Measuring Cognitive Stability and Recovery in Construction Work: Insights from Field Eye-Tracking Data

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

[1]Department of Civil and Environmental Engineering, University of Alberta, Canada
eltahan@ualberta.ca, gaang@ualberta.ca, hamzeh@ualberta.ca

Abstract –
Construction tasks expose workers to fluctuating cognitive demands that influence attention, accuracy, and fatigue. Understanding cognitive performance requires examining not only overload triggers, but also mechanisms that stabilize performance and support recovery. This paper explores the positive side of cognitive regulation which includes the task characteristics, and situational/behavioral factors that help maintain or enhance cognitive stability. Field eye-tracking data were collected from real installation activities. Cognitive load was analyzed relative to individualized baselines, and synchronized video enabled contextual interpretation of recovery triggers. Cognitive fluctuations were quantified using a robust deviation index (Z-MAD), enabling detection of spike, transition, and stable intervals relative to individualized baselines. Recovery was evaluated using two complementary measures: recovery duration, the time required for the signal to return to the stable threshold after a spike, and recovery reduction percentage, the magnitude of normalization in Z-MAD following stabilization. Results show clear differences in recovery mechanisms across metrics. Blinks exhibited the longest and most variable recovery durations and the lowest recovery reduction percentages, indicating slower normalization associated with resource depletion and fatigue processes. In contrast, saccades and fixations demonstrated substantially shorter and more consistent recovery durations, along with higher recovery reduction percentages which reflect rapid re-stabilization of attentional control. A review of 45 representative episodes revealed that low recovery often coincided with routine, end-of-task, or rework-related actions, while high recovery occurred during structured coordination, procedural clarity, or collaborative interaction. The findings establish recovery behavior as a robust indicator of cognitive efficiency and recovery-based cognitive-aware task design and monitoring.

Keywords –
Cognitive load, eye-tracking, recovery, resilience, human factors, construction productivity

1 Introduction

Construction work demands high levels of sustained attention, rapid decision-making, and constant adaptation to dynamic environments. Workers continuously process visual, spatial, and procedural information under pressure, often performing tasks that require precision, coordination, and high level of situational awareness. These conditions impose significant cognitive load, which when prolonged or unmanaged has been linked to mental fatigue, human error, and reduced productivity [1, 2]. Studies across engineering and human-factors research have shown that excessive cognitive demand can impair reaction time, accuracy, and overall task efficiency [3, 4, 5, 6], especially during time-sensitive or complex operations.

To address these challenges, most current research and industry interventions focus on reducing cognitive load: simplifying interfaces, improving task instructions, or removing unnecessary factors imposing cognitive demands [3, 6, 7]. While these efforts are essential, they represent only one side of the picture. Beyond merely preventing overload, there is an equally important opportunity to optimize cognitive performance by identifying the patterns and task characteristics that naturally support mental balance. In other words, instead of solely asking "what makes work harder?", we must also ask "what helps workers stay focused and calm under demand and by how much?" Equally important is understanding what happens after cognitive strain occurs how much recovery time is required before mental equilibrium is restored, and how supportive conditions might accelerate that process.

In this paper, we explore these questions through a field study conducted with an experienced electrician performing routine installation activities in a modular fabrication yard. The participant carried out real production tasks which include cutting, filing and assembling fiberglass cable tray, and lifting and positioning them for installation under authentic site conditions. Throughout the work, the electrician wore a wearable eye tracker equipped with an integrated scene camera which allow continuous monitoring of gaze behavior and cognitive fluctuations during each task sequence. In this study, eye-tracking metrics were used as proxy indicators of cognitive load and recovery. Accordingly, examining blink, saccade, and fixation patterns is central to the study objective, as these measures provide complementary insight into how cognitive strain emerges, stabilizes, and recovers during real construction work. The synchronized video provided contextual insight into what was happening in the environment when mental effort appeared to stabilize or recover. We identified instances of cognitive stability and rapid recovery and analyzed the task features, visual organization, and social interactions that accompanied them by combining physiological signals with observational interpretation. This field-based approach enables to observe how construction workers naturally regulate attention and regain focus amid complex, high-demand operations during their actual duties. Recognizing and reinforcing these stabilizing conditions can provide measurable cognitive and psychological benefits. Understanding how these positive conditions influence cognitive efficiency offers a pathway toward designing more supportive, resilient, and human-centered construction environments.

