borowsky, A., and Oron-Gilad, T. (2013). "Exploring the effects of driving experience on hazard awareness and risk perception via real-time hazard identification, hazard classification, and rating tasks." *Accid. Anal. Prev.*, 59, 548–565.

Borowsky, A., Oron-Gilad, T., Meir, A., and Parmet, Y. (2012). "Drivers' perception of vulnerable road users: A hazard perception approach." *Accid. Anal. Prev.*, 44(1), 160–166.

Borys, D. (2012). "The role of safe work method statements in the Australian construction industry." *Saf. Sci.*, 50(2), 210–220.

Bray, J. H., and Maxwell, S. E. (1985). *Multivariate analysis of variance*, Sage, Newbury Park, CA.

Brooke, P. J., and Paige, R. F. (2003). "Fault trees for security system design and analysis." *Comput. Secur.*, 22(3), 256–264.

Busse, D. K. (2002). "Cognitive error analysis in accident and incident investigation in safety-critical domains." Ph.D. dissertation, Univ. of Glasgow, Glasgow, Scotland.

Carter, G., and Smith, S. D. (2006). "Safety hazard identification on construction projects." *J. Constr. Eng. Manage.*, 10.1061/(ASCE)0733-9364(2006)132:2(197), 197–205.

Cheng, A. S., Ng, T. C., and Lee, H. C. (2011). "A comparison of the hazard perception ability of accident-involved and accident-free motorcycle riders." *Accid. Anal. Prev.*, 43(4), 1464–1471.

Dong, X. S., et al. (2011). "Injury underreporting among small establishments in the construction industry." *Am. J. Ind. Med.*, 54(5), 339–349.

Duchowski, A. (2007). *Eye tracking methodology: Theory and practice*, 2nd Ed., Springer Science and Business Media, London.

Dzeng, R. J., Lin, C. T., and Fang, Y. C. (2016). "Using eye-tracker to compare search patterns between experienced and novice workers for site hazard identification." *Saf. Sci.*, 82, 56–67.

Esmaeili, B., Hallowell, M., and Rajagopalan, B. (2015a). "Attribute-based safety risk assessment. I: Analysis at the fundamental level." *J. Constr. Eng. Manage.*, 10.1061/(ASCE)CO.1943-7862.0000980, 04015021.

Esmaeili, B., Hallowell, M., and Rajagopalan, B. (2015b). "Attribute-based safety risk assessment. II: Predicting safety outcomes using generalized linear models." *J. Constr. Eng. Manage.*, 10.1061/(ASCE)CO.1943-7862.0000981, 04015022.

Esmaeili, B., and Hallowell, M. R. (2012). "Diffusion of safety innovations in the construction industry." *J. Constr. Eng. Manage.*, 10.1061/(ASCE)CO.1943-7862.0000499, 955–963.

EyeLink Data Viewer version 1.11.900 [Computer software]. SR Research Ltd., Mississauga, Canada.

Fleming, M. A. (2009). "Hazard recognition." *By Design*, 8(3), 11–15.

Fung, I. W. H., Tam, C. M., Tung, K. C. F., and Man, A. S. K. (2005). "Safety cultural divergences among management, supervisory and worker groups in Hong Kong construction industry." *Int. J. Project Manage.*, 23(7), 504–512.

Garavan, T. N., and O'Brien, F. (2001). "An investigation into the relationship between safety climate and safety behaviours in Irish organisations." *Irish J. Manage.*, 22(1), 141.

Garrett, J., and Teizer, J. (2009). "Human factors analysis classification system relating to human error awareness taxonomy in construction safety." *J. Constr. Eng. Manage.*, 10.1061/(ASCE)CO.1943-7862.0000034, 754–763.

Goetsch, D. L. (1996). *Occupational safety and health in the age of high technology: For technologists, engineers, and managers*, Prentice Hall, Englewood Cliffs, NJ.

Goh, Y., and Chua, D. (2009). "Case-based reasoning for construction hazard identification: Case representation and retrieval." *J. Constr. Eng. Manage.*, 10.1061/(ASCE)CO.1943-7862.0000093, 1181–1189.

Habibnezhad, M., Fardhosseini, S., Vahed, A. M., Esmaeili, B., and Dodd, M. D. (2016a). "The relationship between construction workers' risk perception and eye movement in hazard identification." *Construction Research Congress 2016*, ASCE, Reston, VA, 2984–2994.

Hair, J. F., Jr., Black, W. C., Babin, B. J., and Anderson, R. E. (2010). *Multivariate data analysis*, Pearson College Division, Upper Saddle River, NJ.

