Eltahan, A., Lee, G., & Hamzeh, F. (2025). Feasibility of Eye-trackers for Monitoring Cognitive Load in Lean Construction 4.0. In O. Seppänen, L. Koskela, & K. Murata (Eds.), *Proceedings of the 33rd Annual Conference of the International Group for Lean Construction* (IGLC33) (pp. 892-904). https://doi.org/10.24928/2025/0141

FEASIBILITY OF EYE-TRACKERS FOR MONITORING COGNITIVE LOAD IN LEAN CONSTRUCTION 4.0

Amira Eltahan[1], Gaang Lee[2], and Farook Hamzeh[3]

ABSTRACT

The dynamic nature of construction environments imposes significant cognitive demands on workers lead to loss of productivity and safety risks. Optimizing cognitive capacity aligns with lean construction principles by reducing waste, overburden and enhancing workers' wellbeing, safety, and productivity. This study assesses the feasibility of eye-trackers for monitoring cognitive load on construction sites. Specifically, given the potential interference between the eye-tracking mechanism and the reflection or glare caused by safety goggles, a critical piece of protective equipment, the authors examined the impact of safety goggles on the signals' quality of eye trackers. A controlled experiment was conducted to compare the eye-tracking signal quality metrics between with and without safety goggles. The results indicate that safety goggles introduced minor inaccuracies in fixation reliability (a 6% increase in fixation error) and blink detection (a 2% reduction in detection rate) but improved accuracy for dynamic tracking (a 27% reduction in tracking error) and maintained comparable recovery times. Furthermore, a questionnaire revealed reduced comfort and visual interference with safety goggles, highlighting the need for ergonomic improvements. This research supports integrating advanced sensor technologies in lean construction 4.0 and offers a pathway for developing practical tools to optimize worker performance and safety.

KEYWORDS

Continuous improvement/kaizen, Waste reduction, Wearable sensors, Safety, Lean construction 4.0

INTRODUCTION

The construction industry operates within a highly dynamic, demanding, and unpredictable environment due to constant changes in project conditions, and task requirements. The complexity of construction activities together with the need to adhere to strict safety regulations and continuously adapting to varying project and task conditions and demands, strain the workers cognitive capacity. Such increased cognitive strain can lead to mental fatigue (Marcora et al., 2009) which is associated with reduced productivity, and safety risks (Jamil Uddin et al., 2024; Xing et al., 2020). Cognitive strain impairs workers by slowing their reaction time, reducing vigilance, diminishing decision making abilities, and lowering their situational awareness (Lappalainen et al., 2021; Lerman et al., 2012). Cognitive capacity is a critical resource in construction that is often heavily utilized. Its effective management aligns with lean construction principles which aim to reduce inefficiencies, optimize resource utilization

[1] Ph.D. Candidate, Hole School of Construction Engineering, University of Alberta, Canada
[2] Assistant Professor, Hole School of Construction Engineering, University of Alberta, AB, Canada
[3] Professor, Hole School of Construction Engineering, University of Alberta, AB, Canada

(Alarcón et al., 2015), enhance productivity and prioritize the well-being of the construction workers (Noueihed & Hamzeh, 2022; Koskela, 1992). Monitoring cognitive load is essential, as sustained overload can lead to mental fatigue and impaired performance. This step is key to understanding and managing worker fatigue.

Previous studies have employed subjective methods to measure and monitor fatigue levels among workers, such as the Fatigue Assessment Scale for Construction Workers (FASCW) (Zhang et al., 2023) , the NASA Task Load Index (NASA-TLX) (Carswell et al., 2010; Rubio et al., 2004), and Subjective Workload Assessment Technique (SWAT) (Rubio et al., 2004). However, these methods have proven to be time consuming and disturbing to the worker's ongoing work. Furthermore, the reliability of these assessments relies heavily on the respondents' ability to accurately recall and reconstruct their experiences, which can vary significantly among individuals (Larson & Csikszentmihalyi, 2014).To tackle this challenge, researchers have adopted technological solutions to measure and monitor the fatigue level of construction workers more objectively. Emerging wearable technologies offer a novel approach to real-time measurement and analysis of cognitive load which have been a part of lean construction 4.0 (L.C 4.0) applications (González et al., 2022; Hamzeh et al., 2021; Sanders et al., 2016). The principles of LC 4.0 emphasize the well-being of construction teams and are further enhanced by advanced technologies, such wearable sensor devices (González et al., 2022; Hamzeh et al., 2021).

Eye-tracking devices can capture metrics such as fixation duration, fixation rate, blink rate and duration, and pupil dilation, which are established indicators of cognitive strain (Ahlstrom & Friedman-Berg, 2006; Di Stasi et al., 2011; Liu et al., 2022). Despite their potential, practical deployment of such technologies in construction settings remains challenging (Eltahan et al., 2024). One of these challenges is the necessity of integrating safety equipment like protective goggles. Eye trackers rely on precise mechanisms to capture eye movements by tracking corneal reflections or pupil movements using infrared light (IR) (Ehinger et al., 2019). The addition of safety goggles could possibly create reflection or glare given that construction-approved safety goggles have to conform to CSA Z94.3 standards which commonly include antireflection coatings (Government of Canada, 2024). It could hinder the performance of the eye trackers as it might alter the IR light as it passes through. The accuracy and quality of the signals in this setup remain unexplored in the literature. This hinders its application on construction sites due to the lack of a reliable assessment of these technologies under real construction settings and safety regulations. Therefore, this study investigates the feasibility of using eye-tracking glasses to monitor cognitive load on construction sites, focusing on the impact of safety goggles on signal quality. It seeks to determine how goggles affect the accuracy and reliability of eye-tracking data. Cognitive capacity is one of the most overutilized resources in construction, and optimizing its use aligns with lean construction principles by reducing waste and enhancing workers' wellbeing, improving safety, and productivity. Measuring cognitive load in real time using wearable sensors presents an innovative approach to understanding and mitigating cognitive strain in lean construction practices. This research advances the integration of innovative technologies into lean construction 4.0 practices by reducing waste, continuous improvement, and avoiding over burden to enhance worker safety, productivity, and well-being.

