COGNITIV
& TASK CO
Ensuring Worker Safety in C

By Mikias Gugssa, Mohammad Nafe Assafi, Jun Wang, Zhujun Pan and Jingdao Chen

SITUATIONAL AWARENESS is essential for worker safety in the architecture, engineering and construction (AEC) industry, as a lack of it can lead to human errors and unsafe behaviors. One main factor affecting situational awareness in daily activities is cognitive fatigue. However, there is very limited work that explores the impact of task complexity on cognitive fatigue. This pilot study examines the effect of task complexity on cognitive fatigue levels using assembly tasks in a controlled laboratory setting. In the experiment, engineering students assembled truss bridges from balsa wood under two experimentally defined complexity levels that differed in design, such as the number of joints and member lengths. A wearable electroencephalography (EEG) was used to capture the brain signals of participants, and cognitive fatigue indexes were computed from EEG data for each complexity level. Participants were also asked to complete the NASA Task Load Index (NASA-TLX; a questionnaire that measures cognitive workload across six factors) survey to evaluate their experience with the experiment. The authors found that higher cognitive fatigue corresponded with high-complexity tasks. Although the experiment was conducted with student participants in a nonconstruction setting, the tasks' spatial reasoning, fine motor demands and time pressure reflect the cognitive demands found in real assembly and other activities in the construction and broader AEC industries. This study provides insights into how task complexity can impact worker cognitive fatigue in safety-critical environments where sustained attention is common, which is expected to enhance effective hazard prevention and interventions to foster safer working environments.

KEY TAKEAWAYS

- **This study employed an electroencephalography (EEG) device to measure brain activities and assess cognitive fatigue, a significant factor leading to errors and unsafe behaviors in assembly tasks in the architecture, engineering and construction (AEC) industry. This article emphasizes the crucial role of cognitive fatigue assessment in ensuring workers' safety.**
- **This article provides insights into cognitive fatigue in assembly tasks with respect to task complexity. This knowledge enhances task design and allocation, ultimately enhancing safety and efficiency in AEC.**
- **The findings reveal a direct correlation between task complexity levels and cognitive fatigue, indicating that higher complexity tasks led to increased cognitive fatigue among participants. Future research could explore individual differences (e.g., age, gender, training level) and validate these findings in real working settings with more workers.**

Introduction

The AEC industry is facing a significant challenge from cognitive fatigue, as cognitive fatigue affects workers' decision-making process (Zhang et al., 2023). Studies have shown that cognitive fatigue can increase risk susceptibility, affect attention and awareness, and lead to unsafe behaviors, which can further threaten the safety of workers on sites (Xing et al., 2020). A report by the National Safety Council (2018) revealed that 97% of the workforce was affected by at least one workplace fatigue risk factor, with 80% experiencing two or more. Fatigue accounted for up to 13% of workplace injuries and affected 94% of construction workers.

To investigate worker cognitive fatigue, multiple methodologies and technologies were employed; these include subjective metrics such as the NASA-TLX (Chen et al., 2017; Li et al., 2019) and visual analog scale, cognition measures (e.g., reaction time and vigilance test) some physiological metrics (such as heart rate variability); technologies such as eye trackers and EEG have been explored for this regard (Melo et al., 2017; Noghabaei et al., 2021). Studies have identified biomarkers for cognitive fatigue in the human brain, particularly in the frontal, central and posterior regions (Tran et al., 2020). The findings of existing studies solidify the appropriateness of using EEG to monitor brain signals for cognitive fatigue assessment. Multiple studies have explored the impact of various factors such as age, sleep deprivation, stress, workload and gender on cognitive fatigue (Chen et al., 2022; Pergher et al., 2021; Wascher & Getzmann, 2014; Zhang et al., 2021). However, the relationship between task complexity or difficulty and cognitive fatigue remains ambiguous and unclear for assembly tasks in the AEC industry (Gu & Guo, 2022; Muñoz-de-Escalona et al., 2020; Xu et al., 2018). The knowledge and comprehension that exist regarding the association of task complexity with cognitive fatigue of workers is very limited, particularly for those workers engaged in assembly activities.