Hasanzadeh, S., Esmaeili, B., and Dodd, M. (2016a). "Measuring construction workers' real-time situation awareness using mobile eye-tracking." *Construction Research Congress*, ASCE, Reston, VA, 2894–2904.

Hasanzadeh, S., Esmaeili, B., and Dodd, M. (2017a). "Measuring the impact of working memory load on the safety performance of construction workers." *Computing in civil engineering*, Seattle, 158–166.

Hasanzadeh, S., Esmaeili, B., and Dodd, M. (2017b). "Measuring the impacts of safety knowledge on construction workers' attentional allocation and hazard detection using remote eye-tracking technology." *J. Manage. Eng.*, 10.1061/(ASCE)ME.1943-5479.000052, 04017024.

Hasanzadeh, S., Esmaeili, B., Dodd, M. D., and Pellicer, E. (2017c). *Using eye movements to identify hazards missed by at-risk workers*." ISEC, Fargo, ND.

Hoffman, J. E., and Subramaniam, B. (1995). “The role of visual attention in saccadic eye movements.” *Percept. Psychophys.*, 57(6), 787–795.

Hoła, B. (2010). “Methodology of hazards identification in construction work course.” *J. Civil Eng. Manage.*, 16(4), 577–585.

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

Holt, A. S. J., and Lampl, F. (2006). *Principles of construction safety*, Blackwell, Oxford, U.K.

Horswill, M. S., and McKenna, F. P. (2004). “Driver's hazard perception ability: Situation awareness on the road.” *A cognitive approach to situation awareness*, S. Banbury and S. Tremblay, eds., Ashgate, Aldershot, U.K.

Huestegge, L., Skottke, E. M., Anders, S., Müsseler, J., and Debus, G. (2010). “The development of hazard perception: Dissociation of visual orientation and hazard processing.” *Transp. Res. Part F: Traffic Psychol. Behav.*, 13(1), 1–8.

Jacob, R. J., and Karn, K. S. (2003). “Eye tracking in human-computer interaction and usability research: Ready to deliver the promises.” *Mind*, 2(3), 4.

James, W. (1913). *The principles of psychology*, Vol. 2, Dover, New York.

Jie, L., and Clark, J. J. (2008). “Video game design using an eye-movement-dependent model of visual attention.” *ACM Trans. Multimedia Comput. Commun. Appl.*, 4(3), 1–16.

Landis, J. R., and Koch, G. G. (1977). “The measurement of observer agreement for categorical data.” *Biom.*, 159–174.

Lee, S. J., Kim, J., and Jung, W. (2013). “Quantitative estimation of the human error probability during soft control operations.” *Ann. Nucl. Energy*, 57, 318–326.

Lopez, R., Love, P. E., Edwards, D. J., and Davis, P. R. (2010). “Design error classification, causation, and prevention in construction engineering.” *J. Perform. Constr. Facil.*, 10.1061/(ASCE)CF.1943-5509.0000116, 399–408.

Mackenzie, A. K., and Harris, J. M. (2015). “Eye movements and hazard perception in active and passive driving.” *Visual Cognit.*, 23(6), 736–757.

Manchi, G. B., Gowda, S., and Hanspal, J. S. (2013). “Study on cognitive approach to human error and its application to reduce the accidents at workplace.” *Int. J. Eng. Adv. Technol.* 2(6), 236–242.

Mitropoulos, P., and Namboodiri, M. (2011). “New method for measuring the safety risk of construction activities: Task demand assessment.” *J. Constr. Eng. Manage.*, 10.1061/(ASCE)CO.1943-7862.0000246, 30–38.

Neter, J., Kutner, M. H., Nachtsheim, C. J., and Wasserman, W. (1996). *Applied linear statistical models*, 4th Ed., McGraw-Hill, New York.

Pernice, K., and Nielsen, J. (2009). “How to conduct eye-tracking studies.” ⟨https://goo.gl/bI45ak⟩ (Apr. 25, 2016).

Popa, L., Selejan, O., Scott, A., Mureşanu, D. F., Balea, M., and Rafila, A. (2015). “Reading beyond the glance: Eye tracking in neurosciences.” *Neurol. Sci.*, 36(5), 683–688.

Pradhan, A. K., Pollatsek, A., Knodler, M., and Fisher, D. L. (2009). “Can younger drivers be trained to scan for information that will reduce their risk in roadway traffic scenarios that are hard to identify as hazardous?” *Ergonomics*, 52(6), 657–673.

