Exploring Cognitive Load and Task Complexity in Dynamic Tracking Tasks: Insights for Construction Workflows

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Abstract -
Construction tasks involve dynamic and visually demanding activities that require continuous monitoring, tracking, and decision-making. These demands can overwhelm workers' cognitive capacity and increase mental strain and reduce efficiency. This study combines two cognitive load assessment methods: objective cognitive load assessment using wearable eye tracking and task-based performance analysis by calculating performance error. It examines the impact of complexity in dynamic tracking tasks on performance and cognitive load. The metrics include blink rate, fixation rate, saccadic amplitude, saccadic peak velocity, saccadic mean velocity, and tracking error. Saccadic amplitude showed a strong positive correlation ($r = 0.891$) which reflect the need to scan broader areas for higher visual complexity. In contrast, saccadic peak velocity ($r = -0.96$), blink rate ($r = -0.967$), and fixation rate ($r = -0.671$) demonstrated negative correlations with task complexity, which suggests increased cognitive demands and a prioritization of accuracy over speed. Saccadic mean velocity showed minimal correlation ($r = -0.07$), which suggests it might not be a sensitive metric for evaluating the impact of task complexity. Performance error was measured as the Euclidean distance between gaze and target, and it revealed a strong positive correlation with task complexity ($r = 0.967$). It indicates reduced performance as complexity increased. These findings highlight the significant impact of complexity on cognitive and visual performance. This is particularly relevant in construction tasks that require continuous monitoring, tracking, and visual processing. Understanding these relationships helps optimize construction workflows, reducing cognitive strain, improving efficiency, and enhancing safety in visually demanding tasks.

Keywords –
Task complexity, Cognitive load, Visual processing, Eye tracking metrics, Dynamic tracking

1 Introduction

Construction tasks are inherently dynamic and visually demanding. This requires workers to continuously monitor, track, and make decisions under challenging conditions. These tasks often involve processing complex visual information while maintaining high levels of accuracy and speed. The cognitive and visual demands of such tasks can overwhelm workers, leading to mental strain, decreased performance, and an increased likelihood of errors. Cognitive load refers to the mental effort required to process information, solve problems, and make decisions [1, 2] . It is influenced by task complexity, time constraints, and environmental factors [3]. Understanding how cognitive load and task complexity impact performance is critical to optimize construction workflows and improve workers’ safety and productivity.

To optimize cognitive load, we first have to measure it. Three methods can be used to measure cognitive load which are subjective, objective, and task- and performance-based techniques[4]. Subjective measurement methods rely on self-reporting tools like the NASA Task Load Index (NASA-TLX) [5], the Subjective Workload Assessment Technique (SWAT), and the Cognitive Task Load Analysis (CTLA) [5]. These approaches involve participants rating their mental workload on predefined scales. However, these methods can be limited by individual biases and interruptions to workflow which reduce their reliability and practicality. Objective measurement techniques utilize physiological indicators to assess cognitive load. It includes monitoring heart rate variability (HRV), brain activity via electroencephalogram (EEG), eye activity, cortisol levels, and skin conductance [4]. This method provides real-time, less-intrusive approach to quantify cognitive load. The task and performance-based technique is usually implemented in experimental studies to supplement wearable sensors and support the results. It assesses cognitive load by measuring task performance through metrics like reaction time, accuracy and error rate [6].

EEG is a widely used tool for assessing cognitive load in construction [7]. However, its application in real-world scenarios is constrained by challenges such as the requirement for controlled environments [8]. Eye-tracking technology is gaining traction as a practical alternative for evaluating cognitive load in construction settings [9, 10] because of its adaptability in the dynamic construction setting. Unlike EEG, its less invasive, portable, and less sensitive to artifacts from the external environment. Previous studies have established that cognitive load influences visual behavior with metrics such as fixation rate, blink rate, saccadic peak velocity, pupil dilation, and saccadic amplitude[11, 2, 12]. However, there is limited research on how these metrics interact in the context of dynamic tracking tasks coupled with varying complexities commonly encountered in construction. This study aims to fill this gap by evaluating the relationship between task complexity and cognitive load in dynamic tracking tasks using eye-tracking data. These findings will contribute to the development of strategies to reduce cognitive strain, enhance tracking performance, and optimize workflows in visually intensive construction tasks.