Therefore, this study examined how task difficulty could influence cognitive fatigue by utilizing EEG to measure participant brain activity while constructing bridges with balsa wood sticks. The experiment for this study involved high- and low-complexity tasks. The obtained findings enhance the understanding of cognitive fatigue in assembly tasks. Gaining insights into how task complexity could affect cognitive fatigue enables the optimization of workforce and task allocation, development of more targeted interventions, and enhancement of job-specific training in the AEC industry, ultimately enhancing both safety and performance.

E FATIGUE
OMPLEXITY
Construction & Engineering

Objective

This study explores how task complexity affects cognitive fatigue in assembly tasks to enhance the safety of workers. To achieve this goal, this study used EEG to test the hypothesis: workers experience higher levels of cognitive fatigue when undertaking assembly tasks at higher difficulty levels (compared to cases with lower difficulty levels). Examining this hypothesis offers deeper insights, such as identifying workers with high cognitive fatigue levels and reducing errors and unsafe behaviors. The knowledge gained may enhance task design and allocation, ultimately enhancing safety and efficiency in assembly and other activities in the AEC industry.

Methodology

Study Design

This study examines how task complexity affects cognitive fatigue during assembly-related tasks in the AEC industry. A controlled laboratory experiment was conducted with a small group of male engineering students as participants. Each participant completed two types of bridge assembly tasks categorized into low and high complexity, allowing the study to compare results within individuals. The tasks were designed with minimal body movement and lightweight balsa wood sticks to minimize the effects of physical motions on brain signals. The spatial reasoning, fine motor demands and time pressure required to perform the designed tasks in the experiment reflect the cognitive demands found in real assembly and other activities in the construction and broader AEC industries.

To assess cognitive fatigue, the study used two methods. First, an EEG device was used to capture and measure brain signals using electrodes placed on the scalp. The EEG signals were preprocessed to effectively remove noise caused by motion and other artifacts (Tehrani et al., 2022). Second, the NASA-TLX, a short survey, was administered to capture participant ratings of how mentally and physically demanding each task felt (Chen et al., 2017; Li et al., 2019). The results for low- and high-complexity tasks were compared using the Wilcoxon signed-rank test, a statistical method suitable for paired data in small samples. The study compared the paired samples to determine whether a significant difference in cognitive levels existed between low and high task complexity conditions, as well as whether high cognitive workload was associated with high-complexity tasks. The significance level for the hypothesis was set at $p = 0.05$.

EEG Data Collection, Preprocessing & Analysis

In this study, brain signals were collected using an Easycap SMARTING EEG cap with 24 electrodes (also called channels; Mbto, n.d.). Signals were sampled at 250 Hz (approximately 250 data points per second) while participants performed the tasks. Raw EEG data were cleaned to remove noise from eyeblinks, muscle movements, head turns and environmental interferences (Jebelli et al., 2018) and were then processed with the EEGLAB toolbox in MATLAB (Delorme & Makeig, 2004). The data cleaning steps involved a 0.5 Hz high-pass filter, automatically detecting and correcting brief disruptions, manual data inspection to ensure quality, and separating useful brain signals using independent component analysis (Chang et al., 2019; Wang et al., 2019).

NATALI_MIS/ISTOCK/GETTY IMAGES PLUS

EEG Channel Selection for Cognitive Fatigue

Although the EEG cap used in this study had 24 sensor locations, previous studies have identified the most effective channels for capturing cognitive fatigue. Therefore, this study used 13 channels: five over the frontal region, three in the central region, three in the parietal region near the top and back of the head, and two in the occipital region at the back of the head. By focusing on these four regions with the targeted channels, this study examined how task complexity affects cognitive fatigue.