Preischl, W., and Hellmich, M. (2013). “Human error probabilities from operational experience of German nuclear power plants.” *Reliab. Eng. Syst. Saf.*, 109, 150–159.

Rozenfeld, O., Sacks, R., Rosenfeld, Y., and Baum, H. (2010). “Construction job safety analysis.” *Saf. Sci.*, 48(4), 491–498.

Schmidt, R. A. (1975). “A schema theory of discrete motor skill learning.” *Psychol. Rev.*, 82(4), 225–260.

Shappell, S. A., and Wiegmann, D. A. (2000). “The human factors analysis and classification system—HFACS.” *Office of Aviation Medicine Rep. No. DOT/FAA/AM-00/7*, Federal Aviation Administration, Washington, DC.

Shorrock, S. T., and Kirwan, B. (2002). “Development and application of a human error identification tool for air traffic control.” *Appl. Ergon.*, 33(4), 319–336.

Sneddon, A., Mearns, K., Flin, R., and Bryden, R. (2004). “Safety and situation awareness in offshore crews.” *SPE Int. Conf. on Health, Safety, and Environment in Oil and Gas Exploration and Production*, Society of Petroleum Engineers, Calgary, AB, Canada.

Spicer, J. (2005). *Making sense of multivariate data analysis: An intuitive approach*, 1st Ed., Sage, Thousand Oaks, CA.

SPSS version 22.0 [Computer software]. IBM, Armonk, NY.

Stamatis, D. H. (2003). *Failure mode and effect analysis: FMEA from theory to execution*, ASQ Quality Press, Milwaukee.

Sun, Q., Xia, J., Nadarajah, N., Falkmer, T., Foster, J., and Lee, H. (2016). “Assessing drivers' visual-motor coordination using eye tracking, GNSS and GIS: A spatial turn in driving psychology.” *J. Spatial Sci.*, 61(2), 1–18.

Sun, Y., Fisher, R., Wang, F., and Gomes, H. M. (2008). “A computer vision model for visual-object-based attention and eye movements.” *Comput. Vision Image Understanding*, 112(2), 126–142.

Sun, Z., Li, Z., Gong, E., and Xie, H. (2012). “Estimating human error probability using a modified CREAM.” *Reliab. Eng. Syst. Saf.*, 100, 28–32.

Teizer, J. (2016). “‘Right-time vs real-time pro-active construction safety and health system architecture.” *Constr. Innovation*, 16(3), 253–280.

Treisman, A. M., and Gelade, G. (1980). “A feature-integration theory of attention.” *Cognit. psychol.*, 12(1), 97–136.

Underwood, G. (2007). “Visual attention and the transition from novice to advanced driver.” *Ergonomics*, 50(8), 1235–1249.

Underwood, G., Crundall, D., and Chapman, P. (2011). “Driving simulator validation with hazard perception.” *Transp. Res. Part F: Traffic Psychol. Behav.*, 14(6), 435–446.

Underwood, G., Phelps, N., Wright, C., Van Loon, E., and Galpin, A. (2005). “Eye fixation scanpaths of younger and older drivers in a hazard perception task.” *Ophthalmic Physiol. Opt.*, 25(4), 346–356.

U.S. BLS (U.S. Bureau of Labor Statistics). (2016). “National census of fatal occupational injuries in 2014.” ⟨https://goo.gl/vnjjH⟩ (Aug. 15, 2016).

Wallis, T. S., and Horswill, M. S. (2007). “Using fuzzy signal detection theory to determine why experienced and trained drivers respond faster than novices in a hazard perception test.” *Accid. Anal. Prev.*, 39(6), 1177–1185.

Wickens, C. D., Hollands, J. G., Banbury, S., and Parasuraman, R. (2015). *Engineering psychology and human performance*, 4th Ed., Routledge, New York.

Wilson, H. A. (1989). “Organizational behavior and safety management in the construction industry.” *Constr. Manage. Econ.*, 7(4), 303–319.

Wolfe, J. M. (2007). “Guided search 4.0: Current progress with a model of visual search.” *Integrated models of cognitive systems*, Oxford University Press, New York, 99–119.

Yarbus, A. L. (1967). *Eye movements and vision*, L. A. Rigss, ed., Vol. 2, Plenum Press, New York.

Zhang, M., and Fang, D. (2013). “A continuous behavior-based safety strategy for persistent safety improvement in construction industry.” *J. Autom. Constr.*, 34(1), 101–107.