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Measuring the Impacts of Safety Knowledge on Construction Workers' Attentional Allocation and Hazard Detection Using Remote Eye-Tracking Technology

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Abstract: Although several studies have highlighted the importance of attention in reducing the number of injuries in the construction industry, few have attempted to empirically measure the attention of construction workers. One technique that can be used to measure worker attention is eye tracking, which is widely accepted as the most direct and continuous measure of attention because where one looks is highly correlated with where one is focusing his or her attention. Thus, with the fundamental objective of measuring the impacts of safety knowledge (specifically, training, work experience, and injury exposure) on construction workers' attentional allocation, this study demonstrates the application of eye tracking to the realm of construction safety practices. To achieve this objective, a laboratory experiment was designed 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, work experience, and injury exposure (independent variables) on eye-tracking metrics (dependent variables) was then assessed by implementing numerous permutation simulations. The results show that tacit safety knowledge acquired from work experience and injury exposure can significantly improve construction workers' hazard detection and visual search strategies. The results also demonstrate that (1) there is minimal difference, with or without the Occupational Safety and Health Administration 10-h certificate, in workers' search strategies and attentional patterns while 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. In sum, practical safety knowledge and judgment on a jobsite requires the interaction of both tacit and explicit knowledge gained through work experience, injury exposure, and interactive safety training. This study significantly contributes to the literature by demonstrating the potential application of eye-tracking technology in studying the attentional allocation of construction workers. Regarding practice, the results of the study show that eye tracking can be used to improve worker training and preparedness, which will yield safer working conditions, detect at-risk workers, and improve the effectiveness of safety-training programs. **DOI: 10.1061/(ASCE)ME.1943-5479.0000526.**

Introduction

Human error is a main contributing factor to accidents in the workplace, especially among construction workers (Sanders and McCormick 1998; Garrett and Teizer 2009). The main human error that leads to accidents and injuries on a construction site is a worker's lack of attention when detecting potential or active hazards, which subsequently results in the worker's failure to react properly (Garrett and Teizer 2009; Rozenfeld et al. 2010). Accordingly, the identification of variables that impact a worker's attention and visual search strategy can have a transformational impact on construction safety performance.

To study attention, one needs a reliable means of measuring it. Because visual cues have a direct impact on attentional allocation, especially in the very first phase of exploration (Hallett 1986), one scientific way of studying attention is to detect eye-movement patterns. Eye tracking is widely accepted as the most direct and continuous measure of attention, because where one looks is highly correlated with where one is focusing his or her attention (Shepherd et al. 1986; Hoffman and Subramaniam 1995). This strong relationship between eye movements and cognitive performance manifests in a variety of domains and explains why eye tracking has been widely implemented in the fields of neuroscience, psychology, and behavioral research (Richardson and Spivey 2004).

Several studies have highlighted the importance of attention in reducing the number of injuries in the construction industry, although few have attempted to empirically measure the attention of construction workers (Garrett and Teizer 2009; Lopez et al. 2010). Because eye tracking exhibits the immense potential of providing deeper insights into construction workers' hazard-identification patterns, researchers have also recently begun to examine potential applications of this novel technology in studying the attention and hazard-identification skills of construction workers (Bhoir et al. 2015; Hasanzadeh et al. 2016; Dzeng et al. 2016). Although these past studies have demonstrated the potential application of eye-tracking technology in construction safety, they face some limitations. For example, although Bhoir et al. (2015) and Hasanzadeh et

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al. (2016) did investigate the feasibility of using eye-tracking technology in studying hazard-detection skills of construction workers, they did not investigate variables that might impact the attentional allocation of construction workers at construction sites. Dzeng et al. (2016) studied the impact of work experience on worker attention; however, their study was limited because stimuli consisted of virtual images of a limited number of hypothetical construction scenarios and not real images taken from constructions sites. Furthermore, the images in Dzeng et al. (2016) did not control for other variables at play in eye tracking (e.g., color, contrast, viewing time), which is a choice that could confound the outcomes of the study. Although these studies manifest the promise of applying eye tracking to construction safety, there remain ongoing gaps in knowledge about the variables that impact the attentional allocation of construction workers. Identifying such factors will facilitate identifying workers who are at greater risk and will thereby further improve construction safety.

To respond to these past limitations, it is vital to understand the three major group factors that affect attention, (1) task parameters, (2) environmental variables, and (3) individual subject characteristics. The first group includes several variables that define the cognitive load required to implement a task, such as difficulty, detectability, complexity, and administrative conditions. Task parameters can also interact with other groups of factors to impact attentional allocation, because environmental and subject characteristics will often influence the worker's experience of the task. The second group includes environmental factors that can affect attentional allocation that are either extraneous to the task itself (such as noise, temperature, and situational variables) or intrinsic to the situation (such as crowded conditions and time of day). It is important to note that the effects of noise and other environmental factors on attention vary across studies due to their respective contexts (Ballard 1996); this reality marks the need for isolating factors and subfactors as much as possible when studying attention in safety contexts. Finally, the third group of factors includes subject characteristics, such as demographics (e.g., gender, work experience, intelligence variations, past experience), personality traits, and arousal level (e.g., medication, fatigue, stress) (Ballard 1996; McBride and Cutting 2015). These subject traits will often impact workers' safety across days and times, which make them valuable discussion points in the context of construction safety. Combined, these different factors will interact to impact construction workers' attentional allocation. Consequently, to reduce the complexity of studying attention in the context of construction safety, it is important to isolate specific processes of interest while controlling for others.

In the context of this paper, the focus is on one of the individual subject characteristics that plays a crucial role in detecting a hazard, assessing a hazard's risk, and selecting proper action: safety knowledge (Chua and Goh 2004). Knowledge manifests in the cognition and/or behaviors of individuals (Argote and Miron-Spektor 2011) and has been divided into two categories: tacit and explicit (Zhang and He 2016). Tacit safety knowledge can be acquired by learning on the job, gaining experience, and being exposed to an injury (Koskinen et al. 2003; Podgórski 2010; Hallowell 2012). These past experiences and exposures will be stored as patterns of knowledge in the brain, and when a worker is subsequently exposed to related situations he or she will have a memory-based intuition to respond correctly (Zhang and He 2016). On the other hand, explicit knowledge can be delivered through safety training (Aboagye-Nimo et al. 2012) or captured from existing theories in books, safety records, and guidelines (Hadikusumo and Rowlinson 2004). Regardless of the type of safety knowledge, there is a consensus in the literature that safety knowledge can be acquired via training, work experience, and exposure (Podgórski 2010; Argote and Miron-Spektor 2011; Aboagye-Nimo et al. 2012). Therefore, it is likely to play a crucial role in guiding worker attention, and it underpins the hazard recognition and responsiveness of workers.

To determine the importance of safety knowledge on construction workers' safety, this paper investigates the relationship between safety knowledge, attention, and hazard recognition. More specifically, the main objective of this study is to track workers' eye movements and visual search strategies to assess the impact of safety knowledge acquired from training, work experience, and past injury exposure on construction workers' attentional allocation toward hazards. To control for other influences on attention (i.e., task parameters and environmental variables), the research team conducted a laboratory-based eye-tracking experiment using images taken from real-life scenarios that manifested a variety of construction hazards. Consequently, this study empirically establishes the relationship between worker's subjective safety knowledge characteristics, their attention, and their safe behavior, filling an ongoing gap in knowledge about the impact of safety knowledge on workers' cognitive processes, and, specifically, attention.

Attention

The cognitive process of attention is a vital component of this study and one that has been advanced by the expansion of eye-tracking research. Unfortunately, a complete review of eye-tracking research is beyond the scope of the present paper because eye tracking (1) has been used in numerous domains, (2) has been used in a variety of ways, and (3) affords the researcher the ability to choose from dozens of different measures dependent on their critical question of interest. Because of the variety of concepts available when examining attention via eye tracking, it is important to provide an inclusive overview of these topics so that the reader has the appropriate context needed to understand this paper's approach and conclusions.

Cognitive processing comprises how the mind receives, stores, and uses information. The process of understanding and using information is highly related to many cognitive processes, including attention, perception, memory, language, imagination, and decision making (Anderson 2005). Before the twentieth century, the roots of this process traced back to philosophy and physiology. However, in the early- to mid-twentieth century, with the development of information-processing approaches, the study of cognition extended beyond psychology and behaviorist perspectives. The findings of Chomsky's study (Chomsky 1959) revealed that understanding cognitive processes is critical to understanding and assessing behavior. Cognitive processes select which pieces of information to attend and which to ignore, and this, in turn, manifests in human behavior. Because the main objective of this research is to assess hazard detection and to study the unsafe attentional distribution of construction workers with various training and experience levels, it was necessary to measure workers' attention as a primary cognitive process.

Attention, an important element in many cognitive tasks, has been studied for over a century in many different domains. Defining attention is difficult because it overlaps with many other cognitive processes (McBride and Cutting 2015). One early proposed definition of attention is the focus of consciousness to a particular stimulus while ignoring other distracting objects in the environment (James 1913). Because humans are finite beings, their capacity for information processing is limited, which influences their attentional abilities. Moreover, emotional arousal, task difficulty, and an observer's interest/motivation in a task can significantly affect the capacity of mental resources and attention abilities (Duchowski 2007). Because of the limited capacity of human information processing as well as the various environmental and individual characteristics at play, this study examines attention in construction safety according to how workers select to attend to or ignore different types of hazards while working in complex and dynamic construction sites.

The authors conducted a comprehensive literature review of studies related to cognition and attention and found that attention, as a prominent process of cognition, can be classified into different levels and that there are various approaches to studying attention. Salient results of this review are provided in the following sections.