Cognitive Fatigue Indexes

Electrodes on the cap measure EEG signals, indicating stress, burnout and cognitive fatigue (Wang et al., 2019). EEG signals have five basic wave bands, including delta (δ), theta (θ), alpha (α), beta (β), and gamma (γ; Li et al., 2019). Previous studies have shown that when people are cognitively fatigued, θ and α values increase, while β values decrease (Kar et al., 2010; Zhao et al., 2012). In addition to these basic indexes, ratio indexes such as θ/α, θ/β and (θ+α)/β have been used by several studies, which found that these indexes show increasing values when an individual experiences cognitive fatigue (Eoh et al., 2005; Jap et al., 2009). In this study, three basic indexes (θ, α and β) and three ratio indexes (θ/α, θ/β and (θ+α)/β) were used to provide insight into each participant's cognitive fatigue levels.

Sample Entropy

In addition to the basic and ratio indexes, this study also used sample entropy to assess cognitive fatigue. Sample entropy is another useful indicator in EEG signal analysis, quantifying the complexity and unpredictability of signals (Sharma et al., 2014). Specifically, cognitive fatigue impacts brain activities, slowing cognitive processes and attention, which results in more regular neural activity patterns, as evidenced by low entropy values (Richman & Moorman, 2000).

NASA Task Load Index

After each bridge assembly, participants filled out the NASA-TLX questionnaire to assess six aspects by rating them 0 (very low) to 20 (very high): mental demand, physical demand, temporal demand, performance, effort and frustration (Li et al., 2020). While EEG signal indexes offer objective measures of brain activities, the NASA-TLX captures the subjective experience of participants regarding these six aspects. The results from the EEG signal analysis were compared with the NASA-TLX scores to understand the relationship between perceived workload and measured cognitive load.

FIGURE 1
EEG CAP USED IN STUDY

Easycap EEG cap with 24 channels and wireless smarting device.

Experiment for Data Collection

The Institutional Review Board approved the experiment (protocol number 22-120). Ten male students in engineering from Mississippi State University participated in the experiment. They were required to have completed the Graphic Communications course and to abstain from caffeine and alcohol for at least 24 hours before the experiment. EEG caps were worn to monitor brain activities with a sampling rate of 250 Hz (Figure 1). Two types of bridge drawings were prepared: high-complexity and low-complexity bridge structures (Figure 2). The high-complexity bridge required more detailed work and took longer to build. Participants needed proficiency in interpreting complex drawings, measuring elements and understanding details relevant to the experiment tasks. Preliminary observation trials were conducted to determine the appropriate time for the experiment. Each experiment lasted 120 minutes, with 90 minutes dedicated to bridge building. The ten male participants performed high-complexity bridge and low-complexity bridge construction on separate days (i.e., each participant committed 4 hours to the experiment). Among them, five participants conducted the high-complexity task first, and the other five participants conducted the low complexity first. It is worth noting the significant difficulties in recruiting participants due to the long experiment duration, EEG cap setup challenges (e.g., hair did not work with the EEG gel), and the required skills. In fact, the authors recruited more than ten participants; however, the EEG setup was successfully completed for only ten. At the end of each experiment, participants completed the NASA-TLX questionnaire.

Data Analysis & Results

Effect of Task Complexity Levels on Cognitive Fatigue

Cognitive Fatigue Indexes

The analysis of basic indexes (θ, α and β) and the ratio indexes [θ/α, θ/β and (θ+α)/β] for both complexity levels are discussed for cognitive fatigue assessment. The Wilcoxon signed-rank test compared the median values of basic and ratio indexes between subjects in high- and low-complexity tasks. Table 1 presents the significant difference values (p) for the basic and ratio indexes. It was found that most of the p-values were less than 0.05, suggesting that there was sufficient evidence to support that cognitive fatigue in high-complexity tasks was significantly different from that in low-complexity tasks. In addition, as demonstrated in Figure 3 (p. 26), all channels exhibited elevated values of θ (indicating a higher level of cognitive fatigue) during high-complexity tasks as compared with low-complexity tasks. Previous studies demonstrated that higher values of θ/α, θ/β and (θ+α)/β indicated higher cognitive fatigue. The ratio indexes shown in Table 1 and Figure 3 [only (θ+α)/β is shown in Figure 3b due to limited space] demonstrated that higher cognitive fatigue levels were associated with the high-complexity tasks.