LITERATURE REVIEW

COGNITIVE OPTIMIZATION AND LEAN CONSTRUCTION PRINCIPLES

Cognitive optimization refers to strategies and practices designed to minimize unnecessary cognitive load on workers which allow them to focus their mental resources on tasks that are critical to safety, productivity, and quality. This concept aligns with lean construction principles, which aim to enhance efficiency, eliminate waste, and improve workflow reliability (Koskela, 2000). Furthermore, lean construction principles advocate for the simplification and standardization of workflows (Sacks et al., 2010), which not only enhance efficiency but also significantly reduce cognitive load. For example, preassembly of materials, visual management tools, and clear task sequences minimize the mental effort required for planning and problem-solving on-site as it reduces the cognitive load required to perform the task.

Also, Davoudabadi et al., (2022) highlighted how effective collaboration between Building information modelling (BIM) and lean construction principles through Team Mental Models (TTM) (Filho and Tenenbaum, 2020) enhance productivity. TMMs directly relate to cognitive load by influencing how team members process, store, and share information during collaborative tasks. Team members could then spend less time and mental effort figuring out how to work together which allows them to focus on solving important problems. In the context of Lean Construction and Building Information Modeling (BIM), TMMs help bridge cognitive and operational gaps between teams by reducing inefficiencies caused by different terminologies, goals, and working methods. Also, another study emphasized the importance of managing workload to prevent overload (Fan et al., 2007). It highlights the value of TMMs in improving team performance, particularly by allowing members to allocate tasks effectively and reduce unnecessary mental effort. Existing research discusses TMMs and cognitive optimization in Lean-BIM contexts from a conceptual and a theoretical perspective; however, a practical application for cognitive load measurement with the focus on cognitive resources as an area for optimization is currently lacking.

MEASUREMENT OF COGNITIVE LOAD

Measurement of cognitive load is a prerequisite for its effective optimization. Effective measurement tools are necessary for optimizing task performance and minimizing errors. Various methods are employed to measure cognitive load which includes subjective (Rubio et al., 2004), objective, and task-based techniques (Paas et al., 2003). Subjective measurement techniques rely on self-reporting tools such as the NASA Task Load Index (NASA-TLX), Subjective Workload Assessment Technique (SWAT), and Cognitive Task Load Analysis (CTLA) (Rubio et al., 2004). These methods involve participants evaluating their mental workload through predefined scales to provide insights into perceived cognitive demands. While these techniques are straightforward, they may lack precision and practicality due to individual biases and disruption to ongoing work. Objective measurement techniques utilize physiological indicators to assess cognitive load based on physiological responses. It includes monitoring heart rate variability (HRV), brain activity via EEG, eye activity such as pupil dilation and blink rate, cortisol levels, and skin conductance (Noueihed & Hamzeh, 2022; Paas et al., 2003). These methods offer real-time, non-disruptive method that quantifies cognitive load. Another method is the Task- and Performance-Based Techniques. It's often used in experimental setups supplemented by wearable sensors to enhance the validity of the results (Mehler et al., 2009). It evaluates cognitive load through the impact on task execution through metrics such as reaction time, accuracy, and error rate in tasks to reflect how cognitive load affects performance (Paas et al., 2003).

Cognitive Load/Mental Fatigue Assessment in Construction

In construction research, the three measurement methods discussed above have been employed to asses' mental fatigue. Subjective self-reporting tools like the Fatigue Assessment Scale for Construction Workers (FASCW) (Zhang et al., 2023) and NASA Task Load Index (NASA-TLX) (Mitropoulos & Memarian, 2013) have proven subjective and prone to biases (Han et al., 2019). To address this, researchers have shifted towards advanced wearable technologies such as Electroencephalography (EEG), wearable eye trackers, and physiological metrics recorders to objectively measure cognitive states in construction environments (J. Li et al., 2019; Mehmood et al., 2022; Wang et al., 2017; Xing et al., 2019).

Jamil Uddin et al., (2024) conducted a systematic literature review on the state of science on using technologies to measure mental fatigue of construction workers. In his work, he highlighted that there is a scarcity of papers published between 2019 and 2023 that attempted to measure mental fatigue of construction workers. EEG is one of the most extensively used tools for assessing mental fatigue in construction. The application of EEG in real-world settings remains limited due to challenges such as interference from external conditions and the need for controlled environments (H. Li et al., 2019). Eye-tracking technology is emerging as a practical alternative for measuring mental fatigue in real-world construction settings. Eye trackers assess cognitive states by analyzing pupil dilation, gaze behavior, and blink rates, which are affected by mental fatigue (Li et al., 2020). Compared to EEG, eye-tracking devices are less susceptible to environmental disturbances such as vibration and electromagnetic interference which make them more suitable for on-site applications (J. Li et al., 2020). Additionally, studies have shown that wearable eye-tracking systems can effectively monitor fatigue in excavator operators and manual laborers, enabling proactive fatigue management to reduce hazards and errors in equipment operation (Mehmood et al., 2022).