Levels of Attention

Sohlberg and Mateer (1989) identified four levels of attention: sustained, selective, divided, and alternating. Sustained attention, or vigilance, is the ability to devote one's whole attention to a single but complex stimulus set over extended periods, without being distracted, to detect infrequent targets (Parasuraman et al. 1998). Sustained attention represents a basic attentional function that specifies the efficacy of one's information-processing capacity and the higher functions of attention (e.g., selective and divided attention). Because the eyes need to retrieve information from the visual field to perceive it, selective attention is considered the gateway to consciousness (Theeuwes et al. 2009). The first step in the selective process is to choose *what* to attend. Eyes and minds do not have enough capacity to focus on every object in the field; therefore, they must select what is most important to process. Observers concentrate on a stimulus using selective attention (focus on only one stimulus) or divided attention (splitting attention between two or more tasks/objects) (Rehder and Hoffman 2005). Finally, alternating attention represents one's cognitive flexibility, or the ability to shift attention among different tasks having different cognitive requirements sequentially (Sohlberg and Mateer 1989). Originally, the intent of this study was to assess workers' selective attention, but because construction is such a complex environment with simultaneous ongoing activities, the focus extended to assess both selective and divided attention across various hazards in a scene.

Modeling Attention

Generally, visual attention plays a crucial role in the control of eye movements, perception, learning, memory, and other interactions with the visual world, although people are not always aware of it (Bisley 2011). A major distinction that has guided all research in the area of cognition and information processing is whether attention is goal driven (top down) or stimulus driven (bottom up). In goal-driven visual attention, observers form deliberate strategies and intentions for controlling their attention. The top-down model is used when the task has a strong influence on where the observer attends and looks (Yantis 1998). In contrast, stimulus-driven attention occurs when salient items in the environment capture attention independent of the observers' intent. For example, people have been shown to initially fixate on salient attributes of the image related to color or contrast, and the initial scanning process is not necessarily relevant to the observer's perceptual goals (Todd and Kramer 1993). More generally, top-down and bottom-up attentional models interact with each other, and it is assumed that any observer viewing a scene has a complex combination of expectations and goals related to processing that scene (Chun and Wolfe 2001). Although current conceptualizations of visual attention acknowledge the strength of bottom-up processing (Torralba et al. 2006), it is important to consider top-down influences in estimating attention allocation, because in the real world, attention tends to be more task relevant and goal driven than just free viewing of scenes (Jie and Clark 2008). Moreover, a recent study by Vecera et al. (2014) has demonstrated that goal-driven attentional control emerges with increased experience with a task, whereas with relatively little experience attentional control tends to be more stimulus driven. In this study, the research team focused on top-down influences by designing an experiment in which workers were asked to purposefully search for hazards in each image. It was anticipated that workers would attend to different parts of the image with a level of intentionality that corresponded to their safety knowledge, so this type of approach allowed for the study of the impacts of their safety knowledge on their attentional modeling.

Attention and Eye Tracking

At any given time an environment contains much more perceptual information than can be processed. The previously mentioned evidence illustrates that what a person sees determines to what that person is going to attend. If a hazard grabs a worker's attention, the worker becomes an active seeker and processor of information that is able to interact intelligently with the environment and consider protective measures. A growing number of psychological and neuropsychological studies have demonstrated the close relationship between attention and eye movements (Sun et al. 2008). In one of the seminal studies, Yarbus (1967) showed that records of observers' eye movements reflect human attention and thought processes. The simple assumption in most attention studies using eye tracking is that by tracking someone's eye movements, one is able to follow the observer's general path of attention. This process will reveal both what simply drew the observer's attention and what fully captures their attention, which in turn will give researchers clues about how the person perceived the scene. Such insights help reveal perhaps one of the most important functions of attention—to guide fixations toward events that are relevant to ongoing behavior (Duchowski 2007).

In the last decade, the use of eye tracking has been flourishing in studies related to human-computer interaction and usability research (Jacob and Karn 2003). On a somewhat smaller scale, eye-tracking research also has been applied to transportation (Suh et al. 2006), driving (Palinko et al. 2010), aviation (Lavine et al. 2002), marketing (Wedel and Pieters 2008), nuclear power control rooms (Ha and Seong 2009), medicine (Zheng et al. 2011), and petrochemical control rooms (Ikuma et al. 2014). Eye tracking in these fields has been used mostly to estimate cognitive load, analyze user behavior, reveal differences in aptitude and expertise, diagnose neurological disorders, and analyze gaze control.

The existing literature on hazard detection and attentional allocation using eye-tracking technology has mainly focused on automotive driving. These studies use visual behavior as an index of hazard-detection skill when drivers are exposed to potential hazards using static pictures or scenarios (Underwood et al. 2005), a movie-based simulator (Underwood et al. 2011; Borowsky et al. 2012; Mackenzie and Harris 2015), or field experiment (Sun et al. 2016). Eye tracking has also been used to study the impact of age (Romoser et al. 2005), experience (Underwood 2007), and cognitive load (such as cell phone conversations) (Muttart et al. 2007) on drivers' safety performance. Furthermore, to improve the hazard-detection skills of drivers, eye-tracking technology has been used to evaluate the effectiveness of interactive training processes (Underwood 2007; Fisher et al. 2007; Pradhan et al. 2009). Although these studies show the potential relationship between eye movement, hazard detection, and safety knowledge, the application of this technology remains unexplored in the field of construction safety. Thus, the study of attention using eye-tracking technology may elucidate the safety behavioral paradigms of workers in dangerous situations on construction sites.

Eye-Tracking Metrics

Each individual research project requires the choice of eye-tracking metrics that are relevant to the tasks and appropriate for attentional allocation and cognitive process analysis. The process used for identifying fixations and monitoring saccades (the rapid movements of the eye between fixation points) in an eye-tracking protocol is the most essential part of eye-movement data analysis (Salvucci and Goldberg 2000; Duchowski 2007). Minimizing the complexity of eye-tracking data by identifying fixations and removing raw saccade data can improve researchers' understanding of attentional allocation and visual processing behavior, because little visual processing is achieved during saccades, and findings related to saccades have not been used in many research applications (Salvucci and Goldberg 2000). To explore the determinants of ocular behavior, many derived metrics stemming from these basic measures (fixation and saccade) have been incorporated in different eye-tracking studies as dependent variables, including fixation-derived and saccade-derived metrics.

Areas of Interest

The first step in assessing eye-movement parameters and establishing dependent measures is to define an area of interest (AOI) in each image used in the study. AOIs are objects and locations of interest within a scene as defined by the research team (Jacob and Karn 2003). For example, in marketing-related studies, specialists might be interested in knowing the total time it takes each observer to view the desired target (brand logo) on a company's home page (Goldberg et al. 2002). Further, in the study of Weibel et al. (2012), to understand dynamic allocation of pilot attention, the AOIs were flight instruments in the cockpits of commercial airplanes. In the present study, the AOIs are defined as the different types of hazards that appeared in the construction scenario images, including fall hazards, struck-by hazards, and housekeeping hazards.

Fixation-Derived Metrics

Fixation is defined as a relatively stationary eye position with a relatively short minimum duration (often 100–200 ms, although longer fixations can also be observed as a function of an individual's processing goals). Although fixations can be interpreted differently in various studies depending on their context, fixation-count and gaze-duration (consecutive fixations) metrics have generally been considered to assess the depth of cognitive processing and the distribution of attention (Zhao et al. 2014). For example, Hauland (2003) indicated that a longer gaze that falls into the specific AOI before an incident happens can be used as a situation awareness anticipation measure. Three commonly used fixation-derived metrics in eye-tracking studies (Bhoir et al. 2015) are (1) first fixation time (the amount of time, i.e., in milliseconds, that passes following the image's first appearance on the screen until the observer first fixates on an AOI), (2) dwell percentage (relative to the amount of time spent viewing an image, the proportion of time in which gaze was fixated on an AOI), and (3) run count (the average number of times that each participant returns their attention to an AOI).

Saccade-Derived Metrics

Saccades, defined as quick eye movements from one location to another, vary in duration but often take about 25–150 ms, depending on the amplitude of the saccade. In most studies, researchers remove the raw saccade data (Salvucci and Goldberg 2000), whereas in other studies they measure saccade-derived metrics to understand the observer's searching duration and to evaluate the design of the interface (Fuchs 1971; Pan et al. 2004). For example, in computer interface and usability studies, larger saccade amplitude indicates a well-designed interface with sufficient cues to enable users to rapidly find the desired targets (Goldberg et al. 2002). Another study showed that regressive saccades during reading are associated with comprehension difficulties (Just and Carpenter 1980).

Visualization of Eye Movement Data

Eye-tracking provides a large amount of data, and the visualization of eye-movement patterns can provide insight through a comprehensive statistical analysis. Visualization techniques commonly used for representing eye-tracking data are heat maps and scan paths (Raschke et al. 2014). A heat map is a two-dimensional visualization in which all fixation values that were analyzed are represented in colors (Bojko 2009). A heat map can be created for an individual or for a group of people. In this study, the fixation count heat map was used to define AOIs and to better compare visual attention of construction workers across the scene. On the other hand, a scan path is a compelling visualization of eye movements defined as a spatial arrangement of a sequence of saccade-fixation-saccade (Poole and Ball 2006). It has been widely argued in previous studies that scan paths reveal considerable information about visual attention and other underlying cognitive processes involved in eye movements (Laeng and Teodorescu 2002; Foerster and Schneider 2013). In this study, in addition to statistical analysis outputs, the research team used heat maps and scan paths to study visual search strategies and cognitive processes of workers in each scene.

Point of Departure

Construction workers need attention to not only complete their activities, but also to enrich their conscious awareness of the entire dynamic environment at a construction site. Training can make a person phenomenally conscious of certain hazards, but attention is also critical to detect, perceive, and react to hazards appropriately. Because attending to something elevates conscious perception of it (De Brigard 2012), workers' lack of attention may expose them to hazardous situations more frequently. Therefore, investigating variables that might impact a worker's attention can be of great importance.