Sample Entropy

In sample entropy analysis, valuable information about the complexity and randomness of brain activity can be found. A lower degree of disorder in sample entropy values may indicate that a participant felt higher cognitive fatigue (Gao et al., 2019). In this study, the sample entropy for channels FP1, FP2, F3, F4, C4, FZ and CZ showed lower values in the high-complexity tasks compared to the ones in the low-complexity tasks, as shown in Figure 4 (p. 26). On the other hand, the sample entropy values were higher in the high-complexity tasks than in the low-complexity tasks for EEG channels C3, P3, P4, O1, O2 and PZ. The results show that the frontal region of the brain (FP1, FP2, F3 and F4), a region highly related to cognitive fatigue, had lower entropy values, indicating a higher cognitive fatigue level. In general, the observed entropy values for most channels showed higher cognitive fatigue in the high-complexity tasks.

NASA-TLX

The NASA-TLX questionnaire was given to participants after every experiment. The median, standard deviation (*SD*), and *p*-values of complexity levels for mental demand, physical demand, temporal demand, performance, effort and frustration are shown in Table 2 (p. 27). The median values for mental demand, performance and effort are higher for tasks with a high complexity level than those with a low complexity level. Conversely, while physical and temporal demand demonstrated equal median values, frustration exhibited a lower median value for the high-complexity tasks. Despite this, the Wilcoxon signed-rank test calculated *p*-values greater than 0.05 for all NASA-TLX indicators, suggesting no significant difference between the cognitive fatigue levels of participants in high- and low-complexity tasks.

Summary of Results & Discussion

This study shows evidence to support that high cognitive fatigue levels are generally associated with tasks with high difficulty levels. For example, high cognitive fatigue is often associated with higher values of θ, and increased values of θ/α, θ/β and (θ+α)/β are associated with higher cognitive fatigue [shown in Figure 3 (p. 26) and Table 1]. Furthermore, lower sample entropy values for high-complexity tasks indicated that more regular or ordered signals led to higher cognitive fatigue compared to the cases in low-complexity

FIGURE 2
BRIDGE DRAWINGS

Bridge drawings: High-complexity bridge (a) and low-complexity bridge (b).