2 Literature Review

2.1 Cognitive Load and Its Impact on Construction

In the construction industry, cognitive load plays a significant role in determining workers' efficiency, decision-making [12] and safety [13]. A study by Kwon et al (2024) highlight the risks posed by cognitive overload in safety-critical situations as a result of multiple safety signs. The study concluded that excessive cognitive demands reduce workers' ability to process visual warnings effectively, particularly when more than nine items are displayed [14]. Mitropolus and Memartian (2013) [15] examined the dimensions of task demands in masonry work. They divided it to mental, physical, and temporal demands and studied their implications on performance and management strategies construction. The study provided evidence that high task complexity and temporal pressures are critical factors contributing to mental overload and reduced attentiveness, which can lead to errors, rework and safety incidents on construction sites. They proposed practical management strategies, such as reducing the task design complexity that creates high physical or mental demands. Memarian et al., (2012)[16] identified work practices that balance high productivity and safety while errors in construction tasks through a case study that analyzed the work practices of a high-reliability field supervisor in a concrete construction project. The findings emphasized the importance of reducing task complexity and aligning high-demand tasks with highly skilled workers. However, the correlation between task complexity in visual tracking tasks and the corresponding impact on cognitive load remains unexplored in literature. Even though several studies have highlighted the impact of task complexity on performance through subjective methods or through wearable sensors, the studies quantifying the impact of task complexity on cognitive load and performance is still lacking.

2.2 Cognitive Load Measurement in Construction

Subjective self-reporting methods have been deployed to assess mental fatigue and cognitive load in construction by Zhang et.al.(2013) [13] using Fatigue Assessment Scale for Construction Workers (FASCW). Others have used NASA Task Load Index (NASA-TLX) to assess cognitive load [14]. However, these subjective methods were proven to bias due to individual variability and recall bias due to participants' reliance on their memory to report their experiences [18]. To overcome this, researchers have shifted towards using objective methods using advanced wearable sensors to measure cognitive load. These sensors measure physiological responses due to cognitive load such as Electroencephalography (EEG), wearable eye trackers, and physiological metrics recorders to objectively measure cognitive states in construction environments [20, 21, 22, 23].

A systematic literature review was conducted by Jamil Uddin et al., (2024) [7] on using technologies to measure mental fatigue of construction workers. The authors reported that EEG was one of the commonly used tools to assess cognitive load in construction. However, EEG has a limited applicability in construction setting due to its sensitivity to the external environmental factors, such as head motions and electromagnetic interferences. Eye tracking has been emerging as an alternative practical measurement to cognitive load [20, 21]. However, research quantifying the relationship between task complexity, performance and cognitive load for dynamic tracking tasks using site-friendly wearable sensors is still lacking. Therefore, this study aims to explore and quantify the impact of task complexity on cognitive load and performance using wearable eye trackers in dynamic tracking tasks.

3 Methods

3.1 Task Design

The experiment will employ a within-subject design where participants perform three identical tasks with one controlled variable "task complexity". This controlled setup ensures that differences in the eye metrics are highly attributable to the varying task complexity. A dynamic task was designed to evaluate participants' ability to track a moving gaze point by displaying a dot that follows a predefined path at three varying speeds. This is particularly important in construction, where workers need to track moving objects, process dynamic visual information, and maintain situational awareness. Deficiencies in situational awareness are a major contributor to workplace accidents, as shown by 28,512 lost-time injuries reported in 2023 [23]with majority of incidents resulting from workers being struck by or caught in objects and equipment**.** These accidents often stem from difficulties in effectively tracking moving objects. For instance, tasks such as crane operations, vehicle maneuvering, and heavy equipment handling require precise visual tracking of moving targets to ensure safety and efficiency. This study aims to capture fundamental visual-cognitive processes that underlie real-world construction tasks by isolating tracking ability in a controlled experiment. The results can inform strategies for reducing cognitive overload and improving workers' ability to maintain focus in complex environments. Level 1 represents the baseline condition and Levels 2 and 3 indicate increasing levels of complexity. The tasks were presented in a randomized order to minimize bias from learning effects. A black background was used as it provides higher contrast with a brightly coloured moving dot (bright green). Green is considered less harsh on the eyes compared to red or blue, making it a good choice for tasks that require sustained tracking.