This study departs from the current body of knowledge because it is one of the earliest studies to empirically measure construction workers' attention using eye-tracking technology. Although some previous studies have been conducted using eye-movement data to measure the situation awareness of air-traffic controllers (Hauland 2003), a limited number of studies have measured construction workers' attention empirically using eye-tracking technology (Bhoir et al. 2015; Dzeng et al. 2016). Additionally, this project focused on controlling for other attentional factors (i.e., task parameters and environmental variables) to more thoroughly examine the chosen factor, specifically safety knowledge acquired from training, work experience, and past injury exposure. A primary objective of this study is to investigate how workers with different levels of work experience, training, and injury exposure (independent variables) attend to a complex construction scene. Thus, to achieve this overarching objective, four null hypotheses were defined and tested (Table 1).

Research Methods

The research hypotheses were tested by collecting information on two types of variables: independent variables (safety knowledge, i.e., training, work experience, injury exposure) and dependent variables (eye-tracking metrics). The independent variable data were collected via a questionnaire, which, in addition to general questions related to the participants' background and years of experience in the construction industry, asked respondents whether they had received the Occupational Safety and Health Administration (OSHA) 10-h training (formal) or any on-site safety training (informal), and whether they had previous injury exposure. The dependent variable data were collected in a laboratory experiment using eye-tracking equipment, described in the following sections.

Apparatus

An EyeLink II (manufactured by SR Research Ltd., Kanata, ON, Canada), with a high spatial resolution and a sampling rate of 500 Hz, tracked and recorded the participants' eye movements to determine where they attended. The EyeLink II is a video-based eye-tracking system that uses cameras mounted on the headset to document the path of a viewer's focus. Participants completed the experiment seated approximately 45 cm from the computer screen on which they observed images (the general procedure can be seen in the left half of Fig. 1).

Participants

Participants were all construction workers who were invited to the study in one of the following three ways: (1) an invitation flyer was posted at construction sites in Lincoln and Omaha, Nebraska; (2) researchers extended invitations by stopping by construction companies' main offices and contacting facility managers at the University of Nebraska-Lincoln; and (3) a flyer with a one-page summary of the research project was sent to Associated Builders and Contractors members and department advisory boards. As a result, a total of 31

Table 1. Tested Null Hypotheses

Hypothesis	Tested null hypothesis
Gaining more experience improves workers' attentiveness to hazards	Null hypothesis 1 (H_1): Workers' work experience (years of experience) has no impact on their attentiveness to hazards on a construction site
Receiving training (formal or informal) improves workers' attentiveness to hazards	Null hypothesis 2 (H_2): Workers' safety training (formal or informal) has no impact on their attentiveness to hazards on a construction site
Exposure to injury impacts workers' attentiveness to hazards	Null hypothesis 3 (H_3): Workers' past injury exposure (either personal injury or seeing somebody else injured) has no impact on their attentiveness to hazards on a construction site
By keeping training as a control variable, gaining more experience improves trained workers' attentiveness to hazards	Null hypothesis 4 (H_4): Work experience (years of experience) of trained workers has no impact on their attentiveness to hazards on a construction site

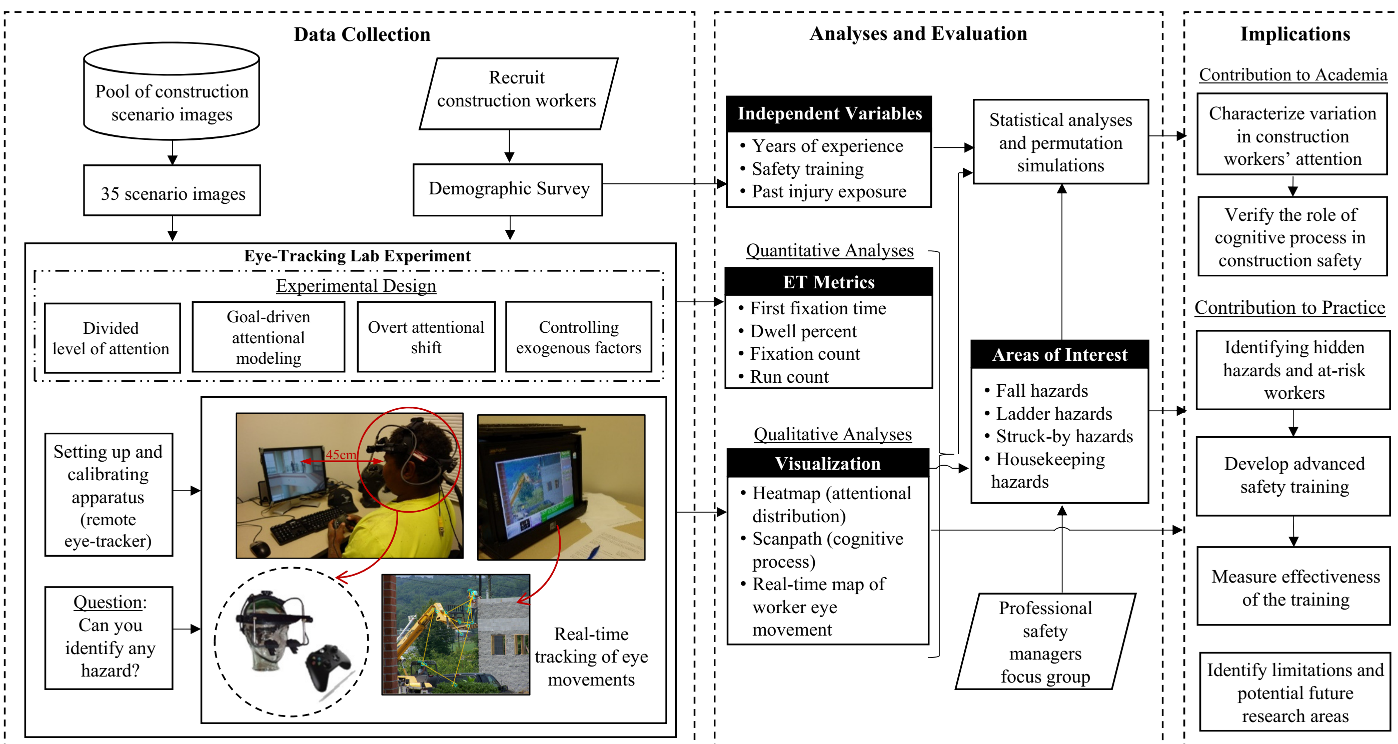


Fig. 1. Research framework (images courtesy of David Ausmus, with permission)

construction laborers (30 males, 1 female) were recruited for the study. Because eye tracking is experimental research, the sample size cannot be as large as it would be for survey-style studies. However, the size of the sample met the parameters of Pernice and Nielsen (2009), who stipulated that sample sizes for eye-tracking studies vary greatly, ranging from 6 for a qualitative study to 30 for a quantitative study. Given the number of subjects used in this study and the number of trials performed by each, the sample is robust enough to match the size recommended for eye-tracking studies.

The participants were mostly young to middle-aged (93% were between the ages of 20 and 55), 35.5% of the participants had fewer than 5 years of experience, 25.8% had between 5 and 10 years of experience, and 38.7% had more than 10 years of experience in the construction field. Sixty percent of the participants had received the OSHA 10-h training, 16% had received informal or on-site safety training, and the remaining 24% had not received any safety training. A total of 69.9% of participants reported that they had been exposed to an injury on the jobsite. 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 were omitted from the analysis because acceptable levels of calibration on the eye tracker could not be achieved. The final analyses were based on the data from the remaining 27 workers. All participants received gift cards as compensation.

Design and Procedure

The eye-tracking experiment consisted of the presentation of 35 construction site images ordered randomly, each of which showed multiple hazards varying in safety risk (four examples of different scenario images are shown in Fig. 2). Construction site images belonged to different private residential and commercial projects taken from real construction sites across the United States. Scenario images covered different types of activities, including but not limited to site work, roofing, lifting materials, finishing, erecting structures, and painting. Each image appeared on the screen for a maximum of 20 s. The participants donned the eye-tracking headset, which was calibrated before each session. Subjects were to scan each image and look for potential hazards. Using a video-game remote control, they then reported whether or not they found any hazards by pushing Button A for Yes or Button B for No. The system gathered eye-tracking data from the moment the image initially appeared through to the moment the participant pushed A or B. Once the participant made a selection, he or she was asked about the number of hazards identified, and then the screen changed to reveal the next image.

In addition to the eye-tracking experiment, participants took a short survey to collect demographic information, including age, gender, nationality, years of experience, obtained certifications, training, and injury exposure. All procedures were approved by the University of Nebraska-Lincoln Institutional Review Board.

Defining AOIs

To extract eye-tracking metrics, an AOI or an overlap or near-overlap of the stimulus (a hazardous situation) and the fixation points needed to be defined. To identify the AOIs, the research team first studied participants' scan paths and heat maps for each picture to understand where they were looking. In the second step, a focus group consisting of five safety managers independently reviewed and discussed the original pictures without the heat maps to identify hazards in each scenario image. All safety mangers were certified and had at least 10 years of experience in residential and commercial projects. The focus group of safety managers was

(a) (b) (c) (d)

Fig. 2. Examples of scenario images (images courtesy of David Ausmus, with permission)

also asked to express the risks they perceived in each scenario. Thus, for each construction scenario image, they indicated the expected frequency of each injury type (categorized based on injury severity). Overlaying and comparing the results of Steps One and Two enabled the research team to finalize the AOIs. In total, 177 hazardous situations (AOIs) in 35 pictures were identified.