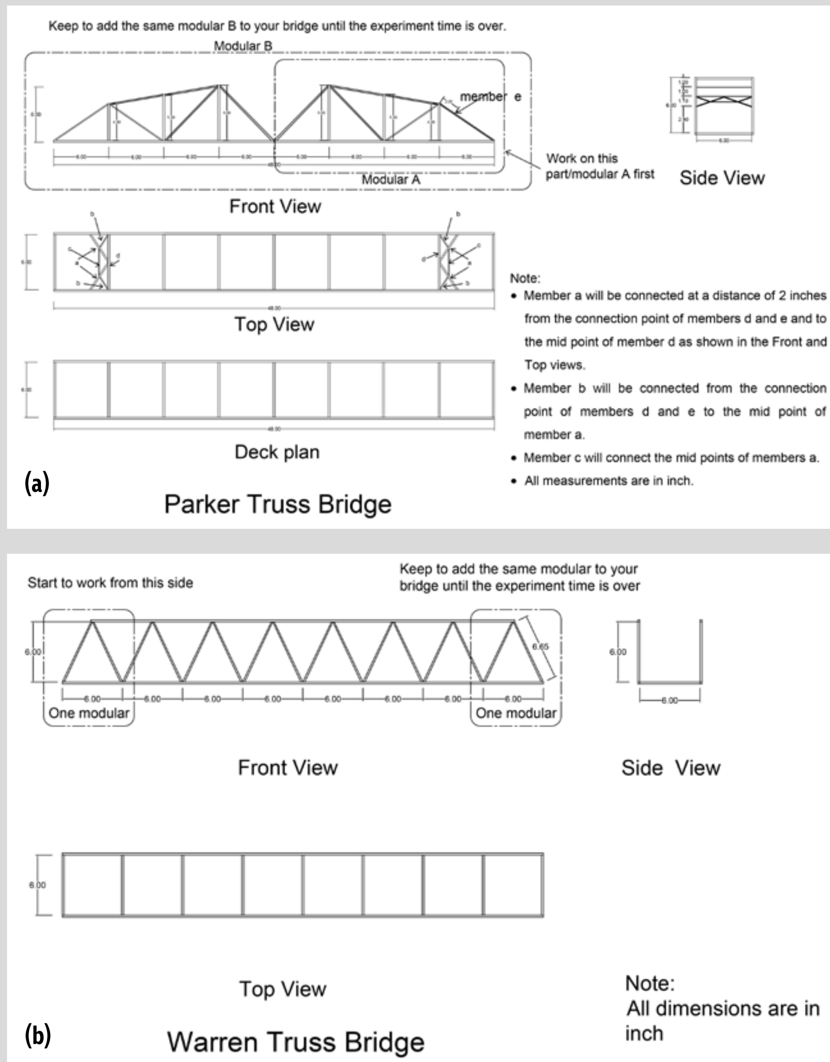


TABLE 1
WILCOXON SIGNED-RANK TEST RESULTS: *P*-VALUES

Index	FP1	FP2	F3	F4	C3	C4	P3	P4	O1	O2	FZ	CZ	PZ
θ	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.106	0.005
α	0.005	0.084	0.007	0.009	0.005	0.005	0.009	0.075	0.169	0.959	0.005	0.017	0.005
β	0.007	0.013	0.005	0.022	0.005	0.007	0.059	0.445	0.017	0.017	0.005	0.022	0.013
θ/α	0.005	0.005	0.005	0.007	0.005	0.005	0.005	0.005	0.005	0.022	0.005	0.005	0.005
θ/β	0.005	0.005	0.005	0.013	0.005	0.005	0.005	0.005	0.022	0.013	0.005	0.005	0.005
(θ+α)/β	0.005	0.005	0.005	0.037	0.005	0.005	0.007	0.007	0.139	0.028	0.005	0.005	0.005

Note. $p < 0.05$ indicates a significant difference, and $p > 0.05$ indicates no significant difference.