3.2 Data Collection

The study employs objective and task and performance-based measurement methods of cognitive load. Five metrics were collected which include blink rate (blinks/sec), fixations rate (fixations/second), saccadic amplitude (px), saccadic peak velocity (px/sec), and saccadic mean velocity (px/sec). Also, gaze coordinates were collected to calculate the average distance between the participants' gaze points and the actual target coordinates by calculating Euclidean distance. All metrics were recorded continuously during each trial using Pupil Invisible Eye Tracking Glasses by Pupil Labs. The eye tracking glasses collects gaze data at 200 HZ, fixations, saccades, blinks, RGB scene video at 30 Hz using a detachable scene camera and gaze mapping. Pearson correlation coefficient was calculated to assess the correlation between task complexity and the metrics.

A total of seven graduate students voluntarily agreed to participate after signing informed consent forms with the option to withdraw two weeks after data collection without consequences. 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. The participants were asked to as accurately as possible follow the moving object. The sample size aligns with similar studies using physiological metrics [13]. In eye-tracking studies, similar sample sizes have been commonly used due to the exhaustive nature of data collection and analysis, as well as the high accuracy of the observed trends [10].

3.3 Data Analysis

To measure the impact of cognitive load on eye movement, five different metrics were calculated. These metrics include saccadic peak velocity (px/s), saccadic amplitude (px), saccadic mean velocity (px/s), blink rate (blink/second), and fixation rate (fixation/second). The metrics were measured for the three different task complexities for each participant. This enabled the comparison of each participant's metrics that reflect his corresponding cognitive load given the varying task complexity. Also, the performance of each participant was calculated by the average Euclidean distance between the gaze and target points for the three complexities. Furthermore, to understand the correlation between the metrics and task complexity, Pearson correlation coefficient was calculated.

4 Results and Discussion

4.1 Eye tracking metrics analysis

4.1.1 Saccadic Peak Velocity (px/s)

Saccadic peak velocity is an essential metric in eye-tracking research as it represents the speed and effectiveness of eye movements during saccades. It is the highest speed achieved by the eye during a saccadic movement. Figure 1 shows the results across all subjects in three tasks of varying complexity. The figure shows that saccadic peak velocity decreases systematically as task complexity increases for all participants. The baseline condition (Level 1) exhibits the highest saccadic velocities which indicates minimal cognitive strain and higher efficiency in executing saccades. Our results reveal a strong negative correlation between task complexity and saccadic peak velocity with an average Pearson correlation coefficient of -0.96. This indicates an inverse relationship between task complexity saccadic peak velocities. It could possibly be because participants prioritize accuracy over speed when visual demand increase.

These findings aligns with existing research which highlighted that saccadic peak velocity decrease as mental load and task complexity increase[11, 24]. And have been reported as an effective measurement for mental load variations in complex tasks [26, 27].

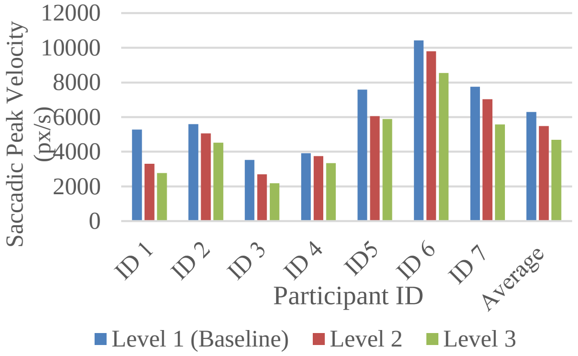

Figure 1. Saccadic Peak Velocity Across Task Complexity Levels

It should be noted that there is variability in saccadic peak velocity across participants. For example, ID 6 consistently exhibits the highest velocities across all levels, while IDs 3 and 4 have relatively lower values. This variability could be attributed to differences in individual cognitive capacity, visual acuity, or familiarity with the task.

4.1.2 Saccadic Amplitude (px)

Saccadic amplitude is the distance the eye travels during a single saccadic movement. Figure 2 presents saccadic amplitude (in pixels) across three levels of task complexity for seven participants (ID 1 to ID 7). The average amplitude is calculated for each level to provide insights into general trends. The average saccadic amplitude increased as task complexity increased. This indicates that participants made larger eye movements as task complexity increased this could be due the need to scan broader areas or manage more challenging visual demands. There is significant variability among participants. ID 6 consistently exhibits the largest amplitudes across all levels, with a sharp increase from 97.73 px (Level 1) to 169.45 px (Level 3). ID 1 and ID 7 show smaller amplitudes compared to others, with more modest increases between levels. The variability suggests individual differences in visual search strategies, task adaptation, or cognitive effort.