2 Literature Review

Cognitive load plays a central role in shaping workers' ability to maintain attention, process information, and regulate performance during construction tasks. Prior research has shown that fluctuating task demands, environmental uncertainty, and coordination requirements produce measurable variations in cognitive load, influencing error likelihood, task efficiency, and safety outcomes [2,8]. Within this context, visual behavior provides a direct window into cognitive states, as the eyes often reflect shifts in attention, momentary overload, and the allocation of mental resources in real time. Studies across applied cognitive science have linked distinct eye-movement patterns—such as increased blink activity, altered saccadic dynamics, and changes in fixation stability to underlying fluctuations in mental workload, fatigue, and information-processing demands [9, 10, 11, 12, 13]. These relationships have enabled eye-tracking to become a widely used method for assessing cognitive behavior in complex work settings, including construction [13, 14, 15].

Several studies have examined how specific eye-movement metrics correspond to different cognitive mechanisms. Blinks have been repeatedly associated with resource depletion, fatigue accumulation, and transitions away from active information processing, making them useful indicators of disengagement or cognitive strain [14, 15]. Saccades, by contrast, reflect rapid orienting and visual search behavior and tend to increase with spatial complexity or task uncertainty [9,12]. Fixations capture sustained attentional engagement with specific task-relevant elements and are often used to infer processing effort and task comprehension [4]. Together, these metrics allow researchers to capture both momentary changes in cognitive demand and the broader dynamics of how workers coordinate visual information within real environments. These metrics occur as discrete rather than as a continuous physiological signal. As prior studies have shown, such event-based distributions tend to be non-Gaussian, skewed, and highly unequal in frequency across event types [18]. This has motivated the use of robust, median-centered statistical measures in cognitive and physiological research, particularly the Median Absolute Deviation (MAD) and its standardized form, Z-MAD, which provide resilience against outliers and heavy-tailed distributions while preserving responsiveness to localized fluctuations in behavior [17, 18, 19]. Robust deviation measures have been recommended for naturalistic, event-based eye-tracking data, where preserving moment-to-moment variability is essential for identifying transitions between stable, transitional, and high-demand periods of cognitive activity. This body of evidence supports the use of Z-MAD in the present study as a theoretically grounded and methodologically appropriate approach for assessing cognitive fluctuations in real construction work.

Current research in construction focus on the negative aspects of cognitive load, such as identifying overload, reduced hazard perception, safety-sign inattentiveness, and impaired decision-making under strain [8, 22]. This work is essential for understanding when and why workers become vulnerable to errors or safety risks. However, far less attention has been given to the positive side of cognitive regulation specifically, the conditions that help workers stabilize after demanding moments, maintain attentional control, and recover efficiently during tasks. Understanding not only what disrupts cognition but also what supports it is equally important for developing interventions that enhance performance and wellbeing on construction sites. Identifying these stabilizing factors and quantifying the extent to which they facilitate recovery represent critical questions that the field has yet to fully address.

This paper addresses these gaps by applying a robust Z-MAD–based spike–stability detection method to event-based eye-tracking data collected during real construction work, quantifying both recovery durations and recovery reduction percentages, and interpreting these patterns through synchronized scene-video analysis to identify the task conditions that facilitate cognitive stabilization.

3 Methodology

3.1 Field Context and Participant

The study was conducted in a modular fabrication yard where electrical installation tasks were being performed under real production conditions. Given the exploratory nature of this study and the logistical complexity of collecting synchronized wearable eye-tracking and scene-video data in an active construction environment, the analysis focused on one experienced electrician to provide an in-depth case study of cognitive recovery patterns during real production tasks. The tasks selected for observation represented typical daily operations that require continuous attention, precision, and hand–eye coordination, including cutting and filing fiberglass trays, assembling metallic brackets, and lifting and installing them into position. These activities were chosen because they involve distinct cognitive phases planning, execution, verification, and adjustment providing opportunities to observe both focused and recovery moments within authentic workflows.