Various types of hazards manifested in the scenario images: ladder related, fall to lower level related, fall protection system related, housekeeping, struck by, caught-in/between, and electrical hazards. However, due to sample and visibility limitations, the research team had to remove caught-in/between and electrical hazards from the analysis. First, there was only a single image in which a caught-in/between hazard existed, which made the sample too small for this type of hazard. Concurrently, because the main type of electrical hazard in the images was powerlines, which are very thin objects, the task of locating fixations on such small and narrow AOIs proved very challenging. Accordingly, the research team decided to remove electrical hazards from the analysis.

Therefore, the research team decided to focus on the following AOIs: fall to lower level (i.e., a worker is in the proximity of an unprotected building edge or roof, unguarded roof and floor openings, scaffolding, skylights); fall-protection systems (i.e., misuse of lanyard and other fall-protection systems); ladder related (i.e., improper use of ladders, such as inappropriate type and length of ladder, ignoring ladder extension rules, unstabilized ladder, unsecured straight ladders, unsafe behavior of workers who are working on the ladder), struck-by hazards (i.e., having the probability of being struck by heavy equipment or falling objects like tools, or collapsing masonry or concrete walls); and housekeeping related (i.e., slippery conditions of working and walking surfaces, unsafe material storage, unsanitary conditions of work environment). These types of hazards are among the most typical safety risks that lead to accidents.

Analysis Procedures

To test the research hypotheses, the research team separated the participants into groups based on the independent variables (training, work experience, and injury exposure). Inferential statistical analyses illustrated how different levels of these variables impacted the eye-tracking metrics (dependent variables), which indicated the attentional distribution of construction workers. To study the impact of training on eye-tracking metrics, participants were grouped based on whether they had previously received safety training. Regarding work experience, 5 and 10 years of experience in the construction industry were considered the cutoffs that determined low- and high-experienced workers. In terms of injury exposure, people were classified based on whether they had been injured and/or had seen someone else injured on a construction site.

The research team linked the eye movement data of participants to individual AOIs for each hazard to enable analysis. The choice of an appropriate eye-tracking metric depends on the research context. According to the results of a 2015 pilot study conducted by Bhoir et al. (2015) three fixation-related measures were preferred to serve as indicators of gaze, because they provide unique insight into visual attention across AOIs. First, the time of first fixation on the defined AOIs was calculated. This metric reveals which hazards captured workers' attention more quickly than others (e.g., how quickly was the AOI fixated). Second, because the time each participant spent scanning each picture was different, the gaze (consecutive fixations) on the target AOI was divided by the total duration of all gazes, yielding the dwell-percentage ratio. The average percentage of all workers in the same group indicated that the dwell percentage on each AOI was a good indicator of which AOIs (or types of hazard) captured workers' attention more than others. Finally, the run-count metric revealed the mean number of times workers returned their attention to each AOI to further investigate the situation, indicating the extent to which workers perceived the AOI to be dangerous. The EyeLink Data Viewer was used to analyze the two-dimensional eye-movement patterns of participants. After grouping participants based on independent variables and extracting the eye-tracking data, the research team faced the challenge of selecting an appropriate statistical test.

Statistical Method

To compare the average of two or more groups, parametric tests, such as the t-test and ANOVA, are the most commonly used techniques. To use parametric tests, one needs to satisfy several requirements, such as testing a random sample from a population, normality, and equality of variances (Anderson 2001; Field 2013). However, the majority of laboratory experiments in psychology and physiology are not based on a random sample from a population, have a small number of subjects, and often do not meet the requirement of distributional assumptions in the parametric test (Ludbrook 1994; LaFleur and Greevy 2009). To overcome these challenges, statisticians have suggested the use of randomization techniques (Edgington 1995; Manly 1997; Ludbrook and Dudley 1998; Gleason 2013).

Randomization provides a reliable alternative test when sample sizes are small, when the sample distributions are nonnormal (either because of outliers or skewed data), when the data have mixed distributions, or when the data were not collected at random (Adams and Anthony 1996; Eudey et al. 2010). Randomization statistical methods (bootstrap and permutation simulation) are computer-intensive techniques using reshuffling and resampling to build large samples (e.g., 1,000 samples) from original data and obtain p-values based on created distributions (Adams and Anthony 1996; Anderson 2001). Therefore, randomization statistical techniques can provide a higher power than other nonparametric techniques, because randomization statistical techniques use the actual data rather than ranks, which are used in nonparametric techniques (Edgington 1995; Adams and Anthony 1996; Ludbrook and Dudley 1998; Drummond and Vowler 2012; Gleason 2013).

The permutation test is a randomization technique that was introduced in the early twentieth century by R. A. Fisher, but it only recently became more popular and practical due to decreases in computational costs (LaFleur and Greevy 2009; Gleason 2013). The fundamental idea behind permutation simulation is to generate a reference distribution by recalculating data statistics using resampling (Berger 2000). In other words, the permutation tests calculate the probability of obtaining a value equal or more than the observed value of a test statistic after randomly shuffling data several times (Anderson 2001; Ernst 2004). Using permutation simulation omits the randomized resampling bias found in the bootstrapping approach, which means that, in most cases, the permutation simulation of actual data is more powerful than the bootstrapping approach (LaFleur and Greevy 2009).

As in other laboratory physiological experiments (Ludbrook 1994; LaFleur and Greevy 2009), this study faced some limitations that inhibited the application of parametric statistical techniques. First, it was impractical to randomly select a sample of participants from a broad population because participants needed to be present in a laboratory at the University of Nebraska's campus; thus, the construction workers who were selected for participation were from a population of workers near Lincoln and Omaha. Second, the sample size of the study was small, which impacts the power of the parametric techniques. Third, there was a mixed-normality across group distributions. Because parametric statistical methods are sensitive to the violation of assumptions, each of these characteristics obviated the use of traditional parametric statistical techniques.

In response, the research team decided to use a randomization technique. Among available randomization techniques, permutation simulations were used (1) to provide higher power even given the nonnormality and mixed-normality across group distributions and the small sample size and (2) to obtain more robust outcomes in the presence of outliers and missing data. Because the permutation simulations are based on permutations of actual data, the influence of extreme data points is reduced compared with parametric counterparts, which are affected considerably by the presence of outliers.

To perform the permutation statistical simulations, the research team used the Deducer package in *Java Graphical User Interface (GUI) for R 1.7-9* of the open-source statistical package R version R2.15.0 (R Development Core Team). The permutation simulations were performed at a level of 95% statistical significance ($p < 0.05$) and 90% moderately statistical significance ($p < 0.1$). The results of these statistical analyses appear in the following sections.

Results and Analysis

Table 2 describes the various groupings of participants. After extracting the eye-movement metrics (run count, dwell percentage, and first fixation time) for each participant on AOIs, the research team then performed the statistical analyses described earlier. Because inferential statistics are important, permutation simulations were run to compare groups' means in terms of eye-movement metrics across different types of hazards. Significant results at 0.05 and 0.1 alpha levels are discussed in more detail.

Work Experience and Worker Attentiveness

Regarding work experience, 38.7% of the respondents had more than 10 years of experience, 25.8% had between 5 and 10 years of experience, and 35.5% had fewer than 5 years of experience in the construction field. To magnify the potential difference between the groups, the research team compared the group with fewer than 5 years of work experience with the group possessing more than 10 years of experience. The descriptive statistics relating eye movement metrics to work experience are provided in Table 3. Workers with less experience (Group A_1) had lower first fixation times on hazardous areas; however, workers with more experience (Group B_1) had higher run counts, meaning they returned their attention to hazardous areas in images more often. In addition, more experienced workers (Group B_1) needed less processing time for ladder and fall-to-lower-level hazards, as demonstrated by their shorter dwell time percentage; experienced workers (Group B_1) also gazed for a longer duration on fall-protection systems and housekeeping hazards.

In total, 18 (three eye movement metrics for six types of hazards) permutation simulations were each run 1,000 times to compare eye-tracking metrics between groups with different levels of experience across different types of hazards (significant differences are indicated on Table 3). Contrary to the null hypothesis H_1, results indicated that work experience has a significant impact on worker attentiveness to hazards on a construction site. The results showed that more experienced workers (Group B_1) returned their attention more frequently to hazardous areas related to fall-protection systems (Welch's $t = -2.862$; $p = 0.015 < 0.05$), ladders (Welch's $t = -2.336$; $p = 0.03 < 0.05$), struck-by hazards (Welch's $t = -3.906$; $p = 0.002 < 0.05$), and housekeeping hazards (Welch's $t = -1.845$; $p = 0.088 < 0.1$). In addition, the results indicated that first fixation times for hazardous areas did not differ significantly among less experienced workers (Group A_1) and more experienced workers (Group B_1). Moreover, eye-movement patterns of experienced workers (Group B_1) showed that they tended to spend significantly more time examining hazardous areas related to fall-protection systems in images (Welch's $t = -1.740$; $p = 0.099 < 0.1$).

Training and Worker Attentiveness

Sixty percent of the participants claimed they had received the OSHA 10-h training, 16% of the participants had informal or on-site safety training, and the remaining 24% had no safety training at all. To test whether having safety training could affect a worker's attentional allocation and hazard-detection skills, the participants were divided into two groups: people who had received safety training, including the OSHA 10-hour training; informal or on-site safety training (Group A_2); and people who had not received any safety training at all (Group B_2). The descriptive statistics for these groups' eye movement metrics across AOIs are summarized in Table 4.