It can be observed that saccadic peak velocity decreased with task complexity while saccadic amplitude increased. However, saccadic peak velocity has been sought to typically increase with the amplitude of eye movements, a relationship known as the main sequence[27]. This relationship is generally considered fixed but can be modulated by external factors such as incentives and motivation[28]. If a task involves scanning a visually complex scene under cognitive strain, participants might make longer saccades to cover larger areas while slowing their saccadic velocity to ensure accuracy[29].

Also, our results show a strong positive correlation between task complexity and saccadic amplitude with an average Pearson correlation coefficient of 0.896. This indicates that saccadic amplitude increases significantly as task complexity increases. This results in longer saccades which lead to an increase in saccadic amplitude. Under cognitive strain, the brain often prioritizes accuracy over speed. This trade-off can cause a reduction in saccadic peak velocity, even as the amplitude increases as reported in our findings. This behaviour aligns with findings that saccadic metrics, such as peak velocity, can vary under cognitive load, while amplitude adapts to task demands[23].

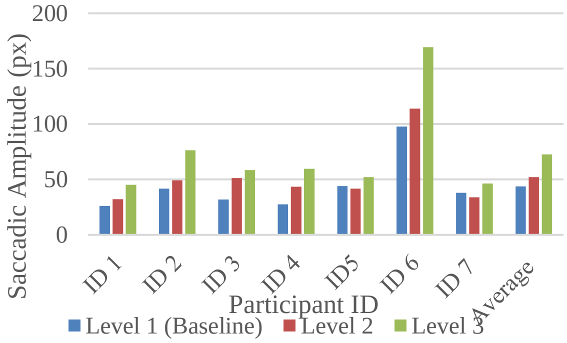

Figure 2. Saccadic Amplitude Across Task Complexity Levels

4.1.3 Saccadic Mean Velocity (px/s)

Saccadic mean velocity is the average speed of the eye during a saccadic movement. Figure 3 shows the saccadic mean velocity across all participants. The average mean velocity decreases as task complexity increases with an overall reduction of 7.26% from Level 1 to Level 3 which indicate that participants generally slow their saccades as task complexity rises indicating higher cognitive demand.

ID 3 shows a consistent increase in velocity across levels, moving from 1432.04 px/s in Level 1 to 1946.94 px/s in Level 3. ID 2 followed a similar trend. This suggests that ID 2 and 3 adapts to increasing task complexity by speeding up their saccadic movements, contrary to the general trend. ID 6 mean velocity increased from Level 1 to Level 2 suggests that ID 6 may approach intermediate complexity with higher efficiency or speed. ID 4 maintains relatively steady velocities which indicate a consistent visual and cognitive strategy across all task levels.

Our findings show a weak negative correlation between saccadic mean velocity and task complexity with an average Pearson correlation coefficient of -0.077. While the overall trend shows a decrease in mean velocity with task complexity, the substantial variability among participants weakens its reliability as a robust indicator of cognitive load. This is in line with existing research that suggest [26, 31] that task complexity had no effect on saccadic mean velocity.

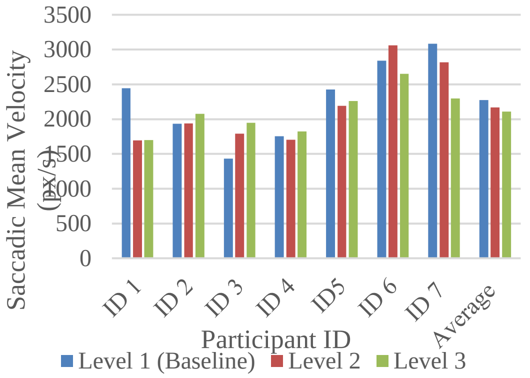

Figure 3. Saccadic Mean Velocity Across Task Complexity Levels

4.1.4 Blink Rate (Blinks/second (Hz))

Another indicator for cognitive load is blinking rate. Figure 4 shows the blinking rate for the seven participants across three levels of task complexity as well as their average. The average blink rate decreases consistently from 1.23 blinks (Level 1) to 0.96 (Level 2) and 0.7 (Level 3) as task complexity increases. Also, our results showed a strong negative correlation between blink rate and task complexity with an average Pearson correlation coefficient of -0.967. This indicates that blink rate decreases significantly as task complexity increases.