3.2 Data Collection

The participant wore a wearable eye-tracking glasses (Pupil Labs Invisible) throughout the work session as shown in figure 1. The device recorded gaze position, and eye movements at 200 Hz, while a scene camera integrated into the headset captured first-person video of the surrounding environment. This setup enabled simultaneous tracking of cognitive load and contextual task events without interfering with the worker's natural movement. Before beginning the work sequence, a within-subject baseline was recorded while the participant stood in a neutral resting state for five minutes.

Figure 1. On-site data collection during the field study using eye-tracking glasses

This baseline served as an individualized reference point against which subsequent fluctuations in cognitive activity could be compared, allowing all observed changes during task execution to be interpreted as relative deviations from the participant's own baseline rather than absolute values. The total recording time was approximately 60 minutes, covering multiple task cycles from setup to completion. All procedures received ethics approval from the University of Alberta Research Ethics Board. The participant was fully briefed on the study objectives and signed an informed consent form. Video and eye-tracking data were anonymized before analysis to protect participant privacy and ensure ethical compliance.

3.3 Data Analysis

The quantitative data analysis consisted of two complementary components: establishing recovery durations and quantifying the extent of recovery improvement. Eye-tracking and scene video data were synchronized using system timestamps. Data were then normalized relative to an individualized baseline recorded during a resting period prior to work. Cognitive fluctuations were quantified using a robust deviation measure (Z-MAD) shown in equation 1 [20], which expresses each sample as a deviation from the participant's individualized baseline.

$$Z_{MAD} = \frac{x - median_{baseline}}{1.4826\ x\ MAD_{baseline}} \quad \text{...equation} \qquad (1)$$

Where x = observed value
$MAD_{baseline}$ = median ($|X_{baseline} - Median_{baseline}|$)

This approach provides a consistent, participant-normalized index of cognitive variation without assuming normally distributed data. To classify cognitive states, Z-MAD thresholds were applied following robust outlier-detection conventions. Periods with Z-MAD < 1.5 were flagged as stable intervals, representing minimal fluctuation. Values within 1.5 ≤ Z-MAD < 2.5 [9,10] were labelled transition periods, reflecting shifts in attention or workload. Observations where Z-MAD ≥ 2.5 were flagged as spikes, indicating transient increases in cognitive demand [19]. Using this flag-based detection method, each recovery duration was measured as the elapsed time between the onset of a spike and the first subsequent sample classified as stable.

To complement the temporal analysis, a second metric "recovery reduction percentage" was computed to capture how effectively the signal amplitude normalized once the spike subsided. For each spike–stable pair, recovery reduction (%) was calculated as the proportional decrease in Z-MAD from the spike peak to the corresponding stable value, with lower percentages indicating minimal normalization and higher percentages reflecting strong recovery.

To contextualize these quantitative differences, fifteen representative episodes were selected for each metric (n=45) across the main quartile bands—including

Q1, the median, Q3, the region between Q3 and the upper whisker, and the upper whisker itself and cross-referenced with synchronized scene-video data. This ensured inclusion of both low-recovery episodes, where the signal showed limited return to baseline, and high-recovery episodes, where stabilization was rapid and efficient. Mapping these episodes to on-site task contexts enabled interpretation of the cognitive meaning behind different recovery levels.