The descriptive analysis revealed that trained workers (Group A_2) were slower to fixate on hazardous areas compared with workers who had not received any safety training (Group B_2). The results of the run-count descriptive analysis showed that these trained workers (Group A_2) also tended to return their attention to hazardous areas (e.g., ladder, fall-protection systems, struck-by hazards, housekeeping hazards) more often, excluding falls-to-lower-level hazards. Moreover, trained workers (Group A_2) generally dwelt less on hazards compared with Group B_2. However, trained workers spent more time examining ladder, struck-by, and housekeeping

Table 2. Groupings of Workers Based on Background: Group A versus Group B

Null hypothesis	Group A	Group B
H_1	(A_1) Workers who had fewer than 5 years of work experience	(B_1) Workers who had more than 10 years of work experience
H_2	(A_2) Workers who had received safety training (formal or informal)	(B_2) Workers who had not received any safety training (formal or informal)
H_3	(A_3) Workers who had been injured on the jobsite	(B_3) Workers who had not been injured on the jobsite
	(A_4) Workers who had seen someone injured on the jobsite	(B_4) Workers who had not seen someone injured on the jobsite
	(A_5) Workers who had been injured and/or had seen someone injured on the jobsite	(B_5) Workers who had not been injured and/or had not seen someone injured on the jobsite
H_4	(A_6) Workers who had trained and had more than 10 years of experience	(B_6) Workers who had trained and had fewer than 5 years of experience

Table 3. Impact of Work Experience on Workers' Attentional Allocation across Different Types of Hazards

			First fixation time (ms)			Dwell percentage			Run count		
Hazards (AOIs)	Group	N	Mean	SD	MD	Mean	SD	MD	Mean	SD	MD
General	A_1	9	3,196.344	631.912	3,211.060	0.104	0.009	0.105	1.833[a]	0.331	1.805
	B_1	11	3,671.524	1,082.945	3,767.006	0.010	0.011	0.099	2.235[a]	0.469	2.229
Ladder	A_1	9	3,225.971	775.104	3,326.000	0.107	0.024	0.095	2.111[a]	0.503	1.889
	B_1	11	3,607.659	1,319.006	3,305.647	0.105	0.018	0.096	2.606[a]	0.695	2.667
Fall to lower level	A_1	9	1,181.896	306.796	1,101.116	0.266	0.047	0.276	3.788	0.886	3.535
	B_1	11	1,412.959	586.633	1,125.949	0.240	0.050	0.250	4.402	1.006	4.326
Fall-protection system	A_1	9	3,620.371	824.743	3,434.400	0.079[b]	0.008	0.079	1.539[a]	0.353	1.532
	B_1	11	4,087.963	1,085.257	3,629.250	0.086[b]	0.010	0.085	2.054[a]	0.452	2.170
Struck by	A_1	9	4,890.770	964.985	5,262.824	0.059	0.020	0.066	1.269[a]	0.294	1.269
	B_1	11	5,189.599	1,965.198	4,920.750	0.071	0.014	0.069	1.969[a]	0.497	1.846
Housekeeping	A_1	9	3,549.130	779.484	3,562.800	0.078	0.015	0.082	1.496[b]	0.327	1.400
	B_1	11	3,798.890	1,437.093	3,777.000	0.080	0.024	0.086	2.012[b]	0.637	2.200

Note: N = number of subjects in each group; SD = standard deviation in each group; MD = median in each group.
[a]$p \leq 0.05$.
[b]$p \leq 0.1$.

hazardous areas. The reasons behind these findings, to be discussed later, may relate to different affective factors, such as workers' background and work experience.

To investigate the differences between these groups, 18 series of permutation simulations were each run 1,000 times. The results of these simulations meant that the authors could not reject the null hypothesis H_2: safety training (formal or informal) has no impact on worker attentiveness to hazards on a construction site. With the resulting $p > 0.05$, it was found that training alone has a minimal (nonsignificant) impact on workers' attentiveness to hazards. The only significant effect of informal or on-site safety training was on identifying struck-by hazards in images (Welch's $t = 2.693$; p-value = 0.032).

Past Injury Exposure and Worker Attentiveness

Among the 27 participants who had reliable eye-tracking data, some of them did not answer the survey questions about their past injury exposure (i.e., four participants did not answer whether they had been injured and three participants did not answer whether they had seen someone injured on a jobsite). Of the remaining 23 workers, 13 had been injured and the other 10 stated that they had never been exposed to any kind of injuries at a jobsite. To better understand the impact of injury exposure on attentional allocation of workers, the research team divided the participants into the groups identified in Table 2. Descriptive statistics of eye movement metrics across AOIs are presented in Tables 5–7. For further investigation, 72 permutation simulations comparing the previously mentioned groups were each run 1,000 times.

The descriptive statistics presented in Table 5 demonstrate the impact on workers' attentional allocation and hazard-detection capabilities of having been or not having been injured (Group A_3 versus Group B_3). Although workers in Group B_3 fixated more quickly on most hazardous areas, detailed analysis of the first fixation time did not provide any meaningful discrimination between groups (Group A_3 versus Group B_3). Interestingly, while run-count analyses showed that workers in Group A_3 returned their attention to hazardous areas (all types of hazards) more frequently, they tended to dwell longer than those in Group B_3 only on ladder, fall-protection system, and struck-by hazards in the images.

Table 6 depicts differences in eye-movement metrics of workers who had (Group A_4) or had not (Group B_4) seen someone else injured on a jobsite. Workers in Group B_4 fixated more quickly on hazardous stimuli than workers in Group A_4. However, further investigation into their eye-movement patterns revealed that although Group A_4 workers returned their attention to hazardous areas more frequently, they did not dwell much on those areas;

Table 4. Impact of Safety Training on Workers' Attentional Allocation across Different Types of Hazards

			First fixation time (ms)			Dwell percentage			Run count		
Hazards (AOIs)	Group	N	Mean	SD	MD	Mean	SD	MD	Mean	SD	MD
General	A_2	19	3,707.500	896.162	3,636.453	0.101	0.009	0.101	2.201	0.459	2.217
	B_2	5	3,233.559	621.273	2,997.412	0.106	0.010	0.106	2.149	0.401	2.117
Ladder	A_2	19	3,498.433	1,044.360	3,326.000	0.108	0.022	0.096	2.608	0.673	2.667
	B_2	5	3,305.928	675.298	3,666.250	0.106	0.017	0.106	2.400	0.666	2.722
Fall to lower level	A_2	19	1,385.279	476.604	1,273.861	0.247	0.045	0.250	4.337	1.003	4.326
	B_2	5	1,087.521	465.293	939.429	0.285	0.049	0.297	4.791	1.314	4.209
Fall-protection system	A_2	19	4,170.635	1,254.556	3,629.250	0.082	0.009	0.082	1.933	0.470	2.064
	B_2	5	4,065.010	939.264	3,874.703	0.082	0.010	0.079	1.838	0.351	1.936
Struck by	A_2	19	5,606.011	1,829.265	5,328.000	0.068	0.015	0.068	1.767	0.497	1.731
	B_2	5	4,686.430	805.299	5,149.000	0.056	0.018	0.064	1.315	0.275	1.269
Housekeeping	A_2	19	4,049.956	1,197.663	4,144.000	0.078	0.019	0.079	1.912	0.529	2.000
	B_2	5	3,669.257	902.123	4,104.800	0.071	0.022	0.059	1.707	0.393	1.733

Note: N = number of subjects in each group; SD = standard deviation in each group; MD = median in each group.

Table 5. Impact of Being Injured on Workers' Attentional Allocation across Different Types of Hazards

			First fixation time (ms)			Dwell percentage			Run count		
Hazards (AOIs)	Group	N	Mean	SD	MD	Mean	SD	MD	Mean	SD	MD
General	A_3	13	3,760.634	797.876	3,876.145	0.101	0.007	0.101	2.469	0.465	2.515
	B_3	10	3,514.459	841.847	3,310.964	0.101	0.013	0.104	1.989	0.399	1.862
Ladder	A_3	13	3,412.060	1,150.025	3,240	0.107	0.015	0.103	2.944	0.650	3.000
	B_3	10	3,560.817	681.234	3,425.756	0.103	0.027	0.091	2.267	0.668	1.944
Fall to lower level	A_3	13	1,346.532	446.439	1,289.581	0.245	0.045	0.244	4.911	1.040	4.488
	B_3	10	1,271.499	520.490	1,107.387	0.254	0.060	0.279	3.928	0.872	3.977
Fall-protection system	A_3	13	4,315.336	1,214.908	4,205.511	0.087	0.011	0.084	2.244	0.579	2.277
	B_3	10	3,961.475	985.744	3,553.077	0.080	0.008	0.082	1.747	0.432	1.638
Struck by	A_3	13	5,473.008	1,278.817	5,060.909	0.071	0.010	0.069	2.027	0.575	1.769
	B_3	10	5,575.305	2,127.791	5,344.615	0.060	0.019	0.061	1.446	0.397	1.462
Housekeeping	A_3	13	4,235.941	1,260.845	4,424	0.070	0.018	0.069	2.051	0.527	2.067
	B_3	10	3,661.517	973.167	3,760.8	0.087	0.016	0.089	1.760	0.546	1.633

Note: N = number of subjects in each group; SD = standard deviation in each group; MD = median in each group.

