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Neurophysiological evaluation of workers' decision dynamics under time pressure and increased mental demand

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ABSTRACT

Productivity demands, time pressure, and cognitively demanding construction tasks increase workers' arousal and stress; however, it is not clear how these factors may worsen risk compensation effects and lead to unanticipated hazards. This paper examined the extent to which limited time and increased mental load amplify the risk compensatory behavior of workers. Using an immersive mixed-reality environment to simulate an electrical construction task, this paper applied a promising neuroimaging approach (functional near-infrared spectroscopy-fNIRS) to study changes in individuals' cognitive responses and decision dynamics under normal and stressful conditions. The results showed that workers failed to process surrounding information due to limited cognitive resources, and misperceived potential risks under time pressure and increased mental demand. These cognitive failures then led to increased overreliance on safety protections and at-risk decisions, and decreased safety performance. This paper offers valuable insights into the potential neural mechanism driving risk-taking and risk compensatory behaviors and the importance of counteracting risk compensation bias in the construction industry.

1. Introduction

While the construction industry employs only 5.3% of the U.S workforce, this hazard-rich industry accounted for >19% of fatal occupational injuries in 2019 alone [1]. Within the electrical sector, 166 fatal electrical injuries and 1900 nonfatal injuries were reported in 2019, representing a 3.75% increase over recent years [2]. Problematically, workers' unsafe behaviors and errors have been identified as the main cause for >49% of incidents on job sites [3], a fact prompting the enforcement of many safety protections and regulations to increase job site safety and reduce human error. While these rules were imposed to protect workers, previous studies argued a lower-than-expected return for workers' safety due to the risk compensation effect, wherein added safety protections decrease workers' risk perception, leading to increased at-risk decision-making [4,5].

Compounding this problem is the reality that while safety is undoubtedly a priority within the industry, the highly competitive nature of the construction industry has driven conversations about increasing productivity [6]. Previous studies indicate that the productivity demand (e.g., being pressed to work faster) negatively impacts worker safety performance [7,8], causing workers to work out of sequence and cut

corners regarding safety to meet schedule and production demands [9]. Furthermore, construction tasks are cognitively demanding tasks that also require adequate attention to remain situationally aware of potential safety hazards [10]. The excessive mental workload negatively influences worker safety behaviors, likely triggering more risky behaviors [11,12].

While several studies have demonstrated that productivity demand (time pressure) and mental demand cause workers to deviate from safety best-practices and overlook hazards to complete their tasks faster [7–9], it is not clear how these external factors may impact workers' risk compensatory behaviors (i.e., suggesting that many safety interventions and technologies may not be as effective as intended because people willingly take risks due to the false sense of security they receive when safety interventions are in place). To fill this gap in knowledge, this study used a high-level risk-case scenario simulating an electrical activity with adequate safety protections in place to empirically examine the changes in subjects' decision dynamics— an interdependent decision-making process that takes place in dynamic environments and is illustrated by brain activations—under time pressure and increased mental demands. This research offers valuable insights into increased risk compensatory behaviors resulting from excessive productivity and

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mental demands on constriction job sites.

Since this study contains several abbreviations, a list of them is provided for the reader's sake: Virtual Reality (VR), Mixed Reality (MR), fNIRS (functional near-infrared spectroscopy), Prefrontal Cortex (PFC), and Dorsolateral Prefrontal Cortex (DLPFC), General Linear Model (GLM).

2. Background

2.1. Wilde's risk compensation theory and risk decision-making

Gerald J.S. Wilde's Theory of Risk Homeostasis suggests people are inclined to trade some of their safety and health to obtain potential gains by taking risks [4]. Based on this psychological theory of human behavior, individuals alter their risk-taking behavior proportional to the amount of risk they perceive and find acceptable (i.e., risk tolerance or target level of risk) [4,13]. These behavioral choices can change based on individuals' characteristics, previous experience, lifestyle, personality, etc. [4]. In particular, four factors influence individuals' target level of risk, including 1) the expected gains of the risky behaviors, 2) the expected losses of the risky behaviors, 3) the expected gains of the safe behaviors, and 4) the expected losses of the safe behaviors [4]. In the context of construction safety, these factors suggest that the benefits of adding safety interventions to reduce the risk of injury will decrease due to workers' increased risk-taking behaviors (i.e., engaging in activities or procedures that may lead to injuries), since the target level of risk may result in a recalibration between the losses and gains of risky and safe behaviors.

Few research studies have investigated risk compensatory behaviors in the construction safety domain. For example, Feng and his colleagues developed a self-reported questionnaire to identify factors contributing to worker behavior in terms of risk compensation through various scenarios [14,15]. These studies argued that more safety protections do not necessarily result in better safety performance. Furthermore, in an empirical study, Hasanzadeh et al. (2020) documented changes in risktaking behaviors and the risk perception of subjects while performing a roofing task in a simulated mixed-reality environment under differing levels of fall risk. They concluded that more protection lowers workers' risk perception and can lead to a false sense of security that motivates these workers to take more risks, such as leaning over edges. Their study also classified the types of safety interventions that affect the levels of risk compensation; for example, injury-preventing interventions—such as guardrails—trigger a greater sense of invulnerability than injuryreducing protections, such as fall arrest systems [16]. In addition, their study identified demographic and psychological factors that considerably impact workers' risk compensatory and risk-taking behaviors [5]. To this end, subjects with high-risk tolerance were distinguished as risk-prone (sensation seekers) who are more likely to engage in risk compensatory behaviors. These studies proved the significant adverse effects of safety interventions on workers' safety behaviors resulting from the cognitive bias of risk compensation. While the impacts of individual characteristics on the risk compensatory behavior of workers have been studied, the compounding effects of such external factors as time pressure/productivity demand and mental demand on workers' risk compensation remain unexplored.

2.2. Impact of time pressure and productivity demand on safety-related behaviors

Time pressure is defined as a lack of time to accomplish work activities and is considered a quantitative workload factor [17–19]. One is under time pressure when attempting to process more than the usual amount of information to make a proper decision in a limited amount of time. The decision-making process often includes several phases: signal detection, signal interpretation or integration, hypothesis generation or selection, and action selection [20]. Insufficient time negatively affects

each of these phases to some degree [20].

Related studies stated time pressure may lead to a perceptual narrowing that leads to less situational awareness and reduced utilization of potential information [21]. Moreover, since it is challenging for an individual to obtain all essential information in a limited time, s/he will try to employ various strategies such as increasing the information processing rate, choosing among the choice alternatives randomly, and focusing on parts of the data subjectively [22]. Therefore, time pressure weakens information processing by stimulating extensive considerations of gains before losses.

The effects of time pressure on safety behaviors have been widely discussed in different arenas, such as driving [23,24] and the construction industry [8,9,25]. In the driving arena, Dogan and his colleagues illustrated that time pressure directly affects the drivers' goal preferences and decision-making [23]. They observed that drivers overlooked safety principles and fuel-saving under time pressure and only focused on completing the journey earlier. In addition, several driving-related studies identified time pressure as a leading factor in such at-risk behaviors as dangerous overtaking, over-speeding, tailgating, and road rage [24,26–28].

In high-risk, complex, and dynamic construction environments, such external factors as time pressure and productivity demands can exacerbate the environments' already hazardous conditions [29]. Productivity demands include high and last-minute workloads required to be performed promptly to avoid production disruptions. This situation mainly occurs when progress is behind schedule, and it provides sudden changes in the workers' speed performance while performing their tasks [8]. Managers will attempt to compensate for the costs of delays by motivating workers to speed up their performance within a limited time. Hinze and Site proposed that the frequency of accidents is related to project progress; projects ahead of schedule reported few injuries; however, projects that were behind schedule had higher reported injuries [30]. Accordingly, productivity demand and time pressure are factors that can adversely impact job site safety and cause workers to focus on completing the task without considering appropriate safety resources, which increase the likelihood of risk compensatory behaviors and accidents [7,8,30,31]. Thus, it is crucial to empirically study the changes in workers' perception and decision-making process under time pressure and productivity demand.

2.3. Impact of mental demand on safety behaviors

Mental demand—also known as cognitive demand or mental load—relates to cognitive processes, including memory, attention, decision-making, and concentration [32]. Specifically, mental demand is a person's mental effort undertaken during a task and is highly linked to decision-making, perceived hazard, and attention [33]. Cognitively demanding tasks require individuals to continuously update and manipulate received sensory information from their surrounding environment. Studies argue that high cognitive demand increases the likelihood of human error in processing the received information and increases the individuals' unsafe behaviors, as explained by the Fuller model of Task Capability Interface [34,35]. This model specifies the reasons behind driving accidents and loss of control, focusing on the balance between the driver's capabilities and cognitive demand. As such, the Fuller model suggests high cognitive demand (i.e., receiving a lot of information simultaneously) can adversely affect individuals' performance.

Mentally demanding situations highly engage cognitive resources, especially working memory. Working memory is a key system of the cognitive process affecting reasoning, decision-making, and behavior. This system is regarded as short-term memory—or the short-term storage of received information enabling individuals to manipulate stored inputs to achieve their purpose [22]. Working memory resources are limited, which means allocating more resources to executing a task can limit resource availability for executing other tasks [12,22]. Under this

framework, if working memory is occupied by many items/tasks, the mental load will increase considerably, adversely affecting individuals' attentional distribution and risk perception in high-risk environments [10].

This negative effect of mental demand has been discussed in various areas, including driving [36,37], aviation [38,39], and construction [10,12]. For example, Richard et al. showed that performing an auditory task (i.e., talking on the phone) as the secondary task while driving (the primary task) decreases drivers' attention toward hazardous elements and causes them to perform unsafe behaviors, such as sudden breaks and speeding [37]. Furthermore, in an aviation-related study, Morris and Leung illustrated individuals' error rates increased when carrying out a primary manipulation task while receiving auditory input simultaneously [38].

The construction industry is a dynamic environment that requires allocating sufficient attentional and memory resources to search for and identify hazards and to remain situationally aware [10,40]. However, due to workers' limited working memory capacity (cognitive resources), performing simultaneous cognitively demanding tasks may result in mental overload situations, wherein workers miss potential risks and make unsafe choices during at-risk decision points [12,41]. Therefore, external factors (time pressure and mental demand) can effectively modulate risk perception and risk compensatory behaviors. Although the effects of such factors on human performance have been widely investigated in the driving research domain, few research studies are available in the construction sector. Given the realities of risk compensation, it is particularly interesting to examine the impacts of cognitive demand on worker safety performance and risk compensatory behaviors when all safety protections are in place.

2.3.1. Mental workload assessment methods

Recent advancements in neuroimaging technologies now enable researchers to quantitatively measure human cognitive load based upon brain signals. Traditionally, subjective approaches—such as work profile (WP), subjective workload assessment technique (SWAT), and NASA task load index (NASA-TLX)—were employed to evaluate mental workload by having individuals report their perceived experience of cognitive load. While successful to some extent, these subjective approaches have been increasingly replaced with such quantitative approaches as functional magnetic resonance imaging (fMRI), electroencephalograms (EEG), and functional near-infrared spectroscopy (fNIRS), which enable improved quantification of risk perception in real-time.

fMRI measures mental workload through changes in blood flow in the brain; when a part of the brain is activated, the blood flow increases in that part, which fMRI can detect through imaging the blood oxygen level-dependent contrast signals (BOLD). Though fMRI does not contain a high temporal resolution—as the blood flow changes occur over time—it has a high spatial resolution. Though such spatial resolution is beneficial in many domains, there are several constraints in using fMRI for data collection in construction-related studies since fMRI is not portable, and subjects cannot move freely and must instead remain enclosed inside a scanner environment.