4 Results

Figure 2 provides an illustrative example of the Z-MAD time series used in the analysis. As shown, periods where Z-MAD values remain below 1.5 are classified as stable, while values between 1.5 and 2.5 represent transition intervals. Values exceeding 2.5 indicate spikes in cognitive demand. Recovery duration is measured as the time between the onset of a spike and the first subsequent return to the stable region. The box plot (Figure 3) illustrates the recovery times across the three eye movement metrics blinks (n=177), saccades (n=549), and fixations (n=737). Blinks exhibited the longest and most variable recovery durations (Mean = 2.34 ms, SD = 2.92 ms), with a wide range from 0.52 s to 30.17 s.The median for blinks lies very close to the lower bound of the interquartile range (IQR) which indicate that most blink recoveries occur near the lower end of the distribution. These findings indicate occasional prolonged recovery episodes. In contrast, saccades (Mean = 0.72 ms, SD = 0.69 ms) and fixations (Mean = 0.67 ms, SD = 0.61 ms) demonstrated considerably shorter and more consistent recovery times, each ranging between approximately 0.17–6.75 ms. The median values reinforce this pattern, showing that both saccades (0.60 ms) and fixations (0.53 ms) recovered substantially faster than blinks (1.61 ms). As depicted in the box plot, the blink data display a pronounced right-skew, reflecting infrequent but extreme recovery outliers, whereas the saccade and fixation distributions are more compact, suggesting stable recovery dynamics following cognitive load fluctuations.

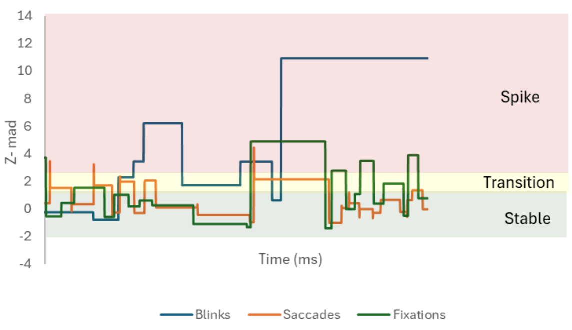

Figure 2. Time series illustrating stable, transition, and spike intervals in eye-tracking data. A representative segment is shown for clarity

Now that the recovery durations were established, the next step was to quantify the extent of recovery improvement between the spike and stable phases. This was expressed as the recovery reduction percentage, representing how much the Z-MAD value decreased once the participant's visual activity returned to a stable state.

As shown in figure 4, Blinks exhibited the lowest and most variable recovery reduction (mean = 77.09%, median = 90.54%, range = 0–166.11%), reflecting that while some episodes achieved strong recovery, others showed incomplete or delayed stabilization. Saccades demonstrated a higher and more consistent reduction (mean= 85.04%, median = 105.36%, range = 0–134.24%), whereas fixations displayed the highest median and mean reduction (mean = 90.83%, median = 99.58%, range = 44.59–153.96%), indicating faster and more efficient recovery.

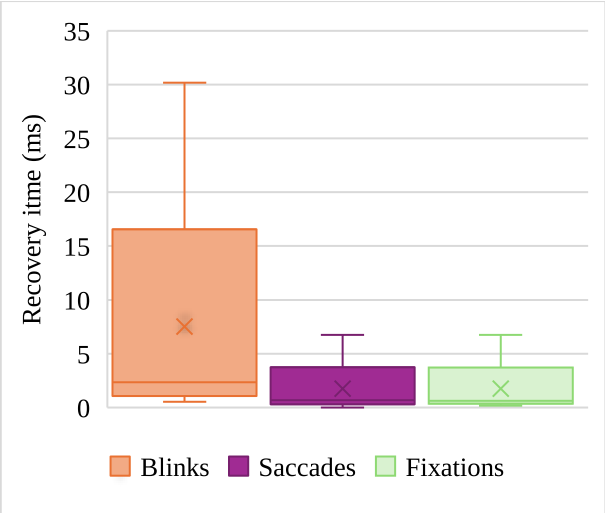

Figure 3. Distribution of Recovery Times across eye tracking metrics (Blinks, Saccades, Fixations)