Table 6. Impact of Seeing Someone Else Injured on Workers' Attentional Allocation across Different Types of Hazards

			First fixation time (ms)			Dwell percentage			Run count		
Hazards (AOIs)	Group	N	Mean	SD	MD	Mean	SD	MD	Mean	SD	MD
General	A_4	13	3,708.054	999.684	3,756.299	0.099	0.010	0.100	2.437	0.454	2.455
	B_4	11	3,381.456	725.299	3,310.964	0.104	0.008	0.105	1.982	0.466	1.860
Ladder	A_4	13	3,689.773	1,137.103	3,458.4	0.100	0.015	0.095	2.838	0.647	2.944
	B_4	11	3,095.264	670.915	3,305.647	0.114	0.025	0.106	2.354	0.768	1.944
Fall to lower level	A_4	13	1,380.634	567.458	1,187.905	0.242	0.056	0.244	4.877	1.048	4.488
	B_4	11	1,199.450	308.056	1,101.116	0.259	0.044	0.275	3.922	0.881	3.767
Fall-protection system	A_4	13	4,256.243	1,174.578	4,205.511	0.085	0.010	0.084	2.223	0.596	2.277
	B_4	11	3,897.974	1,118.337	3,434.4	0.081	0.010	0.079	1.716	0.456	1.681
Struck by	A_4	13	5,631.502	1,849.055	5,289.913	0.068	0.015	0.065	1.917	0.561	1.731
	B_4	11	5,160.357	1,543.208	5,149	0.067	0.016	0.068	1.552	0.553	1.269
Housekeeping	A_4	13	4,230.567	1,281.604	4,593.5	0.075	0.021	0.076	2.082	0.432	2.200
	B_4	11	3,658.894	893.291	3,562.8	0.080	0.017	0.084	1.691	0.600	1.533

Note: N = number of subjects in each group; SD = standard deviation in each group; MD = median in each group.

Table 7. Impact of Being Injured and/or Seeing Someone Else Injured on Workers' Attentional Allocation across Different Types of Hazards

			First fixation time (ms)			Dwell percentage			Run count		
Hazards (AOIs)	Group	N	Mean	SD	MD	Mean	SD	MD	Mean	SD	MD
General	A_5	9	3,910.608	870.891	3,997.135	0.100	0.005	0.101	2.576	0.450	2.593
	B_5	6	3,405.179	714.482	3,310.964	0.103	0.008	0.104	1.899	0.453	1.748
Ladder	A_5	9	3,631.806	1,304.424	3,240.000	0.105	0.015	0.103	3.062	0.563	3.000
	B_5	6	3,387.897	620.099	3,359.556	0.113	0.032	0.100	2.222	0.771	1.917
Fall to lower level	A_5	9	1,316.858	487.587	1,243.721	0.244	0.045	0.244	5.207	1.046	5.628
	B_5	6	1,103.080	184.127	1,081.177	0.263	0.044	0.280	3.791	1.033	3.523
Fall-protection system	A_5	9	4,418.435	1,325.734	4,296.690	0.086	0.012	0.084	2.355	0.631	2.298
	B_5	6	4,008.249	1,182.101	3,592.171	0.079	0.010	0.078	1.628	0.424	1.532
Struck by	A_5	9	5,731.014	1,363.010	5,289.913	0.070	0.009	0.065	2.060	0.557	1.731
	B_5	6	5,687.108	1,713.703	5,392.161	0.058	0.015	0.061	1.346	0.340	1.270
Housekeeping	A_5	9	4,473.882	1,319.159	4,829.600	0.066	0.016	0.066	2.067	0.435	2.067
	B_5	6	3,647.123	944.816	3,577.714	0.081	0.016	0.084	1.522	0.472	1.433

Note: N = number of subjects in each group; SD = standard deviation in each group; MD = median in each group.

instead, they distributed their attention across images, excluding more complex scenes that included struck-by or fall-protection system hazards. This result might imply that this group tended to maintain situational awareness of the environment by distributing their attention across scene.

Notwithstanding, the results showed that Group B_5 (who had neither been injured themselves nor had seen anyone else injured on a jobsite) fixated more quickly on hazardous areas than Group A_5 (who had both been injured and/or seen someone else injured at a jobsite), but these groups (A_5 versus B_5) did not differ significantly in first fixation time on hazards. Of note, Group A_5 spent less time examining hazardous areas in images and tended to distribute their attention across the scene; instead, Group B_5 tended to dwell on specific hazardous areas with the potential cost of failing to identify other hazards (Table 7).

Next, to determine whether the effect of injury exposure on eye movements was greater for certain hazard types, the authors examined the extent to which the characteristics of each group predicted first fixation time, dwell percentage, and run count on each hazard type. The results of the permutation simulations are shown in Table 8. Workers who had previous injury exposure distributed their attention significantly differently in all hazardous situations. Contrary to null hypothesis H_3, injury exposure has a significant impact on workers' attentiveness to hazards on a construction site. Workers who had injury exposure tended to return their attention more frequently to hazardous areas (Welch's $t = -2.846$; $p = 0.015 < 0.05$). Also, workers who personally had been injured at a jobsite distributed their attention significantly differently across scenes that included struck-by hazards. The run-count and dwell percentage analyses verified that these workers more frequently returned their attention to potential or active struck-by hazards in images (Welch's $t = -2.859$; $p = 0.013 < 0.05$) and gazed at these hazards for a longer duration (Welch's $t = -1.816$; $p = 0.083 < 0.1$). Comparing Groups A_3 and B_3 revealed that workers in Group A_3 spent significantly less time on housekeeping hazards (Welch's $t = 2.302$; $p = 0.036 < 0.05$). Significantly, workers in Group A_4 deployed frequent short fixations on housekeeping hazardous situations to detect active or potential hazards without dwelling on one source. The follow-up investigation will be discussed later.

Work Experience and Worker Attentiveness while Controlling for Training

Because the results demonstrate that the standard OSHA 10-h training has a minimal impact (not significant) on search strategy, attentional allocation, and the hazard-identification skills of construction workers, it can be concluded that standard OSHA 10-h training alone cannot be considered a comprehensive tool for improving workers' attention. Moreover, this study's eye-movement data

Table 8. Permutation Simulation Results for Workers Who Had Injury Exposure

Hazard	Eye-tracking metrics	Group A_3 versus Group B_3		Group A_4 versus Group B_4		Group A_5 versus Group B_5	
		Welch's *t*	*p*-value	Welch's *t*	*p*-value	Welch's *t*	*p*-value
General	Run count	−2.656	0.019[a]	−2.409	0.032[a]	−2.846	0.015[a]
Ladder	Run count	−2.441	0.029[a]	−1.652	0.103	−2.292	0.047[a]
Fall to lower level	Run count	−2.463	0.028[a]	−2.425	0.026[a]	−2.588	0.035[a]
Fall-protection system	Run count	−2.357	0.025[a]	−2.357	0.021[a]	−2.667	0.014[a]
Struck by	Run count	−2.859	0.013[a]	−1.600	0.130	−3.080	0.009[a]
	Dwell percentage	−1.816	0.083[b]	−0.069	0.936	−1.752	0.096[b]
Housekeeping	Run count	−1.288	0.210	−1.802	0.086[b]	−2.258	0.053[b]
	Dwell percentage	2.302	0.036[a]	0.702	0.482	1.769	0.113

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

Table 9. Impacts of Work Experience on Workers' Attentional Allocation across Different Types of Hazards, with Training as a Controlling Factor

Hazards (AOIs)	Group	*N*	First fixation time (ms)			Dwell percentage			Run count		
			Mean	SD	MD	Mean	SD	MD	Mean	SD	MD
General	A_6	9	3,931.732	992.628	3,997.135	0.097	0.010	0.098	2.379[a]	0.359	2.320
	B_6	6	3,044.915	603.285	3,161.181	0.105	0.009	0.106	1.701[a]	0.205	1.748
Ladder	A_6	9	3,933.498	1,219.092	3,442.889	0.100	0.016	0.095	2.852[a]	0.479	2.944
	B_6	6	3,132.274	866.041	3,057.133	0.108	0.028	0.094	1.917[a]	0.392	1.833
Fall to lower level	A_6	9	1,541.430	570.365	1,403.628	0.228	0.044	0.232	4.579[a]	0.989	4.395
	B_6	6	1,126.322	,199.763	1,124.571	0.268	0.050	0.276	3.477[a]	0.523	3.477
Fall-protection system	A_6	9	4,250.217	1144.259	3,958.000	0.086	0.011	0.084	2.175[a]	0.373	2.277
	B_6	6	3,318.001	425.332	3,422.200	0.079	0.005	0.080	1.411[a]	0.218	1.457
Struck by	A_6	9	5,442.838	2,043.338	4,920.750	0.072	0.014	0.069	2.009[a]	0.459	1.846
	B_6	6	4,707.313	1,168.006	5,141.417	0.065	0.019	0.070	1.308[a]	0.341	1.231
Housekeeping	A_6	9	3,991.903	1,339.133	3,777.000	0.087	0.019	0.088	2.244[a]	0.408	2.200
	B_6	6	3,407.124	830.206	3,205.900	0.075	0.013	0.079	1.356[a]	0.266	1.367

Note: *N* = number of subjects in each group; SD = standard deviation in each group; MD = median in each group.
[a]$p \leq 0.05$.
[b]$p \leq 0.1$.

results supported the idea that in addition to training, years of experience seem to be a prominent variable in shaping the safety perceptions of workers. To verify this finding, training was considered a controlling factor, and workers were grouped based on their years of experience (less than 5 years or more than 10 years). The descriptive statistics relating eye-movement metrics to work experience while controlling for training are provided in Table 9. Workers with less experience (Group A_6) generally had lower first fixation times on hazardous areas; however, workers with more experience (Group B_6) had higher run counts, meaning they returned their attention to hazardous areas in images more often.

To investigate the differences between these groups, 18 series of permutation simulations were each run 1,000 times. Among trained workers, workers who had more experience (Group B_6) distributed their attention significantly differently across scenes and had significantly higher run counts across all types of hazards: ladder related (Welch's $t = 4.136$; $p = 0.003 < 0.05$), fall to lower level (Welch's $t = 2.804$; $p = 0.023 < 0.05$), fall-protection system (Welch's $t = 4.997$; $p = 0.002 < 0.05$), struck by (Welch's $t = 3.392$; $p = 0.004 < 0.05$), and housekeeping (Welch's $t = 5.109$; $p = 0.001 < 0.05$). Contrary to null hypothesis H_4, the result of the permutation simulations confirmed that training has minimal influence on the attentional allocation and hazard detection of groups and what differentiates trained workers in safety perception is their years of experience in the field.