While eye-tracking technology is a valuable tool for assessing cognitive load and mental fatigue due to its precision and ability to provide real-time insights, its direct application on construction sites faces practical challenges. Construction safety protocols often mandate the use of protective gear, such as safety goggles, which can interfere with the accuracy and functionality of eye-tracking devices. This limitation necessitates testing the quality of eye-tracking signals when worn beneath safety goggles to ensure reliable performance in real-world settings. Furthermore, research investigating this setup is lacking. Therefore, this paper asses the feasibility of eye-tracking technology on-site, which can advance lean construction principles by providing real-time insights into cognitive load which is a critical yet often overutilized resource. It enables the measurement of critical indicators such as prolonged fixation duration, increased blink rates, or scattered gaze patterns which can indicate cognitive overload and consequently allow timely corrective measures to improve performance. This approach also aligns with lean principles as it promotes worker safety and well-being, reduces overburden and waste, and optimize cognitive resources.

METHODS

Figure 1 shows the overview of the research methods. The research started by task design where three different tasks were implemented to compare the quality of signals in static fixation, dynamic tracking and blink recovery as well as a questionnaire to capture the participants' rating fort general comfort and visual disturbance. Then we proceeded with data collection as thoroughly explained under the data collection section and finally data analysis.

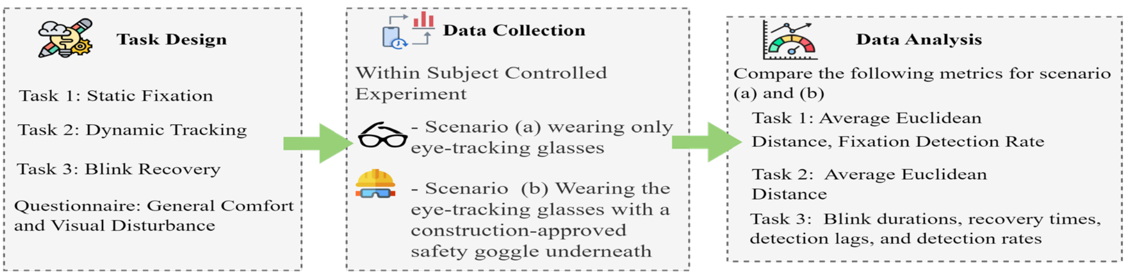

Figure 1: Overview of Research Methods

TASKS DESIGN

The participants were asked to perform three tasks to evaluate and compare the quality of the signals in both scenarios. The first task was fixation accuracy task to measure the accuracy of the fixation points alignment with known targets. To achieve this, the participants were requested to focus on static targets (crosshairs) as they appear sequentially on the screen at 9 different positions to measure both central and peripheral (top left, top middle, top right, etc.). The second task was dynamic tracking task to compare the ability of both scenarios to track moving gaze points by displaying a moving dot that follows a predefined path at three varying speeds. The third task was the blink recovery to compare the ability of both scenarios in accurate tracking after blinking. The participants were asked to follow prompts to blink then to refocus on a fixed target immediately after each blink. The tasks were presented in a randomized order for each participant to minimize bias. The tasks were performed back-to-back under both conditions (with and without safety goggles) for each participant. This ensured that the comparison is not influenced by external factors such as changes in lighting, equipment setup, or participant fatigue. After each scenario the participants were asked to fill in a survey questionnaire that captured their general comfort and visual disturbance on a scale of 1-5.

DATA COLLECTION

The experiment employed a within-subject design where participants performed identical tasks under two scenarios: (a) wearing only eye-tracking glasses "Pupil Invisible Eye tracking glasses by Pupil Labs", and (b) wearing the same eye-tracking glasses with a construction-approved safety goggle underneath. This controlled setup ensured that differences in signal quality are solely attributable to the added safety goggles. The eye tracking glasses collected gaze data at 200 HZ, fixations, blinks, pupil dilation, RGB scene video at 30 Hz using a detachable scene camera and gaze mapping. A total of seven graduate students voluntarily agreed to participate after signing informed consent forms. The within subject experimental design with controlled setup could support the results concluded. In eye-tracking studies, similar sample sizes have been commonly used due to the exhaustive nature of data collection and analysis (J. Li et al., 2020). Since this approach minimizes variability between participants by having each individual act as their own control. Prior to the experiment, each participant was briefed on the objectives and procedures of the study and their questions or concerns were addressed to ensure clarity and comfort. Participation was voluntary with the option to withdraw two weeks after data collection without consequences.