The quartile ranges further highlight the variability and stability patterns among the three eye-movement metrics. For blinks, the interquartile range (IQR) spanned from approximately 62.72% (Q1) to 105.36% (Q3), revealing substantial dispersion and confirming that blink recovery was highly inconsistent across episodes. Saccades exhibited a slightly narrower range, with values extending from 66.16% (Q1) to 113.58% (Q3), indicating greater uniformity in how saccadic behavior returned to baseline following spikes in cognitive load. Fixations showed the tightest central spread, with 77.87% (Q1) and 118.68% (Q3), suggesting that most fixation episodes clustered around high recovery percentages with relatively few extreme deviations. This quartile pattern reinforces that those saccades and fixations generally achieved faster and more stable recovery, while blinks were influenced by larger fluctuations, likely reflecting the variability in attentional disengagement and visual reset processes. Overall, these findings suggest that saccadic and fixation behaviors stabilized more rapidly and reliably following cognitive load fluctuations, whereas blink recovery remained more variable and sensitive to attentional re-engagement demands.

Building on these quantitative patterns, the subsequent stage of analysis aimed to contextually interpret these differences examining what task, environmental, or behavioral conditions supported efficient recovery and why certain episodes, particularly blinks, exhibited delayed or incomplete return to baseline. This phase integrates observational insights with the quantitative findings to better understand how specific site contexts and task characteristics influence the recovery process. For each eye-movement metric, fifteen representative episodes were selected for contextual analysis yielding a total of forty-five episodes. These episodes were distributed across the main quartile ranges, including samples from Q1, the median, Q3, the upper-whisker threshold, and additional high-magnitude cases located between Q3 and the upper whisker. This selection ensured that the analysis captured the full spectrum of recovery behaviour from stable, low-magnitude fluctuations to extreme spikes allowing meaningful comparison of task contexts across different stability levels.

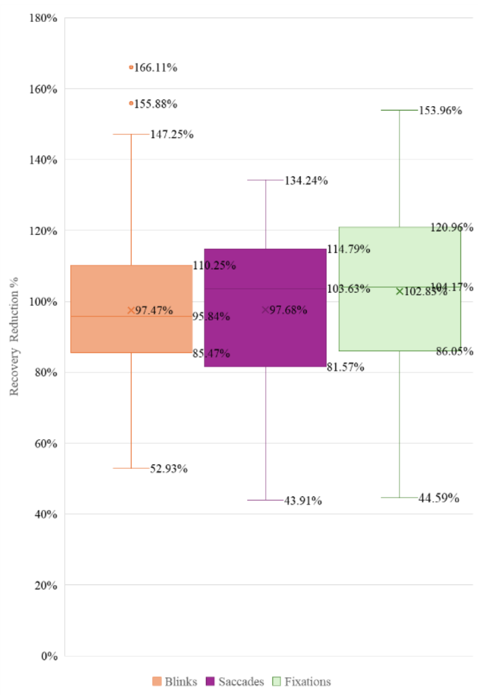

Figure 4. Distribution of recovery reduction (%) across blinks, saccades, and fixations. Higher percentages indicate more efficient return to baseline Z-MAD values following a spike

Table 1 presents the contextual distribution of recovery reduction % across fixation, saccade, and blink metrics. Lower deviation bands (close to Q1) indicate limited reduction in the metric and therefore poorer recovery, whereas higher bands (Q3, between Q3 and upper whisker, and upper whisker) represent stronger normalization back toward or beyond baseline. For blinks, low recovery appeared during failed-lift rework, end-of-task wrap-up, and finishing filing, suggesting lingering cognitive strain or fatigue even after the immediate spike had passed. For fixations and saccades, Q1 episodes included seemingly routine actions such as cutting and filing, putting tools away, and aiding the lift, as well as coordination in confined space. These results imply that even "routine" tasks can mask moments where the worker does not fully restabilize possibly due to subtle uncertainty, time pressure, or physical fatigue.

In contrast, episodes around the median and Q3 generally showed more effective recovery, reflecting situations where the worker experienced a noticeable spike in demand but then successfully settled back into a stable pattern. These included getting or handling tools, filing after cutting, remeasuring and recalculating after a failed lift, and receiving or giving verbal instructions. In these instances, the worker is clearly processing information or correcting errors, but the system is able to "reset" reasonably well, indicating that the task is demanding yet still manageable within their cognitive capacity.