FIGURE 3
MEDIAN COMPARISON

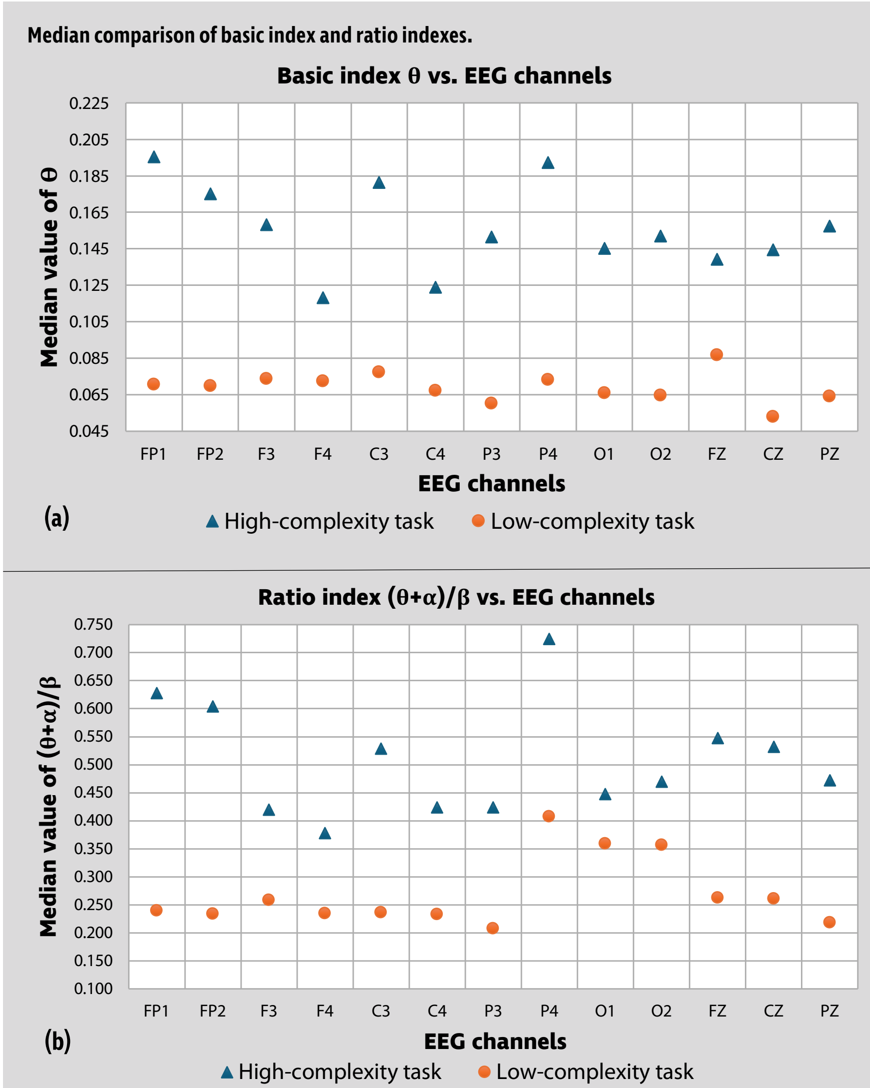
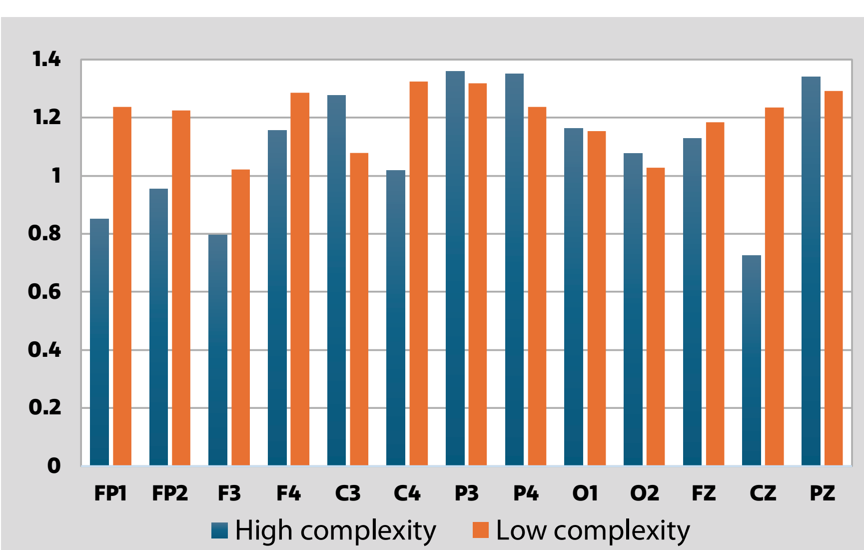


FIGURE 4
SAMPLE ENTROPY FOR THE SELECTED CHANNELS



tasks. The NASA-TLX outcomes showed that metrics such as mental demand, physical demand, temporal demand, effort and frustration had higher mean values for high-complexity tasks in participants, which aligned with the findings of cognitive fatigue indexes.

Understanding the relationship between task complexity and cognitive fatigue levels for assembly tasks has several practical implications (e.g., optimized task assignments and scheduling). Specifically, to enhance workers' safety, the following measures could be taken to reduce and manage their cognitive fatigue during work:

- breaking down complex tasks into smaller or manageable subtasks,
- allocating tasks based on workers' expertise to minimize unfamiliarity of complex tasks,
- conducting task rotation strategies or setting up breaks between subtasks,
- developing training for workers with complex tasks,
- scheduling high-complexity tasks during periods of peak alertness, such as earlier work shifts, and
- identifying tasks with high complexity and cognitive workload to implement additional safety measures.