DATA ANALYSIS

To compare the quality of the signals the following metrics were calculated:1. Fixation Accuracy: Compare the precision of fixations and gaze points tracking on a known target for static and moving objects. The deviation was measured between the fixations recorded and the actual target positions by measuring the Euclidean distance between them. Then the average error and fixation detection rate for both scenarios is compared. 2. Dynamic Tracking performance error: The deviation was also measured by calculating the Euclidean distance between the recorded gaze points and actual target coordinates of the task. 3. Blink Performance: Six metrics were calculated which include camera-detected blink duration, eye tracker-detected blink duration, recovery time after a blink, lag in detecting blink start and end, and blink detection rate. The time taken for the eye tracker to reacquire the gaze point after a blink measured to calculate the recovery time in both scenarios. Also, the blink duration and lag between blink start and end as recorded by a high-speed camera is compared to the blink duration and timestamps recorded by the eye tracking glasses in both scenarios as well as the rate of detected blinks. This could indicate the lag taken by the eyeglasses to detect a blink and its corresponding duration. From these metrics, fixation rate, blink rate, and blink duration are well established metrics to measure cognitive load (Bachurina & Arsalidou, 2022; Liu et al., 2022; Maffei & Angrilli, 2018; Page et al., 2024). Therefore, measuring the error in these metrics could indicate some insights into the accuracy of cognitive load inference when adding safety goggles.

RESULTS AND DISCUSSION

KEY FINDINGS: SIGNAL QUALITY COMPARISON

Task 1: Static Fixation

Task 1 assessed participants' ability to focus on static targets under two scenarios: with and without safety goggles. The metrics recorded were the average Euclidean distance (error) between recorded fixation points and actual target positions (Figure 2) and the fixation detection rate (Figure 3). The average Euclidean distance for Task 1 (with safety goggles) was 600.29 pixels, with a fixation detection rate of 74.60%. Without safety goggles participants demonstrated improved performance. The average Euclidean distance for Task 1 was reduced to 564.05 pixels, and the fixation detection rate reached 100%. Wearing safety goggles increased the average Euclidean distance by ~6%, indicating a slight negative impact on task accuracy due to potential visual interference or physical discomfort. These findings suggest that safety goggles could potentially impact visual task performance, reducing fixation detection reliability and increasing deviation in static tasks.

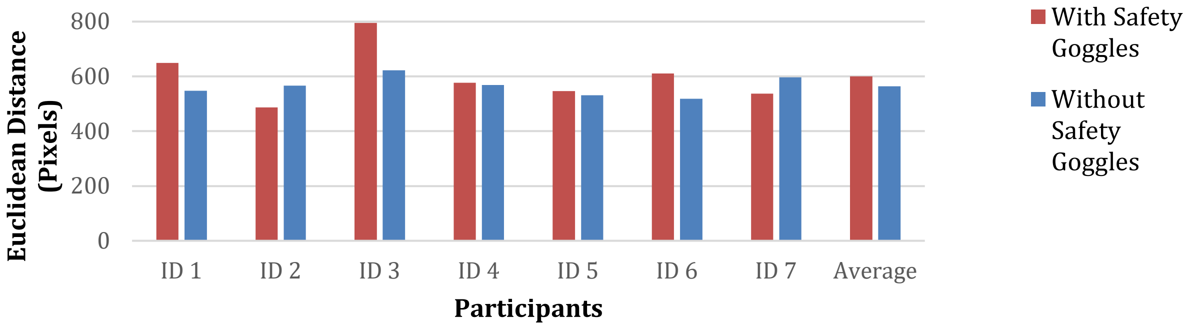

Figure 2: Average Euclidean Distance for Task 1 (With and Without safety goggles)

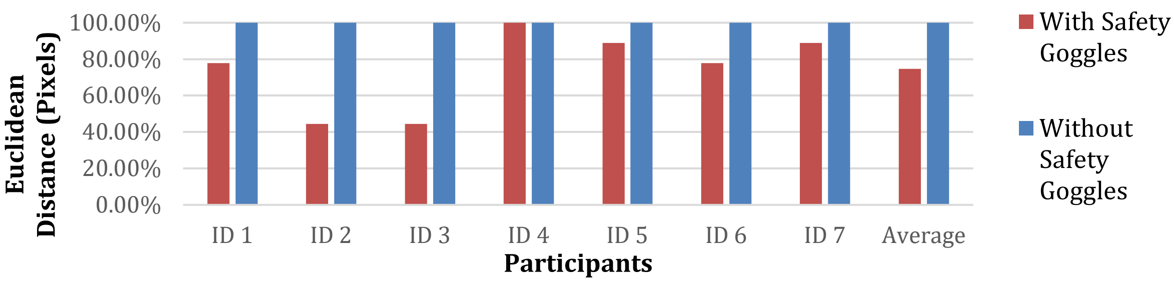

Figure 3: Task 1 Fixation Detection Rate (With and Without safety goggles)

Task 2: Dynamic Visual Tracking

The dynamic visual tracking task was designed to evaluate participants' ability to follow moving gaze points under two conditions: with and without safety goggles. In this task, a moving dot followed a predefined path at three varying speeds across the screen. Participants were required to visually track the moving dot as accurately as possible. The average Euclidean distance (error) was calculated as the deviation between the participants' recorded gaze points and the actual path of the moving dot. This task aimed to assess the impact of safety goggles on dynamic visual tracking accuracy, complementing the static targeting task (Task 1).

The average Euclidean distance (with safety goggles) across all participants was 312.04 pixels (Figure 4). These results indicate moderate accuracy and fixation reliability in the presence of safety goggles. When participants didn't wear the goggles, the average Euclidean distance increased slightly to 426.80 pixels, reflecting varied performance on moving targets. This trend seemed consistent across all participants as shown in figure 4.