The high recovery bands between Q3 and the upper whisker, and at the upper whisker itself, were predominantly linked to high-stakes, coordination-intensive contexts including working at height, attaching or hooking the cable tray to lifting ropes, coordination with another worker, discussion over drawings with a supervisor, and traveling to or moving across the site. Despite these being complex and safety-critical activities, the metrics show very strong recovery, meaning that after a spike, the worker rapidly re-stabilizes their visual behaviour. This pattern suggests that when tasks are highly scripted, well-practiced, or strongly constrained by safety routines or supported by a coworker or a supervisor, the worker can experience sharp but short-lived peaks in cognitive load followed by efficient recovery back to controlled, stable visual patterns.

Table 1. Representative on-site task contexts associated with different deviation ranges across eye-movement metrics.

Recovery reduction %	Fixation episodes	Saccade episodes	Blink episodes
Close to Q1	Routine cutting/filing; tool put-away; brief tool handling; lift support	Lift support; coordination; confined space	Rework; site departure; task finishing; tool placement
Close to median	Tool retrieval; tool handling; post-cut filing; minor correction	Remeasurement; recalculation; filing; tool handling	Confusion; remeasurement; recalculation; departure; task finishing
Close to Q3	Extended filing; remeasurement; post-flip cutting; lift support	Initiation and verbal instruction, Failed lift	Initiation; verbal instruction; coworker communication; rope attachment
Between Q3 and upper whisker	Confined-space coordination; confusion; tray hooking; tool retrieval	Site travel; coworker communication; tool retrieval; return movement	Coordination; ladder climbing; work at height; drawing discussion; supervision
Upper whisker	Calculation check; coworker coordination; tray hooking	Site travel; tool return; carry preparation	Rope attachment; tray lowering; remeasurement coordination

5 Discussion

The observed differences in recovery durations across the three eye-movement metrics reveal distinct mechanisms of cognitive stabilization following fluctuations in task demand. The much longer and more variable recovery times for blinks indicate that depletion-related processes such as fatigue, effort restoration, or transient disengagement require substantially more time to normalize compared to rapid, attention-driven adjustments reflected in fixations and saccades. In contrast, the compact distributions of fixation- and saccade-based recoveries suggest a more adaptive and self-correcting visual system, capable of restoring attentional stability almost immediately after short bursts of complexity. This study was designed as a field-based case study to examine the feasibility of measuring cognitive recovery during real construction work using wearable eye-tracking and synchronized scene-video data. Because the analysis is based on one experienced electrician, the findings should be interpreted as exploratory rather than broadly generalizable. Recovery dynamics are expected to vary across workers depending on factors such as experience, work strategy, fatigue susceptibility, and task familiarity Accordingly, the present results should be viewed as an initial proof of concept that demonstrates the analytical potential of recovery-based metrics in authentic construction settings, while future studies should test the robustness of these patterns across a larger and more diverse worker population.

From a cognitive standpoint, this pattern implies that task-driven attentional shifts recover faster than resource-driven depletion signals. When the worker momentarily increases focus or redirects gaze due to a new visual stimulus, the worker can stabilize quickly; however, when attention is drained or prolonged effort accumulates, as captured by blink behavior, the recovery process is slower and less predictable. This distinction supports the view that blinks serve as an indicator of overall cognitive fatigue rather than localized information-processing effort.

The box plot (Figure 3) illustrate recovery durations across eye-movement metrics provides insights into the temporal dynamics of visual and cognitive stabilization following workload fluctuations. The markedly higher and more variable recovery times observed for blinks suggest that blink behavior is more sensitive to transient increases in cognitive load, possibly reflecting greater demands on attentional disengagement and re-engagement processes. In contrast, the shorter and more consistent recovery observed for saccades and fixations indicates that these micro-movements rapidly stabilize once cognitive demand decreases, aligning with previous findings that link efficient gaze control to lower cognitive strain and task familiarity. The pronounced right-skew in blink recovery further implies that, under certain task conditions, visual recovery may be momentarily disrupted potentially due to information overload, environmental distractions, or task complexity. Collectively, these results suggest that while blink recovery serves as a strong indicator of cognitive effort and fatigue, saccadic and fixation behaviors may reflect more immediate adaptation and sustained visual control during natural work performance.