Alternatively, EEG measures electrical changes in the brain by placing electrodes on the scalp using an EEG headcover [42]. This method contains a high temporal resolution but low spatial resolution, which causes difficulties in specifying the activated brain regions since signals interfere with each other. Therefore, EEG is mainly suitable when the task execution is simple and does not involve movements, as the EEG hardware is highly sensitive to motion artifacts, limiting its application in construction-related studies involving lots of movements [43].

fNIRS technology is viable for measuring complex brain activation processes in more realistic conditions. Worn as a cap, fNIRS is a safe, non-invasive and portable device that measures mental workload by emitting near-infrared light signals between 700 and 900 nm into the

scalp and then processing brain activation using transmitter and receiver optodes. When the light goes through the brain tissues from the transmitter optodes, some scatters and some are absorbed and reflected back to the receiver optodes [44]. Assessing the difference in optical absorption properties of brain tissues, fNIRS quantifies the relative concentration of oxygenated and deoxygenated hemoglobin (oxy-Hb and deoxy-Hb) in the tissue [45]. As increasing cognitive demand increases oxygen consumption by neurons, the hemoglobin concentration changes in the active brain areas [46], thereby revealing cognitive processes.

Unlike fMRI, fNIRS measurements can be taken while subjects execute different tasks in either standing or sitting positions [44], which makes this method feasible for construction studies. In this domain space, fNIRS is also better than EEG since it is less sensitive to motion artifacts while having better spatial resolution [47]. For example, in a construction-related study, fNIRS was used to explore design-cognitive processes and sustainable engineering decision-making among students [48-50]. Additionally, lately, several studies have illustrated the potential of fNIRS when combined with virtual reality tools to investigate human cognitive behaviors [51-53]. Since fNIRS is much more robust to motion artifacts than EEG and can more accurately detect active brain areas, this study employed a wireless fNIRS device to measure participants' mental workload while executing a task under different working conditions simulated in a mixed-reality environment. These data provided objective insights into subjects' risk perception and arousal level, as evidenced by brain activations.

There are two commonly used methods to analyze fNIRS data and extract the hemodynamic changes: the block averaging/classical method and the General Linear Model (GLM) approach. The classical method uses time series fNIRS data containing continuous tasks (blocks) and yields the mean concentration values [54]. Although most studies implement the classical block averaging method to calculate the hemodynamic responses, it has several limitations: Firstly, it overlooks information regarding the shape or time course of the fNIRS data. Secondly, this method uses a simple average function and does not model the effects of various sources of variance, such as cardiac activities and respiration. On the other hand, the GLM method provides more accurate brain activation responses [54] since GLM works based on a linear combination of different components to calculate the final Hemodynamic Response Function (HRF). In particular, GLM models all the sources of variance (e.g., cardiac activities, respiration, blood pressure) while simultaneously estimating the brain activation signals (e.g., oxy-Hb, deoxy-Hb, and total-Hb). The following linear equation represents the GLM structure:

$$Y = \beta X + \mathbf{\xi} \tag{1}$$

where $Y \in R^{T \times N}$ represents a matrix including obtained fNIRS data from time points T and capture channels N. $\beta \in R^{T \times M}$ is the design matrix, which integrates a base knowledge regarding the time duration of the experiment, regressors for physiological noises and drifts relative to the baseline, and an assumed shape of the induced hemodynamic response. $X \in R^{M \times N}$ contains the estimated weights that model confounding components and functional brain activity. The additional term $\xi \in R^{T \times N}$ is the error term. Eventually, the final HRF value for each channel is achieved by a combination of physiological (e.g., blood pressure), functional (e.g., oxy-Hb), and drift (i.e., changes in evoked signal shape considering the baseline) elements plus the additional term:

$$Y = y_{physiological} + y_{functional} + drift + \xi$$
 (2)

This study employed the GLM approach to analyze fNIRS data, which is explained in the Data analysis section in detail.

2.4. Point of departure

Previous studies have indicated that providing safety training or

applying additional safety technological advances may not increase job site safety as workers may fall prey to "risk compensation" cognitive bias, wherein increasing safety protections creates a false sense of security and lower perceived risk. Such risk compensation may indirectly stimulate workers to over-rely on protection and technological advances and increase their risk-taking behavior [5,16]. Given that the construction domain experiences a confluence of limited time, higher expected productivity, and cognitively demanding tasks-all of which embed a balancing between the benefits of faster work and the drawbacks of unsafe behaviors-previous literature argued that these external demands negatively affect workers' safety behaviors. However, the extent to which external factors such as time pressure and cognitive demand impact the risk compensation bias has not been clearly investigated yet. Without investigating this additional parameter of external stress on workers' risk compensation in construction, future investments in protective equipment and safety technologies may be misplaced.

Therefore, this study examines the impacts of time pressure and cognitive demand on participants' neural activity, risk perception, decision dynamics, and performance measures when insulating live electrical lines within a simulated, mixed-reality environment. The research team hypothesizes that increasing stress via time pressure and additional cognitive demand will cause subjects to manifest risk compensatory decision

dynamics (i.e., deciding to perform risky actions to compensate for the safety benefits of interventions and technological advances), evidenced via subjects' safety performance and cognitive performance under differing stressful or unstressful work conditions. Understanding how workers perform under increasingly stressful dynamic environments when there are protected with consistent safety interventions can provide a better understanding of how workers may navigate through everyday decision-making in various hazardous construction tasks. Furthermore, such understanding can guide future investments in protective equipment and/or training that will best protect workers under stressful conditions.

3. Research method

3.1. Scenario development

This study investigates the latent effects of safety interventions on workers' performance while working under time pressure and mental demand. To scope this study, the experiment considered electrical line workers. Working on live transmission and distribution (T&D) lines exposes line workers to hazards that may put their lives at risk, since line workers must be in close proximity to energized powerlines at high elevations, resulting in high exposures to both fall and electrical

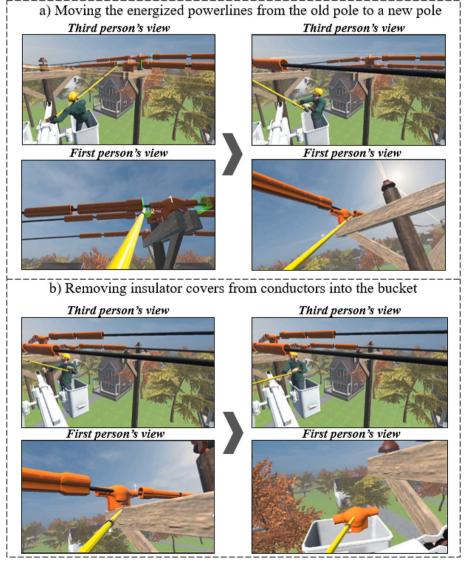


Fig. 1. Electrical tasks in the mixed-reality environment.

hazards—such as arc flashes, which are an electrical discharge that includes burns, blasts, and electrocution hazards. An arc flash produces extremely high temperatures, loud sounds/high dB levels, and intense pressure and radiation. While line workers are often equipped with required safety protections, statistics show that fatalities and injuries have increased by 4% in recent years [1]. Furthermore, while various safety training and interventions are urged to reduce the number of incidents in the electrical construction industry, this sector still experiences one of the highest fatality and injury rates.

To address this situation, this study used a high-level risk-case scenario for line workers in which subjects had to move three live powerlines from an old pole to a new pole without interrupting electricity in a suburban residential area, as represented in Fig. 1. This activity could conceivably face time pressure—e.g., during storm-recovery activities, where power lines may be live, but poles may need to be replaced—and cognitive pressure—e.g., when workers must communicate with other line workers and/or aerial lift operators while performing the replacement tasks. Accordingly, this experimental scenario represents a real-life task that faces critical hazards for line workers, namely the two subtasks: *a*) moving the energized powerlines from the old pole to a new pole, and *b*) removing insulator covers from conductors.

3.1.1. Electrical task experimental design: mixed reality (MR) environment While it is not practical—or even logical—to conduct this research study within an actual workplace and expose workers to high-voltage electricity lines, this study built a simulated scenario in a multi-modal immersive mixed-reality environment to capture the naturalistic behavior of subjects to investigate whether external factors (e.g., time pressure and mental load) can worsen the effect of risk compensation in the electrical construction industry. In particular, the simulated environment used electrical utility poles as these are the backbone of most electric distribution systems. For a variety of reasons, poles need to be replaced and powerlines need to be moved to a new pole. As live line maintenance is common, line workers must be in close proximity to energized powerlines at high elevations, resulting in high exposures to both fall and electrical hazards—such as arc flashes. Live line replacement has been listed as one of the hazardous tasks in electrical safety literature, and the research team worked closely with the National Electrical Contractor of America (NECA) Electri International as well as electrical contractors and electrical safety professionals to build an authentic simulation of the activities involved in pole replacements. These experts provided iterative feedback about the simulated environment to confirm its validity.

To capture the realistic responses of participants to this scenario, the simulation required two orthogonal components: Place Illusion (PI) and Plausibility Illusion (Psi). PI means that the participant must feel they are in the setting—namely, here, the bucket at the top of the electrical pole—so, as they turn their heads, they should see other poles, buildings, the street, and other features of the suburban setting depicted in the simulation. Such details reinforce the feeling of PI. In turn, Psi means that the depicted scenario seems to be occurring, so realistic sensations such as arc flash simulations, sound, and wind effects needed to be added to the mixed-reality model to reinforce the subject's feeling of Psi.

Therefore, to increase the simulated electrical task's validity as well as the participants' sense of the presence, this study used a Mixed Reality (MR) environment that included both passive haptics and a virtual environment. Within their virtual reality headset, participants viewed themselves as performing the task in an actual bucket while wearing all the required personal protective equipment and using a real hot stick. In addition, participants could hear all the sounds of a real environment, such as the sound of cars, birds, etc. as the developed MR environment contained the environmental modalities (i.e., sounds and wind). If the participants approached too close to the simulated energized lines, they experienced an arc flash (accident) and they could see and hear both visual and audio representations of that event. The physical and virtual components were synchronized to develop a close-to-real environment.

The study used HTC VIVE Pro Eye (110° field of view) with millisecond synchronization to immerse participants in the simulated environment. Here, Fig. 2 details both the virtual and physical components:

Virtual Model. The virtual reality (VR) model of this study consisted of four subcomponents:

- 1- Model environment: The research team used Maya (Maya 2020.4) to generate a 3D model environment representing a suburban area in the United States. This 3D model contains a street in which both old and new poles are located.
- 2- VR trackers: Five VR trackers were used to collect individuals' postural positions and to adjust the VR scene and avatar accordingly. These five trackers were attached to the subject's body—wrists (two), arms (two), and waist (one)—and were synchronized with the virtual avatar's body in real-time. Consequently, when wearing the HTC VIVE Pro Eye VR headset, the subject was immersed in the body of the virtual avatar and experienced all synchronized body movements accordingly.
- 3- The case scenario: A simulated virtual arc flash contained both visual and audio representations to effectively simulate a real-world arc flash and to convey the sense of danger and risk.
- 4- Additional environmental modalities: Wind and sound effects were added to the MR model to increase subjects' sense of presence.

To advance the usability of this system, the research team created a Graphical User Interface (GUI) to start and end the experiment and to select the experimental conditions, as needed.