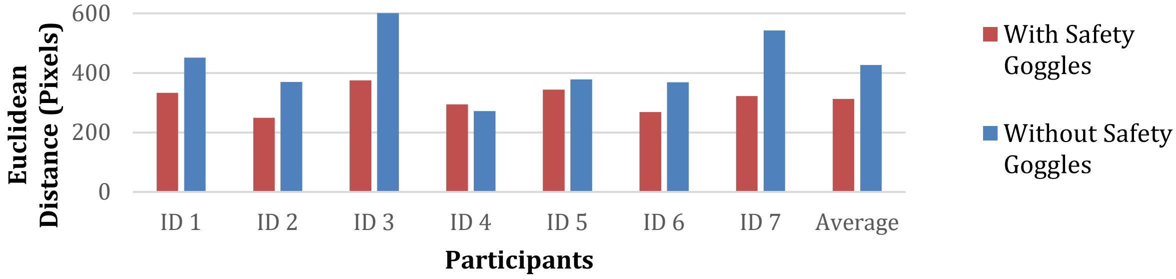

Figure 4: Average Euclidean Distance for Task 2 (With and Without safety goggles)

The results highlight the demanding nature of dynamic tracking tasks and how environmental factors (like wearing goggles) influence performance differently compared to static tasks. Surprisingly, safety goggles may provide a stabilizing effect and limiting peripheral distractions which allows participants to focus better on the moving target.

Task 3: Blink Recovery

The blink recovery task compared performance metrics with and without safety goggles, focusing on blink durations, recovery times, detection lags, and detection rates as shown in table 1 and table 2. Without safety goggles, the camera-detected blink duration averaged 395.21 ms which is closely aligned with the eye tracker's average of 395.88 ms, indicating accurate blink detection. With safety goggles, the camera-detected blink duration averaged 401.55 ms but the eye tracker detected shorter blinks at 469.78 ms which suggests potential interference or inaccuracies introduced by the goggles.

Recovery time after a blink was similar across both conditions averaging 5.21 ms without goggles and 5.08 ms with goggles. This indicates that the goggles did not significantly affect the speed of gaze reacquisition after a blink. For the blink detection lag, the average lag between the camera and eye tracker to detect blink start and end times was 2380.83 ms and 2378.62 ms, respectively without goggles. With goggles, the detection lag was slightly reduced to 2140.08 ms (start) and 2213.63 ms (end). This could reflect differences in how the goggles influence detection timing by reduced external visual stimuli due to the goggles, stabilizing the detection environment. The last metric was the blink detection, all participants achieved a 100% detection rate when not wearing the safety goggles. However, the detection rate averaged 98%, with one participant (ID 4) experiencing a lower rate of 88.90%, likely due to individual variability or increased interference from the goggles.

The results suggest that safety goggles introduce minor inaccuracies in blink duration and detection rate but have minimal impact on recovery time. While safety goggles slightly influence blink detection metrics the overall impact on usability is minimal with the eye tracker demonstrating robust performance across both conditions.

Questionnaire Results

Two surveys were conducted to assess user comfort and visual performance when wearing eye-tracking glasses with and without safety goggles. The first survey ("With Safety") evaluated the combined impact of safety goggles and eye-tracking glasses, while the second survey ("Without Safety") focused solely on wearing the eye-tracking glasses. Participants rated their experience across two sections: general comfort and visual disturbance. For general comfort the participants rated three aspects which include: overall comfort (Q1), facial pressure or discomfort (Q2), impact of combined weight/weight of eye tracker on comfort (Q3) on a scale of 1 to 5 (1= very uncomfortable and 5 = very comfortable). For visual disturbance the participants were asked to rate field of vision reduction (Q4), reflection or glare (Q5), and difficulty focusing on stimuli (Q6) in both scenarios on a scale of 1 to 5 (1= no effect and 5 = Significantly reduced field of vision).

For the “With Safety” survey, responses showed that the participants found wearing the glasses and safety goggles moderately comfortable (Q1 mean: 3.15) while the mean for the “Without Safety” survey for Q1 is 3.57. For Q2, they experienced mild to moderate discomfort in terms of facial pressure (Q2 mean: 3.71) and for the without safety survey the mean is 4.14. In terms of visual interference, the field of vision was slightly affected (Q4 mean: 2.43) in comparison to being 1.71 when only using the eye tracking glasses. Reflections or glare were rare to occasional (Q5 mean: 2.29). The participants reported minimal difficulty focusing on visual tasks due to the setup (Q6 mean: 2.00). These results as shown in table 3 suggest that while the combination of safety goggles and eye-tracking glasses is feasible for use, some improvements in comfort and visual interference could enhance user experience.

Table 1: Blink Recovery Metrics without safety goggles

	Camera Blink (ms)	Eye tracker Blink (ms)	Recovery time (ms)	Blink Start Lag (ms)	Blink End Lag (ms)	Detection Rate (%)
ID 1	320.4444	401.2222	4.9754	1648.8410	1729.6188	100
ID 2	236.3429	402.8978	5.2693	2809.8469	2976.4019	100
ID 3	342.3333	211.8967	5.0770	1949.5651	1809.9084	100
ID 4	344.8889	505.2899	5.6210	2731.5298	2891.9309	100
ID 5	307.5556	442.9630	4.8948	2228.5386	2352.9195	100
ID 6	795.3222	384.1481	5.3027	2880.9485	2469.7744	100
ID 7	419.5556	422.7778	5.3463	2416.5644	2419.7867	100
Average	395.2061	395.8851	5.2124	2380.8335	2378.6201	100

FEASIBILITY OF USING EYE-TRACKING GLASSES IN CONSTRUCTION SETTINGS

The results of this study highlight the feasibility of using eye-tracking glasses in construction settings while adhering to the safety regulation imposed on construction sites. While safety goggles introduced minor inaccuracies in blink detection and slightly reduced fixation reliability, the overall impact on usability was minimal. The eye tracker maintained acceptable accuracy for both static and dynamic tasks, with recovery times after blinks remaining consistent across scenarios. These findings suggest that eye-tracking glasses can effectively capture gaze and fixation data in environments where safety equipment is mandatory. However, to optimize their reliability and usability in construction settings, improvements such as better calibration algorithms, reduced detection lag, and designs that minimize visual interference from safety goggles could enhance performance and user comfort.