While some episodes with 0% recovery reduction were initially considered for exclusion, they were retained because they hold meaningful cognitive implications. The presence of near-zero recovery in blinks and saccades reflects moments of difficulty in visual or cognitive stabilization which is likely linked to fatigue (for blinks) and confusion or reorientation (for saccades) immediately following a cognitive spike. These instances capture the natural variability in workers' ability to regain focus after demanding visual events. In contrast, the lower recovery boundary of fixations (~44.6%) still indicates an active visual control process rather than complete lapse, which may represent germane cognitive load (the productive mental effort associated with processing task-relevant information). Thus, maintaining these low-recovery episodes enriches the interpretation by differentiating between maladaptive cognitive strain and constructive task engagement during recovery dynamics.

For the qualitative contextual analysis, the gradient from Q1 (poor recovery) to upper whisker (very strong recovery) tracks how well the worker and task environment support recovery after demanding moments. Low recovery in otherwise routine or end-of-task actions may flag hidden friction points where redesign, clearer cues, or better workflow could improve stability. Conversely, the strong recovery observed in many high-risk coordination tasks indicates that well-structured procedures and communication can enable rapid re-stabilization, even under complex conditions. This supports the use of recovery reduction % as a positive indicator of robustness in cognitive and visual control, rather than treating all high spikes as problematic in themselves.

6 Conclusion and Future Work

This study examined cognitive recovery dynamics during construction tasks by analyzing recovery durations and recovery reduction percentages across three eye-movement metrics: blinks, saccades, and fixations. The results demonstrate clear differences in the temporal and magnitude-based characteristics of recovery, with blinks exhibiting the longest and most variable return to baseline, while saccades and fixations showed markedly shorter, more consistent stabilization. These findings indicate that resource-driven fatigue processes reflected in blink behavior recover more slowly than the attention-driven adjustments captured by saccadic and fixation movements.

The contextual analysis further showed that recovery performance is strongly influenced by task characteristics and situational conditions. Episodes associated with routine or end-of-task activities frequently demonstrated limited recovery, whereas tasks involving structured coordination, procedural clarity, or collaborative interaction corresponded with more efficient stabilization. This suggests that recovery dynamics are sensitive to both cognitive demands and the organizational properties of the work environment. The analysis contributes to a more comprehensive understanding of how cognitive load normalizes following transient increases in by integrating quantitative recovery metrics with contextual observations. These insights have implications for task design, workflow structuring, and the development of cognitive-aware support systems aimed at improving performance and reducing unnecessary cognitive strain in construction operations.

This study has several limitations. First, the analysis is based on a single experienced worker, which limits the generalizability of the findings. Second, the observed recovery patterns may be influenced by the specific task mix, site conditions, and worker-specific strategies present during the recorded session. Third, although synchronized scene-video supported contextual interpretation, the qualitative mapping of task context remains observational and should be expanded in future studies with broader samples. Future research will extend this analysis by replicating the study across a larger and more diverse sample of workers, tasks, and site conditions to strengthen generalizability and examine inter-individual variability in recovery dynamics. Expanding the range of construction activities will enable assessment of whether the patterns observed here persist across varying levels of task complexity, environmental uncertainty, and production pressure. In addition, subsequent work will focus on systematically identifying and characterizing the negative contextual factors that precipitate cognitive spikes to complement the present study's emphasis on stabilizing conditions. Integrating both the positive and negative determinants of cognitive fluctuation will support the development of more comprehensive models of cognitive regulation in construction work and inform the design of task environments that mitigate overload while enhancing recovery efficiency.

Acknowledgements

This work was funded by the Natural Sciences and Engineering Research Council of Canada (NSERC) through the grant titled "Construction-Oriented Digital Twins for Multi-Dimensional Production Planning and Control" (ALLRP 578484-22).

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