Physical Model. Including realistic haptic feedback in computer-generated environments—such as VR—is essential to improving subjects' sense of involvement [55]. Haptic interfaces have two types, including active and passive. Active haptics are created using computers, while passive haptics convey a sense of reality by simulating objects' physical properties, namely shape, weight, etc. Previous studies showed that using a passive haptic and an active device enhances users' interactions with the virtual environments and improves their spatial perception of a given task [56]. In this study, passive haptics were employed to enhance users' interactions with the simulated environment by reproducing physical features of the virtual model to simulate the touch and force channels. Thereby, the physical model increased users' involvement to help them choose appropriate responses.

Four passive haptics—including insulating gloves, a bucket, a hot stick, and a fall arrest system—were used in the laboratory setting. To improve user interaction with the virtual environment, all passive haptics were the actual ones that line workers utilize in a real job site. The passive haptic systems were well synchronized with the virtual model, enhancing participants' sense of presence during their simulated work with the hot stick. The research team administered a 5-point Likert scale questionnaire at the end of the experiment to measure participants' sense of presence (5 = high, 1 = low); most of the participants reported a high presence score (Mean = 4, SD = 0.5), which demonstrates that the developed mixed-reality environment provided a suitable and valid platform for triggering naturalistic behaviors under the different experimental conditions. Thus, this environment enabled the study to evaluate the risk perception and risk-taking behavior of line workers in a risk-free setting.

While the environment and experimental task were designed to limit the possibility of motion sickness, in the experimental protocol, the research team included contingencies in the event participants experienced motion sickness during the experiment; however, no participant cited discomfort during the experiment, and during the post-trial semi-structured interviews, no participants reported dizziness, motion sickness, or feeling any discomfort. Consequently, the motion-sickness contingencies were not considered in this study's analysis. Furthermore, before immersing the participants in the developed MR environment for the experiment, each participant went through a 30-min training program to learn about the task, practice completing the task in

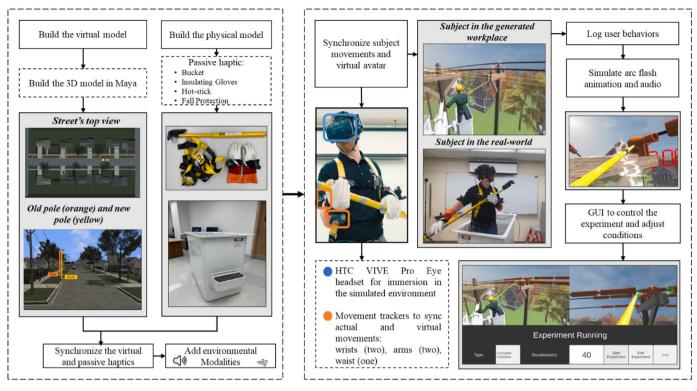


Fig. 2. Mixed-reality environment development process.

the immersive environment, and become familiar with the task and the different scenarios. By incorporating these introductions into the pre-experiment work protocol, the research team ensured that participants' control tests did not include additional, unintended stress. Thus, the fNIRS data were neither affected by motion sickness nor raw performance stressors.

3.2. Data collection

3.2.1. Experimental conditions

A within-subject experiment was designed to examine subjects' risktaking behaviors under three different conditions when completing the electrical tasks with required safety protections (e.g., insulating gloves, hot stick, fall arrest system). The three conditions included (I) completing an electrical task (primary task) under a normal condition, (II) completing the primary task under time pressure, (III) completing the primary task under time pressure and a secondary task (cognitive demand). Here, the implemented cognitive demand task entailed a 2back verbal working memory task, wherein individuals hear a sequence of random numbers and are supposed to say "Yes" when they hear the same number sequence as two trials ago. Under condition III, participants were required to complete the secondary 2-back task while performing the primary task of moving energized lines. The research team provided additional compensation incentives for subjects if they could finish Conditions II and III on time while giving accurate answers for the 2-back memory task in Condition III. The research team determined not to perform a cognitive demand task without time pressure as participants would have been able to take too much time to perform the primary task, a factor that would have confounded the implications of mental demand within a realistic work environment. Table 1 represents a general overview of the experimental conditions and participants' demographic information, which are explained later in detail within the following subsections.

3.2.2. fNIRS neuroimaging experimental design

As explained in the background section, this study assessed workers'

Table 1Overview of experimental conditions.

	-			
Conditions	Duration (second)	Time Constraint	Secondary Task	Number of Participants
Baseline	120	-	-	33 (22 M, 11 F)
Condition I	T = Based on Participants' pace to complete the task	-	-	33 (22 M, 11 F)
Condition II	T Condition $I - 10s$	1	-	33 (22 M, 11 F)
Condition III	T Condition $I - 10s$	1	2-back task	33 (22 M, 11 F)

risk decision-making and neural activities using fNIRS. According to previous literature, the most common experimental designs in examining evoked cognitive responses using fNIRS are block design, eventrelated design, and mixed design [44,54]. Block design contains tasks in a controlled condition with a fixed duration for each task, referred to as a block. A block time varies between 10 and 20 s (a short block) or 60 to 120 s (a long block). Occasionally, the blocks are separated by an interval of around 60 to 120 s, as a rest condition is required to bring the participants' hemodynamic responses back to their normal, baseline, state. Alternatively, an event-related design incorporates tasks with different durations and is randomly ordered. This experimental design is mainly used to monitor neural activation or hemodynamic responses associated with particular tasks or events—for example, in a risk-taking study developed by Holper et al. (2014), participants were asked to perform the task at their own speed and to make decisions at any time; their cognitive activations regarding decision-making events were analyzed to study subjects' risk attitudes and task performance [57]. The experimental design that contains both a block and event setup is called mixed design.

The present study incorporated an event-related experimental design in which neural activities were recorded to assess how subjects responded to situations and made decisions while executing the designated task. The task was designed under three conditions to observe subjects' cognitive responses (Fig. 3). In order to remove the order effect, Conditions *II* and *III* were counterbalanced. A rest time took place between each condition to confirm hemodynamic responses returned to a baseline point for each condition.

3.2.3. Participants

Thirty-three healthy subjects, including 22 males and 11 females, participated in this study. The subjects were recruited from civil engineering, construction engineering and management, and construction management technology programs. On average, participants had 1.5 years of experience working in the construction industry. Recruiting student participants enabled this study to be conducted more rigorously in regulated experimental setups without experiential bias that can impact subjects' risk-taking and risk-compensatory behaviors. All procedures were approved by Purdue University's Institutional Review Board (IRB). The whole experiment was carried out in a single 120-min session. Subjects received gift cards as compensation for participating.

3.2.4. General procedures

All participants were informed about the whole experiment, and they were asked to sign the consent form. They also filled out demographic questionnaires. Thereafter, participants were provided with train-

assess their sense of presence in the MR environment.

3.2.5. Performance measures

To determine the effect of time pressure and mental load on subjects' risk compensatory behaviors, this study first assessed individuals' overall performance based upon three criteria: performing the designed task without experiencing arc flash, completing the task within the defined time (time pressure condition), and accurately performing the 2back working memory task (cognitive demand condition). Specifically, the developed third person's view within the VR model enabled the research team to observe whether participants have completed the task within the defined time and/or whether they have experienced arc flash in course of performing the task. Further, the research team observed the accuracy of each participant's responses in the 2-back task within Condition III and took notes. Based on such observations, a quantitative combination of costs (loss) and benefits (gain) is implemented to measure participants' performance in each condition. The error rate per participant in Conditions was calculated based on Eqs. (3), (4) and (5). The collective error rate was computed by dividing the error rate of each condition over the total number of participants (Eq. (6))

$$Error per participant_{Condition II} = Number of arc flashes + \begin{cases} 0, if completed tasks under imposed time constraint \\ 1, if tasks NOT completed under imposed time constraint \end{cases}$$
(4)

$$Error \ per \ participant_{Condition \ III} = Number \ of \ arc \ flashes + \begin{cases} 0, if \ completed \ tasks \ under \ imposed \ time \ constraint \\ 1, if \ tasks \ NOT \ completed \ under \ imposed \ time \ constraint \\ + \begin{cases} 0, if \ completed \ secondary \ tasks \ with \ a \ 100\% \ accuracy \end{cases}$$

$$+ \begin{cases} 0, if \ completed \ secondary \ tasks \ with \ a \ 100\% \ accuracy \end{cases}$$

$$(5)$$

ing—including PowerPoint presentations about electrical risks and required precautionary behaviors—as well as videos from the VR environment and verbal explanations regarding the main task and the three designed conditions. This training ensured subjects were familiar with the electrical task and the experimental process. Furthermore, a required explanation regarding how to conduct the 2-back memory task was given.

After training, the subjects were equipped with the fNIRS cap while seated on a chair in a comfortable position. After calibration, participants were asked to stand in the bucket and were equipped with the fall arrest system, VR headset, location trackers, insulating gloves, and hot stick to execute the line-replacement task. Subjects received a 120-s break between each experimental condition to ensure participants' hemodynamic responses were back to their normal state. At the end of the experiment, a semi-structured interview was carried out to investigate subjects' risk perception within each experimental condition and to

Collective error rate per condition =
$$\frac{\sum_{i}^{II} Error_{i}}{n}$$
 (6)

where i represents the conditions (I, II, III) and n represents the total number of participants.

3.2.6. Apparatus

This study used a wireless fNIRS (Brite, Fig. 4) to measure changes in oxygenated and deoxygenated hemoglobin (oxy-Hb and deoxy-Hb) throughout five brain regions. The fNIRS cap included ten transmitter optodes to transmit near-infrared light from 730 nm to 850 nm wavelength—with a sampling frequency of 10 Hz—and eight receiver optodes to receive the light along the trajectory of 20 channels. The transmitters and receivers were designed to be located a maximum of

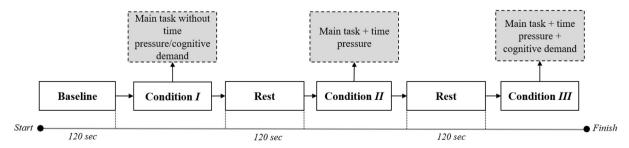
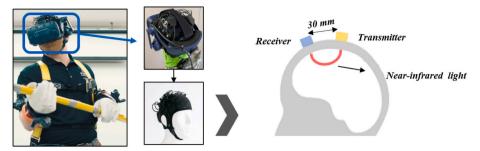


Fig. 3. Event-related experimental design and description of each event (condition). To remove the order effect, Condition II and Condition III were swapped for some participants.



Brite wearable non-intrusive fNIRS

Fig. 4. fNIRS Neuroimaging setup.

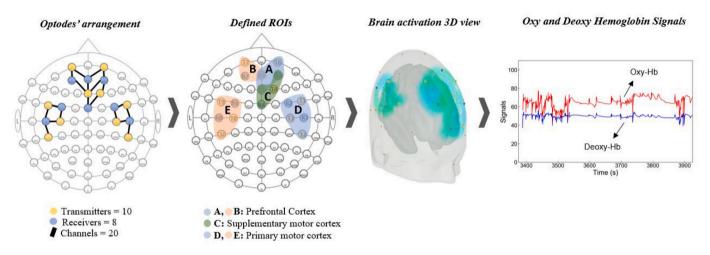


Fig. 5. Graphical representation of optodes arrangement, defined RIOs, and brain activation signals.

Table 2
Brodmann areas, associated anatomic location, and ROI labels.

Brodmann Areas	Anatomic Location	ROI
8, 9, 10	Prefrontal Cortex (Right)	Α
8, 9, 10	Prefrontal Cortex (Left)	В
6	Supplementary Motor Cortex	C
4, 40, 41, 44	Premotor Cortex (Right)	D
4, 40, 41, 44	Premotor Cortex (Left)	E

three centimeters apart (Fig. 4).