The findings of this study align closely with lean construction principles which emphasize minimizing waste and optimizing processes to enhance productivity and safety as well as LC 4.0 principles which prioritize the well-being of the construction team using cutting edge technologies. The study highlights how wearable technology can help streamline workflows and improve decision-making on-site by assessing the feasibility of using eye-tracking glasses while adhering to the mandatory safety regulations. For example, the ability to measure cognitive load using eye tracking data enables better understanding of worker behaviour and task execution which in return could facilitate process optimization and waste reduction of cognitive resources. Furthermore, this research advances the application of wearable sensors on construction sites to monitor cognitive load in real time and it could help identify inefficiencies, such as high cognitive load zones. This could allow targeted interventions which aligns with lean construction's focus on continuous improvement, avoiding over burden (heijunka) and maximizing value (Besklubova & Zhang, 2019; Mao & Zhang, 2008).

Table 2: Blink Recovery Metrics with safety goggles

	Camera Blink (ms)	Eye tracker Blink (ms)	Recovery time (ms)	Blink Start Lag (ms)	Blink End Lag (ms)	Detection Rate (%)
ID 1	327.7778	235.2607	4.8337	2023.0051	1931.8984	100.0
ID 2	277.6250	283.6400	5.2297	2705.5369	2711.5519	100.0
ID 3	394.8889	950.3905	5.1472	2091.5677	2682.1819	100.0
ID 4	304.2222	344.3730	5.2229	2106.9188	2144.0419	88.90
ID 5	345.2222	222.1004	4.7706	1899.1710	1779.7422	100.0
ID 6	690.5556	492.5450	5.3273	2195.0625	1997.0519	100.0
ID 7	470.5556	760.1815	5.0490	1959.2970	2248.9230	100.0
Average	401.5496	469.7844	5.0829	2140.0799	2213.6273	98

Table 3: Mean Survey Responses: With vs. Without Safety Goggles

	Q 1	Q2	Q3	Q 4	Q 5	Q6
Mean (With Safety)	3.14	3.71	4.00	2.43	2.29	2.00
Mean (Without Safety)	3.57	4.14	4.71	1.71	1.29	1.57

CONCLUSION

This study evaluated the performance and usability of eye-tracking glasses in construction settings through three tasks: static fixation, dynamic tracking, and blink recovery. The results demonstrated that eye-tracking glasses are generally effective in capturing gaze behaviour under challenging conditions including the use of safety goggles. While the addition of safety goggles introduced minor inaccuracies in blink detection and fixation reliability, the overall performance of the eye tracker remained robust across tasks. The glasses showed moderate accuracy in static and dynamic tasks with consistent recovery times following blinks. These findings indicate that eye-tracking glasses are a promising tool for monitoring visual behaviour and enhancing safety in construction environments. However, further refinements in design and calibration are recommended to fully optimize their integration with safety equipment and improve usability in real-world scenarios.

Interestingly, participants indicated minimal difficulty in focusing on visual stimuli despite the additional interference from the goggles. This suggests that while there are physical and visual limitations, they do not entirely impede the ability to perform tasks requiring gaze tracking. However, the slightly lower comfort and increased interference ratings with goggles emphasize the need for ergonomic improvements in the design of both the eye-tracking glasses and the safety equipment. The implications of these findings for lean construction are significant as they highlight the potential of eye-tracking technology to optimize workflows and enhance safety management. By providing real-time data on worker focus and behaviour, eye-tracking glasses can help identify inefficiencies, reduce human errors, and ensure compliance with safety protocols. Integrating this technology into lean construction practices can support continuous improvement by enhancing worker performance and optimizing cognitive resources.

The study was conducted under controlled conditions which may not fully capture the dynamic and unpredictable nature of real construction environments, such as varying lighting, weather conditions, or physical obstructions. Furthermore, the participant group was relatively small which may limit the generalizability of the findings. Individual differences in eye-tracking performance were observed which indicate a need for further studies with larger and more diverse samples. Future research should focus on field studies in real construction environments under dynamic, high-risk conditions and explore integrating eye-tracking with other objective cognitive load measures such as Heart Rate Variability (HRV), which reflects stress responses, to enable multimodal assessment and enhance the accuracy and robustness of cognitive state inference in complex construction scenarios. While this study focused on the feasibility of using eye-trackers under safety constraints, future work should extend toward developing a real-time dashboard that integrates cognitive load assessment for on-site monitoring, enabling proactive decision-making to enhance worker safety and productivity.