This reflects increasing cognitive demand as reduced blinking is commonly linked to increased focus and engagement. Blink rate varies among participants due to individual differences which is why a baseline was established. Despite these variations all participants showed a downward trend and a strong negative correlation coefficient. This aligns with previous research [33, 34] and reinforcing blink rate's reliability as a measure of cognitive load and its strong linkage to task complexity.

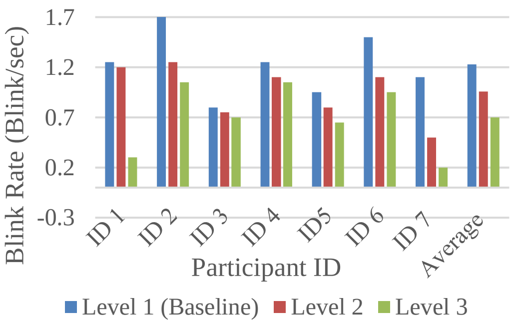

Figure 4. Blink Rate Across Task Complexity Levels

4.1.5 Fixation Rate (Fixations/Second (Hz))

Fixation rate refers to the frequency of fixations made by the eye per unit of time during a task. A fixation occurs when the eye stops moving and focuses on a single point to gather visual information. Fixation rate is typically expressed as fixations per second (Hz) and is a key metric in eye-tracking research. Figure 5 presents data for seven participants across three levels of task complexity with their individual values and overall averages provided for each level. The average fixation rate values decreased as task complexity increased. Also, our results indicate a moderate negative correlation between fixation rate and task complexity with an average Pearson correlation coefficient of -0.671.This aligns with trends seen in cognitive load research, where participants tend to adapt their behaviour as complexity rises and prioritizing precision over speed [2, 35]. All participants showed the same trend except for ID 5 who showed a slight upward trend which might indicate individual variability as adaptation or improved efficiency to handle complexity

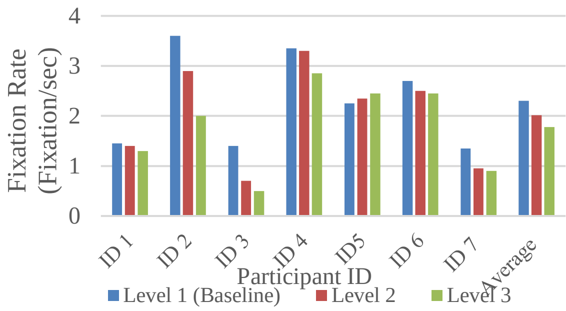

Figure 5. Fixation Rate Across Task Complexity Levels

4.2 Participants' Performance Evaluation

The impact of task complexity and cognitive load on performance was assessed by measuring the average distance between the participants' gaze points and the actual target coordinates. This measurement shows how accurately participants tracked the stimuli as the complexity of the task increased. A higher distance indicates higher error in tracking performance. It indicates that participants found it harder to keep their gaze aligned with the target as tasks became more challenging. The results align with this trend, with higher distances seen at higher task complexity levels.

Figure 6 represents the average Euclidean distance between gaze points and the actual coordinates of the stimuli for seven participants across three levels of task complexity. The Euclidean distance increased consistently as complexity increased. This indicate that as task complexity rises participants experience more difficulty tracking stimuli accurately. While the average trend supports this relationship, individual differences highlight variability in participants' ability to adapt to cognitive and visual demands. This suggests that tracking performance under complex tasks is influenced by both task characteristics and individual capabilities.

Our results show a very strong positive correlation between Euclidean distance and task complexity with an average Pearson correlation coefficient of 0.967. This supports our findings that tracking error has a direct relationship with task complexity.