Fig. 5 demonstrates the arrangement of the optodes' locations along with the five defined regions of interest (ROIs): *A* and *B* are the Prefrontal Cortex (PFC), particularly the Dorsolateral Prefrontal Cortex (DLPFC), which is considered the cognition region and is mainly involved in cognitive behavior (e.g., decision-making). *D*, *E*, and *C* are the premotor cortex and supplementary motor cortex, respectively, which are mostly involved in initiating and executing movements. Further, Table 2 shows the Brodmann areas, associated anatomic location, and the correlated defined ROIs in this study.

3.3. Data analysis

This study used the Homer package (Homer3), a MATLAB-based toolbox, which provides several embedded functions to remove motion artifacts, eliminate physiological noise, and analyze the captured hemodynamic data [58]. It must be mentioned that three subjects' data were excluded in this study due to issues with the calibration process.

While fNIRS signals are resistant to motion artifacts when compared to other brain activation sensors (e.g., EEG), applying necessary filtering during pre-processing to remove motion artifacts and physiological

noise before analysis is vital. Since participants were located in the bucket, their movements were restricted to a limited area, thereby nullifying concerns regarding motion artifacts. Accordingly, merely the physiological noise (e.g., vasomotor blood pressure, respiration, and cardiac activities) were considered and addressed by applying a bandpass filter. For further analysis, the modified Beer-Lambert Law (ppf = 6, 6, 6) was used to convert the recorded optical density data into a relative concentration in terms of oxy-Hb and deoxy-Hb.

As mentioned in the background section, this study employed GLM to analyze fNIRS signals considering its advantages over the block averaging method. In order to employ GLM, different value parameters need to be adjusted based on the experimental settings. Descriptions of these parameters and the used values for this study are provided as:

- "trange" (i.e., the duration of the stimuli): Defined considering the duration of Conditions *I*, *II*, *III*,
- "glmSolveMethod" (i.e., specifies the preferred statistical approach):
 Set to 1, which specifies the GLM method to use the ordinary least squares.
- "idxBasis" (i.e., determines the type of basic function to use for the HRF): Defined as 1 here, which is a consecutive sequence of Gaussian functions.
- "paramsBasis" (i.e., parameters for the basic functiondepend on idxBasis): Set to 1.0, 1.0; values represent the width of the Gaussian and the step between consecutive Gaussians.
- "rhoSD_ssThresh" and "flagNuisanceRMethod" (i.e., related to short separation channels and should be specified based on the setup of short separation channels): Defined as 0 since this study did not use short separation channels because the activity does not include many motions.

 "driftOrder" (i.e., order of polynomial for drift correction): Set to 3, which uses 3rd order polynomial drift correction.

Once all values were adjusted, the HRF was calculated for all participants across channels, and the averaged HRF of involved channels was used for the ROIs. The Shapiro-Wilk's normality test and homogeneity of variances were conducted to select proper statistical analysis for this study. Since the HRF results were not normally distributed (p < 0.05 resulted from Shapiro-Wilk's test), the appropriate statistical methods were used to compare brain neural activations across the normal condition (i.e., Condition I) with stressful conditions (i.e., Conditions II and III).

4. Results and findings

4.1. Overall performance

In Fig. 6, error rates were calculated based on Eqs. (3), (4), (5) and (6); and performance was calculated as "100% - error rate%". On average, subjects' performance under time pressure (Condition II) demonstrated a 13% decrease compared to the normal condition. Similarly, under Condition III, subjects experienced errors more than half the time, an outcome demonstrating significantly poorer safety performance and indicating significantly higher risk behaviors. As the provided protective equipment did not change across the experimental conditions, this degraded safety performance signals increased risky behaviors under the second and third conditions, indicative of increased risk compensation—via overreliance on PPE—among subjects. These changes in visible safety performance served as the ground-truth data for the subsequent cognitive performance analysis.

4.2. Changes in cognitive responses and decision dynamics

As explained in the methodology section, this study employed GLM to derive the HRF from the recorded fNIRS data. The research team was able to control motion artifacts to a reasonable extent by fixing the fNIRS cap on the subjects' heads properly. Further, subjects' movements were minimal as the subjects needed to follow defined movements mostly involving twisting around their waists. Accordingly, motion noise—warned about in the literature—could be kept to a minimum, and the research team was able to monitor the fNRIS software readout to confirm in real-time. In this regard, physiological noises were recognized as the main noises in the recorded fNIRS data. GLM considered potential physiological noise as one of the regressors when calculating HRF [54]. Thus, a low bandpass filter with a corner frequency of 0.5 was used to remove physiological noises (Fig. 7).

Regional brain activation is accompanied by increased cerebral oxygen rate and blood flow, changes in oxy-Hb and total-Hb concentrations, and decreasing deoxy-Hb concentrations throughout the activated

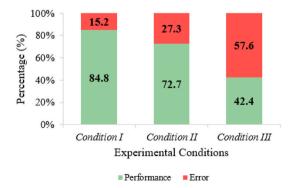


Fig. 6. Overall performance and error rates of participants under different experimental conditions.

ROIs [59]. Accordingly, the following analyses considered changes in oxy-Hb concentration as primary indicators of cerebral activation [60], because these data experience a lower vulnerability to cross-talk as compared to deoxy-Hb [61].

The GLM revealed the HRF results across all channels under the three different experimental conditions. Importantly, these results took into consideration specific weights for each computational component (i.e., physiological, functional, and drift order); the weights were determined via a linear combination of N normalized Gaussian functions. Finally, the average values of the HRF results for each channel were calculated and later specified based upon the ROIs (Figs. 8 & 9) for further analyses.

In order to explore the impacts of gender types, changes in brain activation among defined ROIs (A, B, C, D, E) for males and females are depicted in Fig. 8. Although there were slight differences in oxy-Hb concertation between males and females, no significant differences were observed. However, increasing trends in oxy-Hb concertation from the normal condition (I) to the stressful conditions (II, III) can be seen in all ROIs for both gender types. One reason for this result might be the experimental design: the time pressure and mental load manipulations were strong enough to dominate the impacts of gender types. Thus, participants' risk compensatory behaviors and associated brain activations are primarily influenced by imposed time pressure and cognitive demand. This is in line with previous neuroimaging studies (e.g., [62]), and increasing the sample size is highly recommended to further investigate the gender impact. In the following, the whole sample (both female and male participants) was used for further analysis.

To interpret the results, Condition *I* was considered the baseline for Conditions *II* and *III*. Bean plots in Fig. 9 demonstrate the variations of cortical brain activation across brain regions *A*, *B*, *C*, *D*, and *E* for experimental Conditions *I*, *II*, and *III*. Generally, an increasing rate in oxy-Hb concertation manifested between the normal Condition (*I*) and the stressful conditions (*II*, *III*) for ROIs *A*, *B*, *D*, and *E*; the increasing rates varied based on the regions' functionality and the experimental conditions. As shown, the average oxy-Hb concentration was higher in stressful conditions within the PFC and motor cortex. Generally, the increasing rate of oxy-Hb concentration from conditions *I* to *II* could be seen in the mean values throughout all regions except for region *C*. The reason for this inconsistency in Region C is further discussed in the Discussion Section and documented in Table 3.

Statistical analyses (t-test and Wilcoxon Signed Rank test) were conducted to examine differences in brain activation between the baseline Condition I and the two stressful conditions (II and III) across the five different brain regions. As Table 3 shows, the analysis found no statistically significant differences in oxy-Hb between the normal condition (I) and the time pressure stressful condition (II) across ROIs (p $value_A = 0.151$, p- $value_B = 0.274$, p- $value_C = 0.458$, p- $value_E = 0.124 > 0.124$ 0.05). The partially significant changes in oxy-Hb were identified in Region D (p-value_D = 0.058 < 0.1). As shown in Table 4, there were statistically significant differences in oxy-Hb concentrations across ROIs between the normal condition (I) and Condition III, when subjects experienced both time pressure and cognitive demand: (p-value_A = 0.012, p-value_B = 0.035, p-value_D = 0.016, p-value_E = 0.00 < 0.05). However, no significant results were observed for the brain activation within ROI C when comparing Conditions I and III (p-value_C = 0.578 > 0.05). It must be noted that mean brain activation values for all ROIs were higher in *III* than *I* in all ROIs.

Given the different functions of the brain's right and left hemispheres, the research team conducted further analyses to examine the changes in oxy-Hb concentrations in the right and left hemispheres in the prefrontal and motor cortex. Fig. 10a depicts the distributions of the average cognitive responses in the PFC within regions A (right hemisphere) and B (left hemisphere) across the three experimental conditions. As shown, region A (right hemisphere) demonstrated higher hemodynamic responses than the left hemisphere under all conditions (Fig. 10a). Further, the brain activations in the motor cortex, including the right and left hemispheres, are depicted in Fig. 10b. Similarly, the

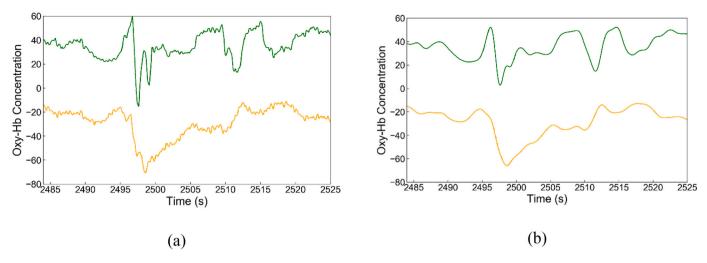


Fig. 7. Graphical representation of the concentration signals of two channels (each color is related to a channel) in brain ROI E. (a) Processed signal with no filter, (b) Processed signal using a bandpass filter.

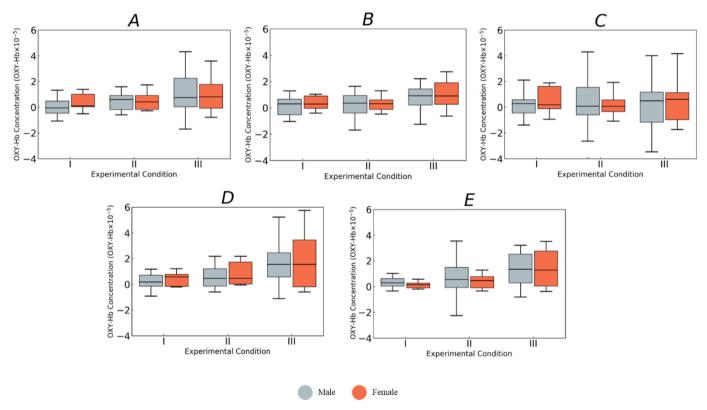


Fig. 8. Differences in Oxy-Hb concentrations between two gender types and across different ROIs (A, B, C, D, E).

right hemisphere of the motor cortex (ROI *D*) showed higher activation than the left hemisphere (ROI *E*). In the discussion section, these differences are connected to behavioral theories and previous literature to better understand workers' behavior and safety performance changes.