REFERENCES

Ahlstrom, U., & Friedman-Berg, F. J. (2006). Using eye movement activity as a correlate of cognitive workload. *International Journal of Industrial Ergonomics*, *36*(7), 623–636. https://doi.org/10.1016/j.ergon.2006.04.002

Alarcón, L. F., Diethelm, S., Rojo, O., & Calderón, R. (2015). Assessing the impacts of implementing lean construction. *Revista Ingeniería de Construcción*, *23*(1). https://doi.org/10.4067/S0718-50732008000100003

Bachurina, V., & Arsalidou, M. (2022). Multiple levels of mental attentional demand modulate peak saccade velocity and blink rate. *Heliyon*, *8*(1), e08826. https://doi.org/10.1016/j.heliyon.2022.e08826

Besklubova, S., & Zhang, X. (2019). Improving Construction Productivity by Integrating the Lean Concept and the Clancey Heuristic Model. *Sustainability*, *11*(17), 4535. https://doi.org/10.3390/su11174535

Carswell, C. M., Lio, C. H., Grant, R., Klein, M. I., Clarke, D., Seales, W. B., & Strup, S. (2010). Hands-free administration of subjective workload scales: Acceptability in a surgical training environment. *Applied Ergonomics*, *42*(1), 138–145. https://doi.org/10.1016/j.apergo.2010.06.003

Davoudabadi, S., Pedo, B., Tezel, A., & Koskela, L. (2022). A Cognitive Review for Improving the Collaboration Between BIM and Lean Experts. *30th Annual Conference of the International Group for Lean Construction (IGLC30)*, 669–680. https://doi.org/10.24928/2022/0174

DeJoy, D. M. (2005). Behavior change versus culture change: Divergent approaches to managing workplace safety. *Safety Science*, *43*(2), 105–129. https://doi.org/10.1016/j.ssci.2005.02.001

Di Stasi, L. L., Antolí, A., Gea, M., & Cañas, J. J. (2011). A neuroergonomic approach to evaluating mental workload in hypermedia interactions. *International Journal of Industrial Ergonomics*, *41*(3), 298–304. https://doi.org/10.1016/j.ergon.2011.02.008

Ehinger, B. V., Groß, K., Ibs, I., & König, P. (2019). A new comprehensive eye-tracking test battery concurrently evaluating the Pupil Labs glasses and the EyeLink 1000. *PeerJ*, *7*, e7086. https://doi.org/10.7717/peerj.7086

Eltahan, A., Shehab, L., & Hamzeh, F. (2024). *Driving the Momentum Towards Adopting Wearable Cognitive Assistance in Lean Construction 4.0*. 1182–1194. https://doi.org/10.24928/2024/0182

Fan, X., Chen, P.-C., & Yen, J. (2007). Learning Cognitive Load Models for Developing Team Shared Mental Models. *In Proceedings of the 8th International Conference on Cognitive Modeling (ICCM)*, 145–150. https://agentlab.ist.psu.edu/lab/publications/ICCM07-124.pdf

González, V. A., Hamzeh, F., & Alarcón, L. F. (2022). *Lean Construction 4.0: Driving a Digital Revolution of Production Management in the AEC Industry*. Taylor & Francis.

Government of Canada, C. C. for O. H. and S. (2024, May 10). *CCOHS: Eye and Face Protectors*. https://www.ccohs.ca/oshanswers/prevention/ppe/glasses.html

Hamzeh, F., González, V. A., Alarcon, L. F., & Khalife, S. (2021). Lean Construction 4.0: Exploring the Challenges of Development in the AEC Industry. *29th Annual Conference of the International Group for Lean Construction (IGLC29)*, 207–216. https://doi.org/10.24928/2021/0181

Jamil Uddin, S. M., Tabassum, N., Ovid, A., Alsharef, A., & Albert, A. (2024). Measuring Mental Fatigue in Construction: State of the Science and Future Opportunities. *Construction Research Congress 2024*, 688–698. https://doi.org/10.1061/9780784485293.069

Koskela, L. (2000). *An exploration towards a production theory and its application to construction*. Technical Research Centre of Finland. https://aaltodoc.aalto.fi/items/076e4e0b-d86b-4171-b205-a68e85af8bd6

Lappalainen, E. M., Seppänen, O., Peltokorpi, A., & Singh, V. (2021). Transformation of construction project management toward situational awareness. *Engineering, Construction and Architectural Management*, *28*(8), 2199–2221. https://doi.org/10.1108/ECAM-12-2020-1053

Larson, R., & Csikszentmihalyi, M. (2014). The Experience Sampling Method. In M. Csikszentmihalyi (Ed.), *Flow and the Foundations of Positive Psychology: The Collected Works of Mihaly Csikszentmihalyi* (pp. 21–34). Springer Netherlands. https://doi.org/10.1007/978-94-017-9088-8_2

Lerman, S. E., Eskin, E., Flower, D. J., George, E. C., Gerson, B., Hartenbaum, N., Hursh, S. R., & Moore-Ede, M. (2012). Fatigue Risk Management in the Workplace. *Journal of Occupational & Environmental Medicine*, *54*(2), 231–258. https://doi.org/10.1097/JOM.0b013e318247a3b0

Li, H., Wang, D., Chen, J., Luo, X., Li, J., & Xing, X. (2019). Pre-service fatigue screening for construction workers through wearable EEG-based signal spectral analysis. *Automation in Construction, 106*, 102851. https://doi.org/10.1016/j.autcon.2019.102851

Li, J., Li, H., Umer, W., Wang, H., Xing, X., Zhao, S., & Hou, J. (2020). Identification and classification of construction equipment operators' mental fatigue using wearable eye-tracking technology. *Automation in Construction, 109*, 103000. https://doi.org/10.1016/j.autcon.2019.103000