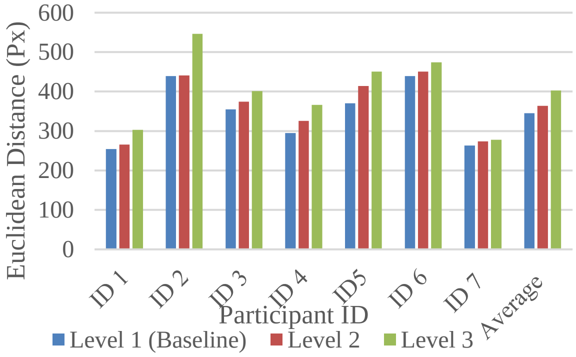

Figure 6. Euclidean Distance Across Task Complexity Levels

5 Insights for Construction Workflows

This study highlights the impact of visually demanding tasks on cognitive load and consequently performance. This could be particularly relevant to tasks of complex demand that require continuous monitoring, tracking, precise focus, and rapid decision-making based on visual information. This could include operating heavy machinery, rigging and lifting operations, welding and cutting, working at heights, and installation tasks.

Table 1 outlines specific recommendations for optimizing construction workflows based on findings from eye-tracking metrics and cognitive load analysis. Each recommendation is directly supported by observed data trends. This table provides actionable recommendations based on insights from cognitive load and eye-tracking metrics. By addressing specific challenges like task complexity, visual distractions, and worker fatigue, these strategies can enhance safety, productivity, and efficiency in construction workflows. Each recommendation is supported by findings that directly link eye-tracking data to cognitive performance under varying task complexities.

Table 1. Insights for Construction Workflows

Recommendation	Support by Findings
Focus on Reducing Task Complexity	Higher Euclidean distances indicate that increased task complexity reduces tracking accuracy. Construction tasks should be simplified where possible by breaking them into smaller, manageable steps to reduce cognitive load and improve worker precision.
Enhance Training for High-Complexity Task	Participants who showed increased errors at higher complexity levels highlight the need for specialized training.
Design Visual Environment	The findings suggest that visual demands influence performance. Construction workflows should minimize unnecessary visual distractions and use clear, standardized markings to guide workers' attention, ensuring accurate tracking of critical elements.
Leverage wearable sensors to monitor workers cognitive load	Metrics like blink rate, fixation rate, peak velocity reflects how task complexity impact cognitive load. Real-time monitoring could identify high-stress periods and offer feedback to enhance accuracy.
Monitor Worker Performance and Adjust Workloads	Significant differences in metrics like mean velocity and tracking performance highlight the need for personalized task assignments.
Incorporate Rest Breaks in Workflows	Reduced blink rates at higher complexity could reflect visual fatigue which can be mitigated with rest breaks.

6 Limitations and Future Work

The study revealed significant individual differences in metrics like saccadic mean velocity, fixation rate, and tracking performance. These variations limit the ability to generalize findings across a broader population. Also, experiments were conducted in a controlled setting which may not fully replicate the dynamic and unpredictable nature of real-world construction sites. The participant pool was relatively small, which may not provide sufficient statistical power to generalize results to all workers in construction or other fields. Furthermore, the study tasks were simplified representations of real-world construction workflows. More complex or nuanced tasks could yield different cognitive load and performance patterns. While metrics like blink rate, fixation rate, and saccadic velocities were useful, they may not capture all dimensions of cognitive load. Other physiological indicators such as heart rate variability or pupil dilation, could provide additional insights.

7 Conclusion

This study examined the impact of task complexity on cognitive load and performance in construction workflows using eye-tracking metrics. These metrics include blink rate, fixation rate, saccadic amplitude, saccadic peak velocity, saccadic mean velocity, and tracking accuracy (Euclidean distance). The findings provide insights into how workers respond to visually and cognitively demanding tasks.

The findings indicate that blink rate decreased with increased task complexity which could reflect higher cognitive load. Fixation rate and saccadic amplitude increased which suggests higher visual processing demands and the need to scan broader areas as task complexity increased. Saccadic peak velocity decreased which align with previous research that indicates a compensatory mechanism to prioritize accuracy over speed in complex scenarios. Saccadic mean velocity showed significant individual variability and a weak correlation coefficient; therefore, it's a less reliable metric for measuring cognitive load across participants. The participants' tracking performance was measured by Euclidean distance between gaze points and target coordinates. All participants showed higher error at higher complexity levels. This highlight reduced accuracy in visually challenging tasks. These results emphasize the strong relationship between task complexity, cognitive load, and performance.

Recommendations to enhance worker focus, accuracy, and safety include simplifying task designs, providing targeted training, leveraging wearable eye-tracking technology, and incorporating regular rest breaks. This research provides a foundational understanding of how cognitive and visual demands affect worker performance and offers actionable recommendations for optimizing construction tasks and improving workplace safety and efficiency.

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