5. Discussion

This study used fNIRS data to investigate whether time pressure and cognitive demands affect workers' risky decision-making when they are exposed to electrical risk while using required safety protections. In general, under a risky condition, workers' decision dynamics will be highly influenced by their risk perception [63]. Workers' analytical and logical assessment of received hazard information and their resulting

risk perception engage cognitive brain resources. Taking advantage of fNIRS, a promising neuroimaging approach, the research team could assess individuals' brain activations associated with risk perception, risk-taking behaviors, and decision-making dynamics in real-time. Specifically, the cortical hemodynamic activations of various ROIs (A, B, C, D, and E), corresponding to the prefrontal and motor cortices, were studied while subjects completed risky electrical tasks under three experimental conditions (normal condition I and III). Brain activation serves as a reliable physiological assessment of workload, representing continuous variations in working memory load and cognitive demand over the task execution [64]. While several studies within the driving-safety domain have used fNIRS to observe decision-making and brain activation during risky situations [45,65,66],

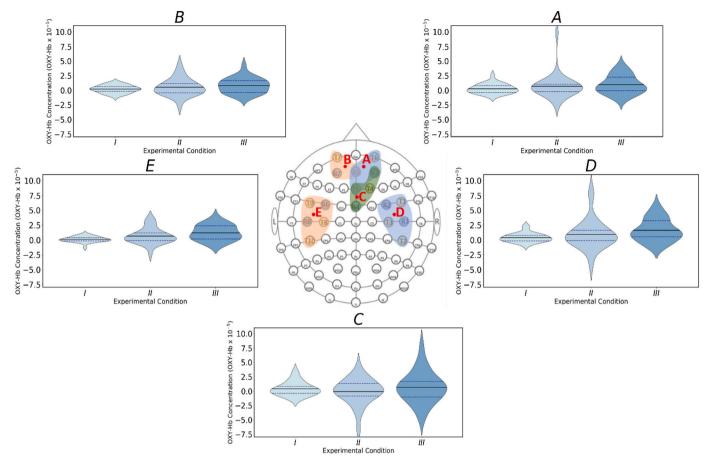


Fig. 9. Oxy-Hb concentrations across different ROIs A, B, C, D, E for the three experimental conditions (A and B: prefrontal cortex, C: supplementary motor cortex, D and E: premotor cortex).

Table 3 Statistical results comparing the normal, fully protected, Condition I and the stressful, time pressure, Condition II across ROIs.

ROI	Conditions	Mean	STD	Test Statistics	p-value
A	I	2.889	8.043	-1.435 ^b	0.151
	II	7.423	20.962		
B	I	2.325	6.109	-1.117^{a}	0.274
	II	5.893	14.761		
C	I	4.184	12.048	0.753^{a}	0.458
	II	1.483	18.085		
D	I	4.346	7.139	-1.898^{b}	0.058*
	II	10.556	23.990		
\boldsymbol{E}	I	1.139	4.637	-1.538^{b}	0.124
	II	5.951	12.881		

^{**} p-value < 0.05.

there is a paucity of corresponding research in construction settings [44,53].

5.1. Impacts of stressful and demanding conditions on prefrontal cortex activation

Under experimental Condition *II*, subjects were required to complete the task under time pressure while all required protections were in place. One of the areas of the brain that was monitored while the subjects were completing the task was the prefrontal cortex (PFC). The findings of this study showed that brain activation was increased in the

Table 4Statistical results comparing the normal, fully protected, Condition *I* and the stressful, time pressure and cognitive demand, Condition *III* across all ROIs.

ROI	Conditions	Mean	STD	Test Statistics	p-value
Α	I	2.889	8.043	-2.710^{a}	0.012**
	III	10.772	16.392		
\boldsymbol{B}	I	2.325	6.109	-2.220^{a}	0.035**
	III	9.106	13.198		
C	I	4.184	12.048	-0.564^{a}	0.578
	III	7.151	26.728		
D	I	4.346	7.139	-2.403^{b}	0.016**
	III	14.913	18.392		
\boldsymbol{E}	I	1.139	4.637	-3.976^{a}	0.000**
	III	11.193	13.495		

^{*} *p*-value < 0.1.

PFC area under time pressure (Condition II) as compared to the normal state (Condition I), suggesting that subjects' decision-making dynamics and cognitive processes were negatively affected by time pressure and the corresponding stress. The PFC is considered the primary part of the brain that supplies bias signals to other brain areas to activate neural pathways and map the inputs and outputs required to carry out a given task [67]. Therefore, changes in PFC activation are related to one's thinking, information processing, and decision-making while performing a task. Important for our context is the fact that working under time pressure increases the task difficulty since one needs to sustain attention and process received information from the environment in a relatively

^a t value from t-test.

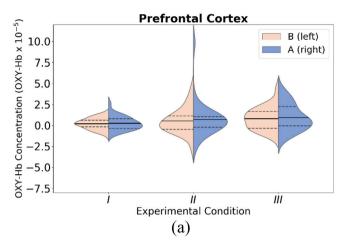
 $^{^{\}mathrm{b}}$ Z value from Wilcoxon Signed Rank test.

^{*} p-value < 0.1

^a t value from t-test.

b Z value from Wilcoxon Signed Rank test.

^{**} p-value < 0.05.



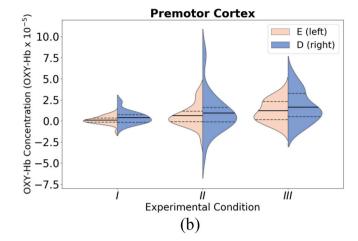


Fig. 10. Oxygenated hemoglobin (oxy-Hb) concentrations of the right and left hemispheres within prefrontal and motor cortices under the three different experimental conditions

shorter amount of time than under a normal condition (Condition *I*). Previous research demonstrated that task difficulty positively correlates with the PFC activation [68,69], so the more difficult a task is, the more the PFC will be activated. This fact makes PFC activation a significant proxy for attempts undertaken in decision-making [68]. Consequently, the findings indicated in Fig. 9 and Tables 3 and 4—namely, that experimental Condition *II* caused a higher activation in the PFC than the normal condition (Condition *I*)—reveal time pressure increased the difficulty imposed on the participants to complete the task under this condition. This conveys that as they found the situation difficult while experiencing a false sense of security (due to having required protections), they focused on increasing their gains (i.e., completing the task on time and obtaining additional compensation) in a limited time and overlooking the risk inherent in the task.

In Condition *III*, participants performed the same task under both time pressure and a designed 2-back test, which highly engaged working memory. Working memory is mainly regarded as short-term memory, relies most closely on the PFC, and is involved in the maintenance, integration, and manipulation of received information [12]. An increase in working memory load causes increased cognitive activation across the PFC, specifically in the DLPFC (dorsolateral prefrontal cortex) [68]. The results of this study illustrated a significant increase in oxy-Hb concentration over the DLPFC under Condition *III* compared to the normal condition (Condition *I*). This high increase in the brain activation within the PFC demonstrated the extent to which working memory was engaged in processing the received information. Considering limited

working memory capacity, our application of a 2-back test during the subjects' risky primary electrical task imposed a high demand on working memory, leading to failed processing of all hazard information associated with the surrounding environment, overlooked associated details, and/or overreliance on safety interventions. Our findings are well-aligned with various studies that have investigated drivers' cognitive behavior and induced changes in working memory load by conducting n-back tests during simulated driving activities [36,70].

Additionally, the results show predominant lateralization to the right side of the DLPFC due to multiple demands placed on subjects' working memory and their required attention under stressful conditions (Conditions II and III). Such results indicate weighting of risks and gains toward decision making in these conditions involves a complex neural network in the DLPFC area. Increased DLPFC activation during dynamic risky decision-making is linked to both cognitive and affective components, and within such demanding conditions as conditions II and III, while equipped with safety protections, participants highly focused on gains (i.e., extra compensation) rather than focusing on losses (i.e., experiencing arc flash). These observations are in accord with a risktaking study, in which participants with a higher focus on gains, demonstrated higher activation within the DLPFC [57]. Furthermore, with respect to the differences in both activation and the functionality of the left and right parts of the PFC, the results of this study are wellaligned with previous studies that have indicated working memory load can induce a higher activation within the right DLPFC [36,70].

Fig. 11 depicts heat maps of brain activations of a participant across

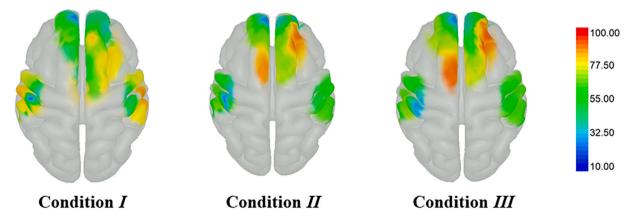


Fig. 11. Heat maps representing the brain activation of a participant across three experimental conditions (*I, II, III*). The range represents the brain activations, which can change from low activation (blue) to high activation (red). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

the three experimental conditions. As shown, the induced brain activation is evident across different ROIs from Condition *I* to Condition *III*, as task difficulty and cognitive demand increase. The PFC illustrates a higher cognitive response (red), which overlaps here with more stressful—and, per the discussion above, riskier—Conditions *II* and *III*, reaching the highest in Condition *III*. These findings demonstrate the dominant function of the PFC in the risk decision-making process. In addition, greater activation is visible in the right part of the brain versus the left across different conditions, indicating a more significant cognitive response in the right PFC (particularly in the DLPFC) for working memory demanding situations.

5.2. Impacts of stressful and demanding conditions on motor cortex activation

This study also measured the activation of the motor cortex-represented in ROIs C, D, and E-while subjects completed the electrical tasks. ROI \mathcal{C} is mainly the supplementary motor cortex, which is correlated with the decision-making process for starting a movement and plays an important role in the initiation of movements; ROIs D and Eare mostly considered the primary motor cortex used to execute movements. The findings demonstrate an increasing rate in the oxy-Hb concentration in both regions D and E from Condition I to Condition III. Previous literature stated that work intensity directly modulates brain hemodynamic changes, as higher work intensity results in more pronounced brain activations [71-73]. Since this research simulated the designed task in a mixed-reality environment, participants carried out the same work, using a real hot stick with the same weight and length analogous to an actual one used in a real workplace. To this end, during stressful conditions, they made more efforts to move the hot stick quickly. Accordingly, the derived results showed an increased activation rate associated with the motor cortex regions (D and E) that perfectly supported the positive correlation between work intensity and brain activation.

Holper and his colleagues indicated that motor cortex activation is highly correlated with task complexity [74]. They observed higher hemodynamic responses over the same regions related to the motor cortex for a complex finger tapping task compared to a simple task. The results of this present study revealed the same fact: as the experimental condition got more complicated from Condition I (normal condition) to Condition II (stressful and complex condition), the hemodynamic responses increased within ROIs D and E. Therefore, both work intensity and complexity increase workers' mental arousal associated with the motor cortex. This high level of arousal can increase their mental fatigue and impair their situational awareness, factors directly related to increased risky behaviors.

ROI C, besides initiating movements, plays a broader role in cognitive behavior, making it an important factor in our study to determine how task conditions affect risk compensation. ROI C is involved in different cognitive functions such as planning movement sequences, inhibiting and controlling complex movements, and learning new movements [75-77]. This ROI plays an important role in linking cognition to action as it modulates the coordination between the PFC and the motor cortex [75,76]. In this study, subjects always experienced the normal condition as the first experimental condition, so when they were performing the same task under Condition II, ROI C started to work automatically in a routine fashion based on learned-movement skills in the previous condition. As such, the brain activity in ROI C decreased as participants mastered the required tasks. This observation is in accord with previous literature stating that learning and practicing a task will lower brain activations within the supplementary motor cortex (i.e., ROI C in this study) [78,79]. Thus, previous experience with the electrical task in Condition I played an influential role in the sense of complacency with the task, especially under stressful and demanding conditions.