Findings and Discussion

Work Experience

The first null hypothesis, which aimed to test whether years of work experience had an impact on workers' attentiveness to hazards on a construction site, was rejected. The findings indicated that more experienced workers (>10 years) returned their attention to hazardous areas more often than less experienced workers. These hazards may be comprehended by experienced workers as more dangerous than others or perhaps extensive experience is required with certain stimuli before one classifies it as a potential hazard. Previous literature showed that hazard-detection skill can be impacted by safety experience, i.e., one of the indicators of tacit knowledge (Zhang et al. 2014; Hadikusumo and Rowlinson 2004), so the outcomes confirm existing theory.

The results presented in Table 3 revealed that when the construction environment includes potential or active sources of hazards, more experienced workers tended to maintain a balance between processing and searching the scene by spending less time exploring hazardous areas and by more frequently tracking back to those hazardous areas. The results of previous studies (Choudhry and Fang 2008; Chi et al. 2005) indicated that both young and less experienced workers are more prone to accidents, and when these workers gain more experience, they become more aware of safety requirements. Moreover, a study conducted by Sawacha et al. (1999) showed that there is a strong relationship between the experience of operatives and their level of safety performance; however, the Sawacha study was based on a questionnaire; thus, the present study takes this investigation a step further by supporting this claim using empirical data.

First time of fixation was not significant for any of the AOIs, which means that more experienced workers were not faster to fixate on potential hazards; however, these workers were more likely to return to the AOIs multiple times. Generally, more experienced workers spent less processing time than less experienced workers, which is an outcome that agrees with the study by Dzeng et al. (2016). Similarly, the duration of time that more and less experienced workers spent dwelling on fall-protection system hazards was significantly (moderately) different (p-value = 0.099). The results presented in Table 3 revealed that when the construction environment includes potential or active sources of fall-protection system hazards, more experienced workers tended to maintain a balance between processing and searching the scene by spending more time exploring fall-protection system hazardous areas and frequently tracked back to those areas.

In a previous study that used eye tracking to compare the hazard identification of workers, Dzeng et al. (2016) noted that experienced workers did not perform significantly better than novices in identifying hazards. Although their findings are in contrast with the results of the current study, it is critical to note the points of departure between the two studies. First, the authors of the current study have defined experienced workers as those with more than 10 years of experience and novices as those with less than 5 years of experience. Dzeng et al. (2016) qualified experienced workers as those with a minimum of 5 years of experience and, more critically, their novice sample consisted of students, not construction workers, who had no work experience and never received safety training of any substantive nature. In other words, Dzeng et al. (2016) compared workers with experience with students without any experience, which significantly impacted the results of their study. Comparatively, the central objective in the current study is to study whether gaining more experience on a construction site improves workers' hazard-identification skills (as manifested by attention and eye movements); thus, all participants in this study were required to have experience working on a construction site. All of the participants in the current study are professional construction workers, and the authors took rigorous steps to divide them into two distinct groups.

Second, whereas the Dzeng et al. (2016) stimuli consisted of a limited number (only four) of virtual images of hypothetical construction scenarios, the current study's 35 images were taken from real construction sites and represented a wide range of common hazards. In addition, there were at least 20 AOIs for each type of hazard across the images, which helped to obtain more reliable outcomes by measuring the average performance of workers in identifying different types of hazards. As such, although the study Dzeng et al. (2016) conducted is an important step in applying eye-tracking technology to a construction setting, the present study considerably expands the scope of what can be studied via eye tracking in construction safety.

The findings of this study can further be compared with the results of other previous eye-tracking studies. Underwood (2007) suggested that the efficiency of visual search strategies relates to the changes in driving skills that mark the transition from novice to experienced drivers. Many other studies have provided support for the notion that driving experience is a key predictor of crash rates, with young novice drivers being at a greater risk (Chapman and Underwood 1998; Konstantopoulos et al. 2010). Similarly, learning by doing and gaining experience can be one of the best training options for construction workers (Choudhry and Fang 2008). This study shows that as construction workers gain experience, their hazard-detection skills improve, enabling them to search and examine scenes more intuitively. Thus, it can be concluded that gaining experience in construction is strongly related to effective and efficient visual search and attentional distribution.

Safety Training

The second null hypothesis of the study stated that past safety training (formal or informal) would have minimal (nonsignificant) impact on workers' attentiveness to hazards on a construction site. The hypothesis could not be rejected for formal training. The results showed no significant differences in the search strategies or attentional patterns of workers with or without the OSHA 10-h certificate training when they were exposed to hazardous situations. The findings of this eye-tracking experiment can be alarming for construction safety professionals, because it implies that the most common and basic training (i.e., OSHA 10-h certificate) may not considerably improve hazard-detection skills. Although the results do not state that the OSHA 10-h certificate is ineffective, they do suggest that developing more innovative and interactive training techniques can improve workers' hazard-detection skills [e.g., using OSHA visual inspection training, which is interactive and game-based training; using a three-sided virtual reality, such as cave automatic virtual environment Perlman et al. (2014)].

Regarding informal training, however, the second null hypothesis was rejected for run count on struck-by hazards. The results indicated that the attentional pattern of workers who have had informal training (i.e., through on-site training or participation in safety meetings) was significantly different for struck-by hazardous situations (Welch's $t = 2.693$; p-value = 0.032). To study this finding further, attentional distributions (heat maps) of two workers, one who had informal training and the other who had no safety training, were created. As the heat map comparison shows (Fig. 3), the worker with informal training appears more attentive to struck-by hazards and fixates on areas that show potential for struck-by accidents. These workers distributed their attention across the scene and scanned areas close to a potential hazard, checking the proximity of equipment to workers and other equipment in the scene.

Past Injury Exposure

The third null hypothesis, which tested whether workers' past injury exposure affected their attentional patterns, was also rejected. The results of the analysis demonstrated that injury exposure significantly impacts the cognitive processes of those who had previously been exposed to specific hazards (Table 8). The test subjects in this group behaved more conservatively and tended to check the surrounding environment frequently with short fixations, seeking potential and active sources of hazards. This finding conforms with some previous studies (Törner and Pousette 2009; Shin et al. 2014), which found that past injury exposure increases workers' risk awareness. It was interesting that workers who had been injured before had no significant differences in attentional allocation to housekeeping hazards compared with those who had no injury exposure. The reason behind this finding may correlate with the type(s) of hazards they had been exposed to before. According to workers' self-reports, none of the workers had experienced injury with housekeeping or a cluttered environment as sources of hazard.

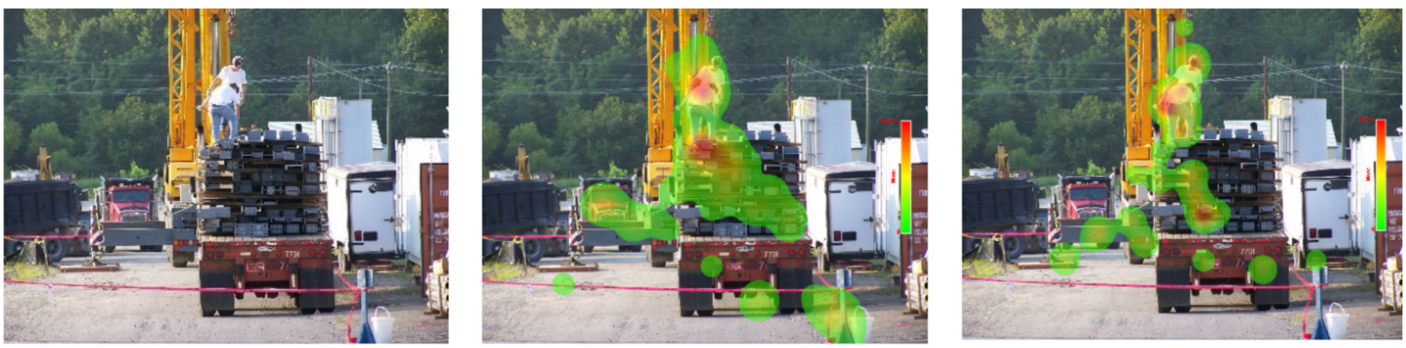
Workers who had past injury exposure became more conservative and careful regarding struck-by hazards in a dynamic construction environment. Jacob and Karn (2003) showed that a higher dwell percentage on particular elements is a sign of that element's importance for that group, leading to the conclusion that workers with past injury exposure would dwell longer and return their attention more often to comprehend the complexity of a dynamic hazardous situation (struck-by hazard) than workers with no injury exposure. The findings also indicated that workers who had been injured or had witnessed another's injury tended to not dwell on specific hazards and distributed their attention over the scene while frequently returning their attention to better comprehend all dimensions of a hazardous area. On the other hand, the mean dwell time percentages for workers without any injury exposure experience were longer, and they tended to focus their attention on specific hazards, possibly misidentifying other active hazards or failing to anticipate potential hazards on the construction site.

Furthermore, grouping workers based on their past experience of seeing another worker injured provided additional insight into the cognitive processes of construction workers. Having seen another worker injured impacted the attentional allocation of the current participants. These workers appeared to become more concerned about their safety and health, and when they faced hazardous situations, they tended to maintain situational awareness. Although the workers who had witnessed someone else injured frequently checked AOIs related to housekeeping (p-value = 0.086) and ladder hazards (p-value = 0.103) (moderately significant), their run count to fall hazards was more significant (p-value = 0.026). Self-reports of workers revealed that approximately 70% of them had experienced witnessing another worker injured due to fall incidents, such as falling from scaffold, falling from an unprotected edge, or falling from height due to broken cable. Scan paths for a representative worker of each group verified the statistical findings that workers who saw another worker falling from height exhibited differential visual behaviors and followed a different search strategy (Fig. 4). Moreover, the run count associated with struck-by–related hazards was not significantly different between these groups. Returning to the workers' self-reports of their injury experience also confirmed that none of the workers acknowledged seeing another worker being injured due to struck-by accidents.