Li, J., Li, H., Wang, H., Umer, W., Fu, H., & Xing, X. (2019). Evaluating the impact of mental fatigue on construction equipment operators' ability to detect hazards using wearable eye-tracking technology. *Automation in Construction, 105*, 102835. https://doi.org/10.1016/j.autcon.2019.102835

Liu, J.-C., Li, K.-A., Yeh, S.-L., & Chien, S.-Y. (2022). Assessing Perceptual Load and Cognitive Load by Fixation-Related Information of Eye Movements. *Sensors*, *22*(3), Article 3. https://doi.org/10.3390/s22031187

Maffei, A., & Angrilli, A. (2018). Spontaneous eye blink rate: An index of dopaminergic component of sustained attention and fatigue. *International Journal of Psychophysiology*, *123*, 58–63. https://doi.org/10.1016/j.ijpsycho.2017.11.009

Mao, X., & Zhang, X. (2008). Construction Process Reengineering by Integrating Lean Principles and Computer Simulation Techniques. *Journal of Construction Engineering and Management*, *134*(5), 371–381. https://doi.org/10.1061/(ASCE)0733-9364(2008)134:5(371)

Marcora, S. M., Staiano, W., & Manning, V. (2009). Mental fatigue impairs physical performance in humans. *Journal of Applied Physiology*, *106*. https://doi.org/10.1152/japplphysiol.91324.2008

Mehler, B., Reimer, B., Coughlin, J. F., & Dusek, J. A. (2009). Impact of Incremental Increases in Cognitive Workload on Physiological Arousal and Performance in Young Adult Drivers. *Transportation Research Record: Journal of the Transportation Research Board*, *2138*(1), 6–12. https://doi.org/10.3141/2138-02

Mehmood, I., Li, H., Umer, W., Arsalan, A., Shakeel, M. S., & Anwer, S. (2022). Validity of facial features? Geometric measurements for real-time assessment of mental fatigue in construction equipment operators. *Advanced Engineering Informatics*, *54*, 101777. https://doi.org/10.1016/j.aei.2022.101777

Mitropoulos, P., & Memarian, B. (2013). Task Demands in Masonry Work: Sources, Performance Implications, and Management Strategies. *Journal of Construction Engineering and Management*, *139*(5), 581–590. https://doi.org/10.1061/(ASCE)CO.1943-7862.0000586

Noueihed, K., & Hamzeh, F. (2022). Envisioning a Human Centric Approach to C4.0 Technologies. Lean Construction Journal. *Lean Construction Journal (LCJ)*, 2022–2156.

Paas, F., Tuovinen, J. E., Tabbers, H., & Van Gerven, P. W. M. (2003). Cognitive Load Measurement as a Means to Advance Cognitive Load Theory. *Educational Psychologist*, *38*(1), 63–71. https://doi.org/10.1207/S15326985EP3801_8

Page, C., Liu, C. C., Meltzer, J., & Ghosh Hajra, S. (2024). Blink-Related Oscillations Provide Naturalistic Assessments of Brain Function and Cognitive Workload within Complex Real-World Multitasking Environments. *Sensors*, *24*(4), Article 4. https://doi.org/10.3390/s24041082

Rubio, S., Díaz, E., Martín, J., & Puente, J. M. (2004). Evaluation of Subjective Mental Workload: A Comparison of SWAT, NASA-TLX, and Workload Profile Methods. *Applied Psychology*, *53*(1), 61–86. https://doi.org/10.1111/j.1464-0597.2004.00161.x

Sacks, R., Koskela, L., Dave, B. A., & Owen, R. (2010). Interaction of Lean and Building Information Modeling in Construction. *Journal of Construction Engineering and Management*, *136*(9), 968–980. https://doi.org/10.1061/(ASCE)CO.1943-7862.0000203

Sanders, A., Elangeswaran, C., & Wulfsberg, J. (2016). Industry 4.0 implies lean manufacturing: Research activities in industry 4.0 function as enablers for lean manufacturing. *Journal of Industrial Engineering and Management*, *9*(3), 811. https://doi.org/10.3926/jiem.1940

Wang, D., Chen, J., Zhao, D., Dai, F., Zheng, C., & Wu, X. (2017). Monitoring workers' attention and vigilance in construction activities through a wireless and wearable electroencephalography system. *Automation in Construction*, *82*, 122–137. https://doi.org/10.1016/j.autcon.2017.02.001

Xing, X., Li, H., Li, J., Zhong, B., Luo, H., & Skitmore, M. (2019). A multicomponent and neurophysiological intervention for the emotional and mental states of high-altitude construction workers. *Automation in Construction*, *105*, 102836. https://doi.org/10.1016/j.autcon.2019.102836

Xing, X., Zhong, B., Luo, H., Rose, T., Li, J., & Antwi-Afari, M. F. (2020). Effects of physical fatigue on the induction of mental fatigue of construction workers: A pilot study based on a neurophysiological approach. *Automation in Construction*, *120*, 103381. https://doi.org/10.1016/j.autcon.2020.103381

Zhang, Z., Xiang, T., Guo, H., Ma, L., Guan, Z., & Fang, Y. (2023). Impact of physical and mental fatigue on construction workers' unsafe behavior based on physiological measurement. *Journal of Safety Research*, *85*, 457–468. https://doi.org/10.1016/j.jsr.2023.04.014