Furthermore, this study coincided with several studies indicating the involvement of the supplementary motor cortex (i.e., ROI C) in

attention-demanding situations, where high-level cognitive processes are required to coordinate cognitive behaviors (e.g., decision-making) and movement executions (e.g., acting) [80-82]. In this study, the subjects were familiar with the task but needed constant attention to avoid electrical accidents (i.e., arc flash) while simultaneously providing accurate responses to the 2-back task in Condition III, which increasingly activated the brain within ROI C. This result indicates complex activities can impose high mental demands on humans. This observation is in accordance with Wilson et al., whose research investigated the activation of the supplementary motor cortex using fNIRS when participants were performing in-phase (i.e., symmetrical) and anti-phase (i.e., asymmetrical) movement patterns [83]. They found that the supplementary motor cortex was more activated during anti-phase movement patterns, which needed more attention. Due to limited attentional resources, we anticipate that high cognitive demands can significantly increase at-risk behaviors by causing workers to overlook potential electrical hazards. It is worth mentioning that despite a wide range of research, the supplementary motor cortex is still one of the controversial brain areas in the neuroscience domain, and it needs further research.

5.3. Impacts of stressful and demanding conditions on risk perception and risk compensatory behaviors

Notably, when the research team asked participants about the risks they perceived in each condition, they reported Conditions II and III as high-risk because subjects reported feeling stressed. However, as reported by them, their evaluated risk and stress were merely because of the likelihood of losing additional compensation, not due to the potential possibilities of fatal consequences resulting from risky actions. Results show that such high mental demand increased the subjects' error rate (Fig. 6), conceivably because cognitive resources (e.g., working memory) are capacity limited; allocating more cognitive recourse to a task will reduce the resource availability for other tasks. Consequently, individuals could not process and analyze the received information properly, and they failed to perceive potential risks (i.e., lower risk perception), which significantly increased their risk compensatory behaviors. Consequently, over-relying on safety interventions, not paying attention to the potential hazards and risks, and focusing on benefits (gains) caused workers to ignore electrical threats, leading to a decrease in their safety performance and well-being. Translated into a real-world context, the increase in mental workload in the face of a risky construction task can lead to performance breakdown, with potentially fatal consequences.

Therefore, the observed changes in the intensity of prefrontal activation (oxy-Hb concentration) correlated with changes in subjects' perceived risk as well as with their overall safety performance, all of which indicate time pressure and increased mental load affect workers' decision dynamics and risk compensatory behaviors. In particular, while the simulated energized lines were completely insulated to reduce the likelihood of electrical incidents, arc flashes still occurred due to subjects' lower perceived electrical risk, overreliance on the protections in place, and violating clearance distance, all of which combine to show increased risk-taking behavior and the risk compensation effect. As an external factor, time pressure caused subjects to overlook the electrical risk (loss) since protections were in place and to merely focus on gains (extra compensation). As such, they decided to speed up to complete the task on time by over-relying on the safety protections. Interestingly, participants' performance decreased further when they were required to complete the designated task under both time pressure and cognitive demand. As Fig. 6 shows, there was a 42% decline in individuals' overall performance under the time pressure and cognitive demand condition (III) compared to Condition I. In addition, the error rate increased due to reduced accuracy in the cognitive demand task, inability to complete the task under time pressure, and lower safety performance (experiencing more arc flashes). As such, when both time pressure and cognitive demand were in place, participants completely ignored the electrical risk

inherent in the task. Importantly, the protections in place within the scenario only reduced the likelihood of incidents, so precautionary behaviors were needed to complete the task safely. Therefore, with lower perceived electrical risk and the increased work intensity and mental demand, the subjects focused on completing the task on time while performing the secondary task accurately, which significantly increased their risk-taking behaviors and error rates. Accordingly, the negative impact of risk compensation worsened when the participants were under stressful conditions; they over-relied on the insulating devices while working on live lines.

Furthermore, participants' cognitive resources (i.e., working memory) were engaged in stressful conditions to analyze the situation, perceive the associated risks, manipulate the information, and decide accordingly. As discussed, working memory is capacity limited, and high–cognitive demand situations can result in information processing failures. In such situations, individuals need to process a high amount of information simultaneously which can eventually lead to misperception and impaired task performance [84]. The results in Condition *III* confirm this point as participants were asked to complete the main task while concentrating on the secondary task. They were under high cognitive demands, which highly engaged working memory, and they were unable to analyze the risk associated with the condition correctly; thereby, their overall performance decreased.

In summary, the research team hypothesizes that increasing stress via time pressure and additional cognitive demand will cause subjects to manifest risk compensatory decision dynamics, evidenced via subjects' worsening safety and cognitive performance under the stressful work conditions. We tested this hypothesis by placing subjects within an immersive mixed-reality environment that simulated a real, high-risk electrical task and observed their different behaviors and neurophysiological responses within a neutral, controlled (unstressful), condition and then under different stress loads (time pressure, and time-andincreased mental load pressure). By maintaining the safety interventions across all three conditions, we were able to see how subjects' risk-taking changed when faced with different stress loads-any observed degradation in safety performance (manifested here by increased counts of simulated arc flashes within the mixed-reality environment) would identify risk compensation bias because despite risks continuing at the same level, worsening safety behaviors would illustrate a recalibration in the subjects' cost-benefit analysis. Furthermore, by monitoring safety performance alongside fNIRS data, this experimental design allowed the study to test whether outward safety behaviors map to neurophysiological data to determine whether risk compensation coincides with worsening cognitive performance under stressful conditions. Any significant alignments between safety performance and fNIRS data would suggest opportunities for harnessing fNIRS data to passively monitor workers' worsening safety performance in real time.

5.4. Contributions and limitations

Many researchers have attempted to explain stressed decision-making processes using various theoretical and methodological approaches. In a high-risk work environment, making a decision necessitates incorporating and integrating all information regarding the decision's potential positive and negative outcomes. But under time pressure and higher mental demand, workers may not be able to integrate all information sensibly, a reality that may lead to changes in their risk-taking behaviors or strategies. Compensatory decision-making is one such common strategy shift, wherein individuals under time pressure and/or mental load become more gain-seeking and more likely to overlook, underestimate, or misperceive the risk(s) inherent in a task. In other words, if the risk profile and safety behaviors of a task have not changed but the perceived benefits associated with changing procedures/disregarding safety precautions have changed due to time pressure and/or mental load, compensatory decision-making will likely manifest.

This study found that time pressure and high mental load affect workers' safety behaviors significantly more when they are provided with safety protections, a result that suggests stressed workers recalibrate their cost-benefit risk analysis to a greater degree when provided with additional safety interventions. The present study's findings provide an innovative approach to investigating how time pressure and mental load affect workers' decision dynamics by examining these changes in subjects' risk perception, risk-taking behavior, and performance measures. By understanding the negative effects of risk compensation in construction industry during time-pressured or mentally taxing task loads, this project is able to reveal how humans navigate through everydaydecision-making under time pressure, productivity demands, and mental load in a variety of contexts. Such work lays the foundation for improving the current T&D safety training and for designing an evidence-based intervention to effectively mitigate the negative impact of risk compensation.

The proposed study contributes to the existing body of knowledge by providing empirical evidence that the effectiveness of safety interventions can be negated due to stressful working conditions (i.e., working under time pressure and mental demand). Beyond providing evidence for why investments in safety do not always deliver expected returns, the results here illustrate that demanding conditions can exacerbate the negative effects of the risk compensation bias and induce workers to finish their tasks faster while taking additional risks—which they feel empowered to do given their protective equipment. Even in the immediate term, such results reveal opportunities for obtaining safety improvements through workplace-culture changes, especially those related to stress—i.e., time pressure and mental demand. While business stressors will continue to sow stress in construction environments, the results here suggest immediate amendments to workloads and time constraints may deliver immediate returns to safety.

Additionally, the empirical evidence here lays the foundation for future research targeting novel technological interventions in conjunction with other safety practices to effectively mitigate the negative effects of risk compensation within the construction domain. In particular, this research's findings highlight opportunities to harness neurophysiological data in the construction-safety setting to potentially assess problematic mental effort involved in worker operations; accordingly, such evidence demonstrates neurophysiological sensors may provide a promising tool for measuring neural efficiency in many contexts, including various safety assessments and training scenarios. In-situ monitoring of workers' mental effort raises a valuable potential resource for providing feedback to the workers themselves or to the automated systems/robots that they are interacting with in future job sites, rendering impact in the near and long term.

This research still faces several limitations that future studies can tackle. First, in this study, the subjects were students with related experiences. Second, risk compensation was studied at the individual level. Third, while the research team collected several neuropsychophysiological responses for this study, only fNIRS neuroimaging was discussed here to capture the physiological data associated with individuals' brain activation under risky situations.

6. Conclusions

Given the risk compensation effect hypothesized to diminish the safety gains of personal protective equipment and safety interventions in the construction domain, this paper described the latent effects of safety interventions on subjects' decision dynamics by applying fNIRS technology to measure cognitive brain responses while subjects performed a simulated powerline replacement task within a mixed-reality environment. To demonstrate how productivity demand (i.e., being pushed to work faster) and cognitive demand (i.e., performing a parallel secondary task) can adversely influence safety performance and worsen the negative effects of risk compensation, subjects conducted the simulated powerline replacement task under a normal condition, a time-pressure

condition, and a cognitive demand—with–time pressure condition.

The considerable increasing rate visible in the brain's cognitive responses between Condition I (i.e., normal condition) to Conditions II and III (i.e., stressful conditions) across all defined ROIs reveals that the effectiveness of safety interventions decreases within stressful conditions due to the increased risk-taking behaviors of workers, who experienced more simulated electrical accidents under stressful conditions. Greater activation was found in the right part of the brain across different conditions—as was especially visible in the more significant cognitive response in the right PFC (particularly in the DLPFC) for the stressful and taxed working memory situations. Notably, under stressful conditions, when participants perceived the situation as safe (due to the protections in place), they changed their decision strategies, a result that suggests risk compensation recalibrated the cost-benefit analysis. As a result, the subjects' brain activations illustrated lower perceived electrical risk while they focused on gains (i.e., completing the defined task in less time and performing additional cognitive tasks to receive additional compensation). Thus, a better understanding of how neural activity changes with time pressure, productivity, and cognitive demand in risky construction tasks offers valuable insights into understanding the potential neural mechanisms driving risk-taking and risk compensatory behaviors.

There are many possible avenues for future research developments based on the present study: Firstly, the experiment can be repeated using electrical workers with various work experiences to determine whether experience impacts performance. Secondly, future researchers might assess the impacts of peer effect on workers' decision-making under risk. Thirdly, future studies should investigate the impacts of changes in time pressure–intensity and the complexity level of the working memory task or the main task (i.e., the line replacement task implemented in this research) on workers' risk compensatory behavior and decision dynamics.

Declaration of Competing Interest

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

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References

- Injuries, Illnesses, and Fatalities. https://www.bls.gov/iif/, 2021 (accessed June 29, 2021).
- [2] ESFI, Workplace Fatalities and Injuries 2003–2019. https://www.esfi.org/resource/workplace-fatalities-and-injuries-2003-2019-791, 2021.
- [3] R.A. Haslam, S.A. Hide, A.G.F. Gibb, D.E. Gyi, T. Pavitt, S. Atkinson, A.R. Duff, Contributing factors in construction accidents, Appl. Ergon. 36 (2005) 401–415, https://doi.org/10.1016/J.APERGO.2004.12.002.
- [4] G.J.S. Wilde, The theory of risk homeostasis: implications for safety and health, Risk Anal. 2 (1982) 209–225, https://doi.org/10.1111/j.1539-6924.1982. tb01384.x.
- [5] S. Hasanzadeh, J.M. de la Garza, Productivity-safety model: debunking the myth of the productivity-safety divide through a Mixed-Reality residential roofing task, J. Constr. Eng. Manag. 146 (2020) 04020124, https://doi.org/10.1061/(ASCE) CO.1943-7862.0001916.
- [6] H.-S. Park, S.R. Thomas, R.L. Tucker, Benchmarking of construction productivity,
 J. Constr. Eng. Manag. 131 (2005) 772–778, https://doi.org/10.1061/(ASCE)
 0733-9364(2005)131:7(772).