Years of Experience while Controlling for Training Impacts

The fourth null hypothesis, which aimed to test whether years of work experience of trained workers had an impact on their attentiveness to hazards on a construction site, was rejected. The results suggested that as trained workers gain more experience in the construction field, they will be more aware of safety requirements on jobsites and of the full extent of all potentially hazardous items/situations in the environment. This outcome is consistent with previous studies in which workers become better at detecting hazards and behaving safely by gaining experience and being exposed to hazardous situations (tacit knowledge) rather than by receiving formal training with traditional educational methods (explicit knowledge) (Podgórski 2010).

For example, as seen in Figs. 5(a–c), the less experienced worker is more stimulus driven and concentrated on imminent hazards,

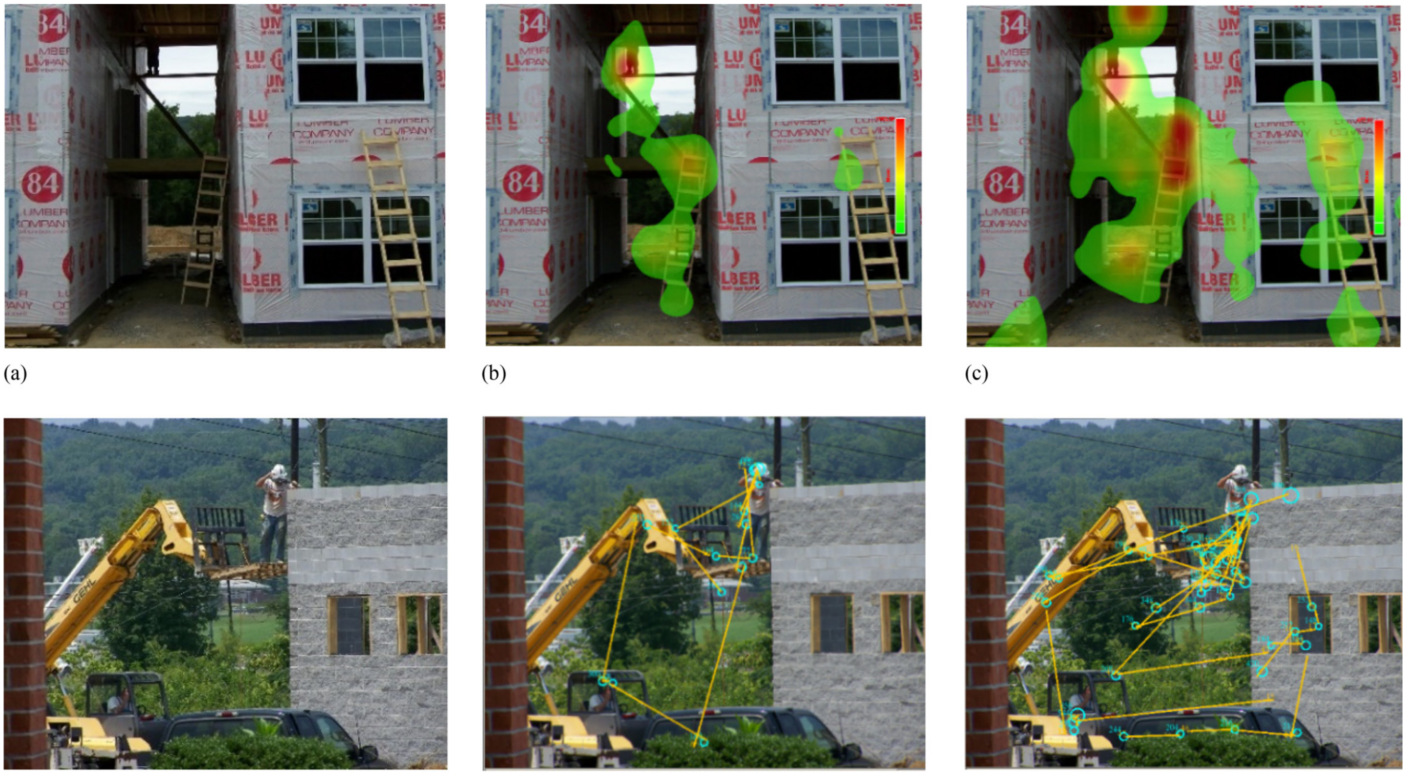


(a) (b) (c)

Fig. 3. Attentional distributions (heat maps) (images courtesy of David Ausmus, with permission): (a) original picture; (b) worker who had informal safety training; (c) worker who had no safety training

(a) (b) (c)

Fig. 4. Difference in cognitive process (search strategy) (images courtesy of David Ausmus, with permission): (a) original picture; (b) worker who had not seen someone injured due to fall hazards; (c) worker who had seen someone injured due to fall hazards



(a) (b) (c)

(d) (e) (f)

Fig. 5. Differences in cognitive process and attentional allocation (images courtesy of David Ausmus, with permission): (a and d) original picture; (b) attentional distribution for the group of workers who had received safety training and fewer than 5 years of experience; (c) attentional distribution for the group of workers who had received safety training and more than 10 years of experience; (e) visual search strategy for a worker who had received safety training and fewer than 5 years of experience; (f) attentional distribution and visual search strategy for the group of workers who had received safety training and more than 10 years of experience

such as the danger to the man standing on the scaffold, but the more experienced workers showed a balance in focusing and dividing their attention across the scene and are more goal driven. To better understand the difference between the search strategies and cognitive processes of these groups, scan paths were obtained from one worker in each group. Scan paths suggest that experienced workers optimized their attention by distributing it across the scene and scrutinized more areas to maintain their awareness about potential or active sources of hazards in scene. The study of Aboagye-Nimo et al. (2012) points out that "explicit knowledge […] will not be sufficient in practice in order to prevent accidents" (p. 419). They highlighted the important role of tacit knowledge, namely work experience, in learning safe work practices. In sum, these findings align with the study of McBride and Cutting (2015), who verified that as a result of years of experience and training, the controlled attentional allocation for hazard detection in less experienced workers turned into an automatic attentional allocation in more experienced workers.

Conclusions

One of the root causes of accidents is human error (Abdelhamid and Everett 2000), i.e., the lack of attention and the failure of workers to identify hazards. If workers are distracted or lack attentiveness, then they cannot identify and properly respond to a hazard. Because there is a direct link between visual cues and attentional allocation, one of the scientific methods of studying attention is tracking the eye movements of people. Although eye tracking has been extensively used to study attention in other domains of science (Duchowski 2007), its applications remain relatively unexplored in the field of construction safety.

To address this knowledge gap, the research team used eye-tracking technology to measure the impact of safety knowledge (in terms of training, work experience, and injury exposure) on construction workers' attentional allocation. It was found that although work experience and injury exposure significantly impact visual search strategies and attentional allocation, the difference between workers with and without the OSHA 10-h certificate is not significant. One should note that the results do not state that the OSHA 10-h certificate is ineffective, but it calls for developing more innovative training techniques, such as interactive and game-based training, which can improve workers' hazard-detection skills. The results indicate that by integrating both tacit knowledge (work experience and injury exposure) and explicit knowledge (e.g., interactive training), future endeavors to enhance worker safety knowledge will achieve superior outcomes in terms of worker safety awareness.

This study's results increase the field's understanding of the variables that impact attentional allocation and provide a novel approach for improving construction site safety by using eye-tracking technologies that have been widely accepted as the most direct and continuous measure of attention. The results of the study reported in this paper make a significant contribution to the existing literature. First, the eye-tracking metrics that characterize the variation in construction workers' attention while they search for hazards were identified. Second, given the established link between eye movements and cognitive processes, the findings of this study lay the foundation for using eye-tracking technologies to further study the role of cognition in construction safety. The previously described approach can be used by other researchers to advance knowledge regarding the way that attentional allocation of construction workers impacts the likelihood of accidents and can subsequently lead to the development of new accident-causation theories.

The results also make a significant contribution to practice. Because of these results, one can conclude that traditional teaching methods (e.g., lectures, media) for construction worker education and training do not improve workers' visual search skills sufficiently to identify hazards. More effective interactive methods should be applied instead of conventional teacher-student training. For instance, safety knowledge could be more effectively acquired using interactive and experiential learning methods. The need to find more effective training methods becomes more urgent in the face of the fact that 185,000 new workers are predicted to join construction in this decade (NCCER 2013). Eye-tracking technology can provide a viable solution for this challenge by providing real-time tracking of the eye movements of construction workers to measure the effectiveness of their training (via pretest and posttest monitoring). Eye tracking can further be used for innumerable purposes inclined toward achieving safer working conditions, such as identifying hidden hazards, measuring the situation awareness of workers, and improving the effectiveness of safety-training programs.

This study has some limitations and areas that future work can address. First, the research team examined the gaze exhibited toward static images of construction sites rather than dynamic real-world construction sites. One might argue that since the images are merely pictures on a screen, they do not translate to construction sites; workers may act differently in interactions with real-world construction sites. To completely address this issue, future research may examine the workers' gazes and assess their hazard-detection skills on real-world construction sites using a mobile eye tracker. Another limitation of this study relates to sampling and the number of participants. Because of practical limitations, the research team only recruited workers located near Lincoln and Omaha. In addition, although the sample of the present study was relatively large for an eye-tracking study, the practical limitations of recruiting construction workers to participate in the experiment in a laboratory setting restricted the number of participants. Future studies might address this limitation by replicating the study in other geographical regions and also increasing the number of participants.

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