- [7] J.D. Nahrgang, F.P. Morgeson, D.A. Hofmann, Safety at work: a meta-analytic investigation of the link between job demands, job resources, burnout, engagement, and safety outcomes, J. Appl. Psychol. 96 (2011) 71–94, https://doi. org/10.1037/a0021484.
- [8] P. Mitropoulos, T.S. Abdelhamid, G.A. Howell, Systems model of construction accident causation, J. Constr. Eng. Manag. 131 (2005) 816–825, https://doi.org/ 10.1061/(ASCE)0733-9364(2005)131:7(816).
- [9] M.P. Nepal, M. Park, B. Son, Effects of schedule pressure on construction performance, J. Constr. Eng. Manag. 132 (2006) 182–188, https://doi.org/ 10.1061/(ASCE)0733-9364(2006)132:2(182).
- [10] S. Hasanzadeh, B. Dao, B. Esmaeili, M.D. Dodd, Measuring the impact of working memory load on the safety performance of construction workers, in: ASCE International Workshop on Computing in Civil Engineering, American Society of Civil Engineers, 2017, pp. 158–166, https://doi.org/10.1061/ 0709784480947 2020
- [11] S. Hasanzadeh, B. Esmaeili, M.D. Dodd, Measuring the impacts of safety knowledge on construction workers' attentional allocation and hazard detection using remote eye-tracking technology, J. Manag. Eng. 33 (2017) 04017024, https://doi.org/ 10.1061/(ASCE)ME.1943-5479.0000526.
- [12] G. Liko, B. Esmaeili, S. Hasanzadeh, M.D. Dodd, R. Brock, Working-memory load as a factor determining the safety performance of construction workers, in: Construction Research Congress 2020: Safety, Workforce, and Education, 2020, pp. 499–508, https://doi.org/10.1061/9780784482872.054.
- [13] S. Peltzman, The effects of automobile safety regulation, J. Polit. Econ. 83 (2015) 677–725, https://doi.org/10.1086/260352.
- [14] Y. Feng, P. Wu, G. Ye, D. Zhao, Risk-compensation behaviors on construction sites: demographic and psychological determinants, J. Manag. Eng. 33 (2017) 04017008, https://doi.org/10.1061/(ASCE)ME.1943-5479.0000520.
- [15] Y. Feng, P. Wu, Risk compensation behaviours in construction workers' activities, Int. J. Inj. Control Saf. Promot. 22 (2013) 40–47, https://doi.org/10.1080/ 17457300.2013.844714.
- [16] S. Hasanzadeh, J.M. de la Garza, E.S. Geller, How sensation-seeking propensity determines individuals' risk-taking behaviors: implication of risk compensation in a simulated roofing task, J. Manag. Eng. 36 (2020) 04020047, https://doi.org/ 10.1061/(ASCE)ME.1943-5479.0000813.
- [17] A.J. Kinicki, R.P. Vecchio, Influences on the quality of supervisor–subordinate relations: the role of time-pressure, organizational commitment, and locus of control, J. Organ. Behav. 15 (1994) 75–82, https://doi.org/10.1002/ JOB.4030150108.
- [18] P.E. Spector, S.M. Jex, Development of four self-report measures of job stressors and strain: interpersonal conflict at work scale, organizational constraints scale, quantitative workload inventory, and physical symptoms inventory, J. Occup. Health Psychol. 3 (1998) 356–367, https://doi.org/10.1037/1076-8998.3.4.356.
- [19] S. Sonnentag, U.V. Bayer, Switching off mentally: predictors and consequences of psychological detachment from work during off-job time, J. Occup. Health Psychol. 10 (2005) 393–414, https://doi.org/10.1037/1076-8998.10.4.393.
- [20] C.D. Wickens, Multiple resources and mental workload, Hum. Factors 50 (2008) 449–455, https://doi.org/10.1518/001872008X288394.
- [21] J. Orasanu, Training for aviation decision making: the naturalistic decision making perspective, in: Proceedings of the Human Factors and Ergonomics Society 39th Annual Meeting, 1995, pp. 1258–1262, https://doi.org/10.1177/ 154193129503902004.
- [22] J.G. Miller, Information input overload and psychopathology, Am. J. Psychiatry 116 (1960) 695–704, https://doi.org/10.1176/ajp.116.8.695.
- [23] E. Dogan, L. Steg, P. Delhomme, The influence of multiple goals on driving behavior: the case of safety, time saving, and fuel saving, Accid. Anal. Prev. 43 (2011) 1635–1643, https://doi.org/10.1016/J.AAP.2011.03.002.
- [24] S. Cœugnet, H. Miller, F. Anceaux, J. Naveteur, How do time pressured drivers estimate speed and time? Accid. Anal. Prev. 55 (2013) 211–218, https://doi.org/ 10.1016/J.AAP.2013.02.040
- [25] S. Han, F. Saba, S. Lee, Y. Mohamed, F. Peña-Mora, Toward an understanding of the impact of production pressure on safety performance in construction operations, Accid. Anal. Prev. 68 (2014) 106–116, https://doi.org/10.1016/J. AAP 2013 10 007
- [26] D. Parker, J.T. Reason, A.S.R. Manstead, S.G. Stradling, Driving errors, driving violations and accident involvement, Ergonomics 38 (1995) 1036–1048, https:// doi.org/10.1080/00140139508925170.
- [27] E. Rendon-Velez, P.M. van Leeuwen, R. Happee, I. Horváth, W.F. van der Vegte, J. C.F. de Winter, The effects of time pressure on driver performance and physiological activity: a driving simulator study, Transport. Res. F: Traffic Psychol. Behav. 41 (2016) 150–169, https://doi.org/10.1016/J.TRF.2016.06.013.
- [28] S. Cœugnet, J. Naveteur, P. Antoine, F. Anceaux, Time pressure and driving: work, emotions and risks, Transport. Res. F: Traffic Psychol. Behav. 20 (2013) 39–51, https://doi.org/10.1016/J.TRF.2013.05.002.
- [29] L.M. Goldenhar, L.J. Williams, N.G. Swanson, Modelling relationships between job stressors and injury and near-miss outcomes for construction labourers, Work Stress. 17 (2003) 218–240, https://doi.org/10.1080/02678370310001616144.
- [30] J. Hinze, The distractions theory of accident causation, in: L.M. Alvez Diaz, R. J. Coble (Eds.), Proceedings of International Conference on Implementation of Safety and Health on Construction Sites, CIB Working Commission International, Rotterdam, 1996, pp. 357–384.
- [31] T. Rundmo, H. Hestad, P. Ulleberg, Organisational factors, safety attitudes and workload among offshore oil personnel, Saf. Sci. 29 (1998) 75–87, https://doi.org/ 10.1016/S0925-7535(98)00008-3.
- [32] J.K. Sluiter, High-demand jobs: age-related diversity in work ability? Appl. Ergon. 37 (2006) 429–440, https://doi.org/10.1016/J.APERGO.2006.04.007.

- [33] H. Rao, M. Korczykowski, J. Pluta, A. Hoang, J.A. Detre, Neural correlates of voluntary and involuntary risk taking in the human brain: an fMRI study of the Balloon Analog Risk Task (BART), NeuroImage. 42 (2008) 902–910, https://doi. org/10.1016/j.neuroimage.2008.05.046.
- [34] R. Fuller, The task-capability interface model of the driving process, Recherche -Transports - Sécurité 66 (2000) 47–57, https://doi.org/10.1016/S0761-8980(00) 90006-2.
- [35] P. Mitropoulos, G. Cupido, Safety as an emergent property: investigation into the work practices of high-reliability framing crews, J. Constr. Eng. Manag. 135 (2009) 407–415, https://doi.org/10.1061/(ASCE)CO.1943-7862.0000002.
- [36] A. Unni, K. Ihme, M. Jipp, J.W. Rieger, Assessing the driver's current level of working memory load with high density functional near-infrared spectroscopy: a realistic driving simulator study, Front. Hum. Neurosci. 11 (2017) 167, https://doi. org/10.3389/FNHUM.2017.00167/BIBTEX.
- [37] C.M. Richard, R.D. Wright, C. Ee, S.L. Prime, Y. Shimizu, J. Vavrik, Effect of a concurrent auditory task on visual search performance in a driving-related imageflicker task, Hum. Factors 44 (2002) 108–119, https://doi.org/10.1518/ 0018720024494874.
- [38] C.H. Morris, Y.K. Leung, Pilot mental workload: how well do pilots really perform? Ergonomics. 49 (2006) 1581–1596, https://doi.org/10.1080/ 00140130600857987.
- [39] P.C. Schutte, A.C. Trujillo, Flight crew task management in non-normal situations, in: Proceedings of the Human Factors and Ergonomics Society 40th Annual Meeting, 1996, pp. 244–248, https://doi.org/10.1177/154193129604000422.
- [40] S. Pooladvand, H. Taghaddos, A. Eslami, A.N. Tak, U. Hermann, Evaluating mobile crane lift operations using an interactive virtual reality system, J. Constr. Eng. Manag. 147 (2021) 04021154, https://doi.org/10.1061/(ASCE)CO.1943-7862 0002177
- [41] M.R. Endsley, Toward a theory of situation awareness in dynamic systems, Hum. Factors 37 (1995) 32–64, https://doi.org/10.1518/001872095779049543.
- [42] Y. Liu, M. Habibnezhad, S. Shayesteh, H. Jebelli, S. Lee, Paving the way for future EEG studies in construction: dependent component analysis for automatic ocular artifact removal from brainwave signals, J. Constr. Eng. Manag. 147 (2021) 04021087, https://doi.org/10.1061/(ASCE).
- [43] M.W. Eysenck, M.T. Keane, Cognitive Psychology: A Student' Handbook, Psychology Press, 2015 (ISBN: 9781315778006).
- [44] M. Hu, T. Shealy, Application of functional near-infrared spectroscopy to measure engineering decision-making and design cognition: literature review and synthesis of methods, J. Comput. Civ. Eng. 33 (2019) 04019034, https://doi.org/10.1061/ (ASCE)CP.1943-5487.0000848.
- [45] H. Tsunashima, K. Yanagisawa, Measurement of brain function of car driver using functional near-infrared spectroscopy (fNIRS), Comput. Intellig. Neurosci. 2009 (2009), 164958, https://doi.org/10.1155/2009/164958.
- [46] R.B. Buxton, E.C. Wong, L.R. Frank, Dynamics of blood flow and oxygenation changes during brain activation: the balloon model, Magn. Reson. Med. 39 (1998) 855–864. https://doi.org/10.1002/MRM.1910390602.
- [47] Y. Zhu, C. Rodriguez-Paras, J. Rhee, R.K. Mehta, Methodological approaches and recommendations for functional near-infrared spectroscopy applications in HF/E research, Hum. Factors 62 (2020) 613–642, https://doi.org/10.1177/ 0018720819845275
- [48] J. Du, Q. Zhu, Y. Shi, Q. Wang, Y. Lin, D. Zhao, Cognition digital twins for personalized information systems of smart cities: proof of concept, J. Manag. Eng. 36 (2019) 04019052, https://doi.org/10.1061/(ASCE)ME.1943-5479.0000740.
- [49] M. Hu, T. Shealy, M. Hallowell, D. Hardison, Advancing construction hazard recognition through neuroscience: measuring cognitive response to hazards using Functional Near Infrared Spectroscopy, in: Construction Research Congress 2018: Safety and Disaster Management, American Society of Civil Engineers, 2018, pp. 134–143, https://doi.org/10.1061/9780784481288.014.
- [50] M. Hu, T. Shealy, J. Grohs, R. Panneton, Empirical evidence that concept mapping reduces neurocognitive effort during concept generation for sustainability, J. Clean. Prod. 238 (2019), 117815, https://doi.org/10.1016/J. JCIEPRO.2019.117815.
- [51] E. Aksoy, K. Izzetoglu, E. Baysoy, A. Agrali, D. Kitapcioglu, B. Onaral, Performance monitoring via Functional Near Infrared Spectroscopy for virtual reality based basic life support training, Front. Neurosci. 13 (2019) 1336, https://doi.org/ 10.3389/fnins.2019.01336.
- [52] J. Ansado, C. Chasen, S. Bouchard, G. Northoff, How brain imaging provides predictive biomarkers for therapeutic success in the context of virtual reality cognitive training, Neurosci. Biobehav. Rev. 120 (2021) 583–594, https://doi.org/ 10.1016/J.NEUBIOREV.2020.05.018.
- [53] Y. Shi, Y. Zhu, R.K. Mehta, J. Du, A neurophysiological approach to assess training outcome under stress: a virtual reality experiment of industrial shutdown maintenance using Functional Near-Infrared Spectroscopy (fNIRS), Adv. Eng. Inform. 46 (2020), 101153, https://doi.org/10.1016/J.AEI.2020.101153.
- [54] M.A. Yücel, A.V. Lühmann, F. Scholkmann, J. Gervain, I. Dan, H. Ayaz, D. Boas, R. J. Cooper, J. Culver, C.E. Elwell, A. Eggebrecht, M.A. Franceschini, C. Grova, F. Homae, F. Lesage, H. Obrig, I. Tachtsidis, S. Tak, Y. Tong, A. Torricelli, H. Wabnitz, M. Wolf, Best practices for fNIRS publications, Neurophotonics. 8 (2021), 012101, https://doi.org/10.1117/1.NPH.8.1.012101.
- [55] N.A.A. Martin, V. Mittelstädt, M. Prieur, R. Stark, T. Bär, Passive haptic feedback for manual assembly simulation, Proc. CIRP 7 (2013) 509–514, https://doi.org/ 10.1016/J.PROCIR.2013.06.024.
- [56] M.A. Gutiérrez A., F. Vexo, D. Thalmann, Stepping into Virtual Reality, Springer, London, 2008 (ISBN: 9781848001169).

- [57] L. Holper, R.H.W. Ten Brincke, M. Wolf, R.O. Murphy, fNIRS derived hemodynamic signals and electrodermal responses in a sequential risk-taking task, Brain Res. 1557 (2014) 141–154, https://doi.org/10.1016/j.brainres.2014.02.013.
- [58] T.J. Huppert, S.G. Diamond, M.A. Franceschini, D.A. Boas, HomER: a review of time-series analysis methods for near-infrared spectroscopy of the brain, Appl. Opt. 48 (2009) 280–298, https://doi.org/10.1364/AO.48.00D280.
- [59] R. Sitaram, H. Zhang, C. Guan, M. Thulasidas, Y. Hoshi, A. Ishikawa, K. Shimizu, N. Birbaumer, Temporal classification of multichannel near-infrared spectroscopy signals of motor imagery for developing a brain-computer interface, NeuroImage. 34 (2007) 1416–1427, https://doi.org/10.1016/J.NEUROIMAGE.2006.11.005.
- [60] K.K. Kwong, J.W. Belliveau, D.A. Chesler, I.E. Goldberg, R.M. Weisskoff, B. P. Poncelet, D.N. Kennedy, B.E. Hoppel, M.S. Cohen, R. Turner, H.M. Cheng, T. J. Brady, B.R. Rosen, Dynamic magnetic resonance imaging of human brain activity during primary sensory stimulation, Proc. Natl. Acad. Sci. U. S. A. 89 (1992) 5675–5679, https://doi.org/10.1073/PNAS.89.12.5675.
- [61] G. Strangman, M.A. Franceschini, D.A. Boas, Factors affecting the accuracy of near-infrared spectroscopy concentration calculations for focal changes in oxygenation parameters, NeuroImage 18 (2003) 865–879, https://doi.org/10.1016/S1053-8119(03)00021-1.
- [62] S. Fecteau, A. Pascual-Leone, D.H. Zald, P. Liguori, H. Théoret, P.S. Boggio, F. Fregni, Activation of prefrontal cortex by transcranial direct current stimulation reduces appetite for risk during ambiguous decision making, J. Neurosci. 27 (2007) 6212–6218, https://doi.org/10.1523/JNEUROSCI.0314-07.2007.
- [63] A. Perlman, R. Sacks, R. Barak, Hazard recognition and risk perception in construction, Saf. Sci. 64 (2014) 22–31, https://doi.org/10.1016/J. SSCI 2013 11 019
- [64] M.A. Just, P.A. Carpenter, A. Miyake, Neuroindices of cognitive workload: neuroimaging, pupillometric and event-related potential studies of brain work, Theor. Issues Ergon. Sci. 4 (2003) 56–88, https://doi.org/10.1080/ 14630220210159735
- [65] H.J. Foy, P. Runham, P. Chapman, Prefrontal cortex activation and young driver behaviour: a fNIRS study, PLoS One 11 (2016) 0156512, https://doi.org/10.1371/ JOURNAL PONE 0156512.
- [66] A.S. Le, H. Aoki, F. Murase, K. Ishida, A novel method for classifying driver mental workload under naturalistic conditions with information from near-infrared spectroscopy, Front. Hum. Neurosci. 12 (2018) 431, https://doi.org/10.3389/ FNHUM.2018.00431/BIBTEX.
- [67] E.K. Miller, J.D. Cohen, An integrative theory of prefrontal cortex function, Annu. Rev. Neurosci. 24 (2001) 167–202, https://doi.org/10.1146/ANNUREV. NEURO.24.1.167.
- [68] S.H. Fairclough, C. Burns, U. Kreplin, FNIRS activity in the prefrontal cortex and motivational intensity: impact of working memory load, financial reward, and correlation-based signal improvement, Neurophotonics 5 (2018), 035001, https:// doi.org/10.1117/1.NPH.5.3.035001.
- [69] K. Kotegawa, A. Yasumura, W. Teramoto, Activity in the prefrontal cortex during motor imagery of precision gait: an fNIRS study, Exp. Brain Res. 238 (2020) 221–228, https://doi.org/10.1007/S00221-019-05706-9.
- [70] A. Unni, K. Ihme, H. Surm, L. Weber, A. Ludtke, D. Nicklas, M. Jipp, J.W. Rieger, Brain activity measured with fNIRS for the prediction of cognitive workload, in: 6th IEEE International Conference on Cognitive Infocommunications (CogInfoCom), Institute of Electrical and Electronics Engineers Inc., 2015, pp. 349–354, https://doi.org/10.1109/COGINFOCOM.2015.7390617.
- [71] S.G. Horovitz, J.C. Gore, Studies of the sensitivity of Near Infrared Spectroscopy to detect changes in levels of brain activation due to manipulations of motor tasks, in: Proceedings of the 25th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (IEEE Cat. No.03CH37439), 2003, pp. 1106–1108, https://doi.org/10.1109/IEMBS.2003.1279441.
- [72] N. Kuboyama, T. Nabetani, K.I. Shibuya, K. Machida, T. Ogaki, The effect of maximal finger tapping on cerebral activation, J. Physiol. Anthropol. Appl. Hum. Sci. 23 (2004) 105–110, https://doi.org/10.2114/JPA.23.105.
- [73] P. Rasmussen, E.A. Dawson, L. Nybo, J.J. Van Lieshout, N.H. Secher, A. Gjedde, Capillary-oxygenation-level-dependent near-infrared spectrometry in frontal lobe of humans, J. Gereb. Blood Flow Metab. 27 (2007) 1082–1093, https://doi.org/ 10.1038/sj.jcbfm.9600416.
- [74] L. Holper, M. Biallas, M. Wolf, Task complexity relates to activation of cortical motor areas during uni- and bimanual performance: a functional NIRS study, NeuroImage. 46 (2009) 1105–1113, https://doi.org/10.1016/J. NEUROIMAGE.2009.03.027.
- [75] P. Nachev, C. Kennard, M. Husain, Functional role of the supplementary and presupplementary motor areas, Nat. Rev. Neurosci. 9 (2008) 856–869, https://doi. org/10.1038/nrn2478.
- [76] G. Rizzolatti, G. Luppino, The cortical motor system, Neuron. 31 (2001) 889–901, https://doi.org/10.1016/S0896-6273(01)00423-8.
- [77] A. Rahimpour, L. Pollonini, D. Comstock, R. Balasubramaniam, H. Bortfeld, Tracking differential activation of primary and supplementary motor cortex across timing tasks: an fNIRS validation study, J. Neurosci. Methods 341 (2020), 108790, https://doi.org/10.1016/J.JNEUMETH.2020.108790.
- [78] O. Hikosaka, K. Sakai, X. Lu, H. Nakahara, M.K. Rand, K. Nakamura, S. Miyachi, K. Doya, Parallel neural networks for learning sequential procedures, Trends Neurosci. 22 (1999) 464–471, https://doi.org/10.1016/S0166-2236(99)01439-3.
- [79] K. Nakamura, K. Sakai, O. Hikosaka, Neuronal activity in medial frontal cortex during learning of sequential procedures, J. Neurophysiol. 80 (1998) 2671–2687, https://doi.org/10.1152/jn.1998.80.5.2671.
- [80] P.G. Zanone, A. Monno, J.J. Temprado, M. Laurent, Shared dynamics of attentional cost and pattern stability, Hum. Mov. Sci. 20 (2001) 765–789, https://doi.org/ 10.1016/S0167-9457(01)00055-0.

- [81] J.J. Temprado, P.G. Zanone, A. Monno, M. Laurent, Attentional load associated with performing and stabilizing preferred bimanual patterns, J. Exp. Psychol. Hum. Percept. Perform. 25 (1999) 1579–1594, https://doi.org/10.1037/0096-1523 25 6 1579
- [82] A. Monno, A. Chardenon, J.J. Temprado, P.G. Zanone, M. Laurent, Effects of attention on phase transitions between bimanual coordination patterns: a behavioral and cost analysis in humans, Neurosci. Lett. 283 (2000) 93–96, https://doi.org/10.1016/S0304-3940(00)00924-1.
- [83] T.W. Wilson, M.J. Kurz, D.J. Arpin, Functional specialization within the supplementary motor area: a fNIRS study of bimanual coordination, NeuroImage. 85 (2014) 445-450 https://doi.org/10.1016/J.NFJROIMAGE.2013.04.112
- 85 (2014) 445–450, https://doi.org/10.1016/J.NEUROIMAGE.2013.04.112.
 [84] S. Pooladvand, B. Kiper, A. Mane, S. Hasanzadeh, Effect of time pressure and cognitive demand on line workers' risk-taking behaviors: assessment of neuropsychophysiological responses in a Mixed-Reality environment, in: Construction Research Congress 2022, American Society of Civil Engineers, Reston, VA, 2022, pp. 759–769, https://doi.org/10.1061/9780784483985.077.