Taking the construction context as an example, understanding how task complexity contributes to cognitive fatigue could enable construction managers and safety officers to implement evidence-based strategies to reduce cognitive-related risks. For example, site supervisors could rotate ironworkers who assemble steel frames from higher-complexity tasks (e.g., overhead welding of steel members) to lower-complexity similar tasks (e.g., installing and tightening bolts on steel members at ground levels) to reduce sustained high cognitive workload. Similar methods could be applied to other roles as well; for example, excavator operators working on high-complexity tasks such as a precision trench excavation near utilities could reduce cognitive fatigue by rotating to lower-complexity excavation tasks or by optimizing the work schedules.

These insights extend beyond general labor to roles such as project planners, quality inspectors and safety officers. In the AEC industry, for example, architects and design professionals are involved in high-complexity tasks such as creating complicated digital models and integrating multiple systems into designs. To reduce the cognitive fatigue for these design professionals, managers could methodically rotate the professionals to lower-complexity tasks or optimize breaks between tasks. Although wearing EEG equipment during daily work is challenging, with rapid technological advancements, combining EEG-based cognitive fatigue monitoring with supportive tools and safety protocols (such as real-time fatigue monitoring) remains highly promising for the future for effectively managing workers' cognitive fatigue and ensuring safer working environments.

In addition to task complexity, age is a factor affecting worker cognitive fatigue. In this study, all participants were undergraduate students within a very narrow age range, so the age factor was not considered. The experimental tasks were conducted in a controlled environment, not a real construction environment. For future studies, especially when testing the proposed methodology with workers in real construction tasks to validate and expand upon the obtained findings, age would be an important factor to consider. Also, all participants in this study were male students, which limits the generalizability of the results to the broader population, including women, people of diverse ages or experienced workers. The designed experiment in this study required participants to have graphical reading skills and involved a lengthy duration (240 minutes required), and the application of conductive gel on the scalp discouraged many from participating. As a result, the final sample size was small and limited to male students. This study originally included an exploration of the differences in cognitive fatigue levels between male and female participants (i.e., the gender factor) while performing the tasks at the same difficulty level. Although the authors actively recruited more female participants, the final sample size remained smaller than anticipated due to practical challenges (e.g., failed setup of EEG and applying gel and sensors to participants with long, thick hair). Thus, in this study, the outcome of gender differences with cognitive fatigue was not presented. For future studies, getting insight into the effect of gender-based differences on cognitive fatigue would also have practical implications in designing and assigning tasks in the AEC industry.

Moreover, each participant's performance in the bridge building was not considered while evaluating cognitive fatigue indexes, although the experiment required that all participants had completed the Graphic Communications course. In the future, participants' performance in completing tasks can be considered in cognitive fatigue analysis to get more in-depth insight.

TABLE 2
MEDIAN OF NASA-TLX

Median, *SD*, and *p*-value of NASA-TLX for high- and low-complexity tasks.

	Median			
Metrics	**High complexity**	**Low complexity**	***SD***	***p***
Mental demand	7.000	4.000	4.408	0.123
Physical demand	1.000	1.000	4.216	0.465
Temporal demand	5.000	5.000	5.626	0.767
Performance	9.000	7.000	3.765	0.859
Effort	10.000	6.000	5.350	0.405
Frustration	2.000	4.000	5.533	0.754

Conclusion, Limitations & Future Work

This study investigated the impact of task difficulty on cognitive fatigue for safety enhancement using a controlled experiment with assembly tasks. Researchers used an EEG device to detect brain activity in participants when they performed tasks continuously throughout the experiment. Basic and ratio indexes and sample entropy were used to measure brain activities during cognitive tasks for cognitive fatigue assessment. The outcomes indicate strong evidence that high cognitive fatigue levels are generally associated with higher complexity task levels. This study contributes to the knowledge by providing insight into the cognitive fatigue domain for workers engaged in different difficulty levels of tasks. The findings have the potential to enable the construction and broader AEC industries to optimize workforce allocation, lead to more targeted interventions and enhance job-specific training, ultimately reducing injuries and fatalities. PSJ

Acknowledgment

The authors gratefully acknowledge the financial support of the Deep South Occupational Safety and Health Education and Research Center at the University of Alabama at Birmingham for this research (Sponsor Award No.: 000535051-SP006-SC005). The views expressed in this article are those of the authors and do not necessarily reflect the views or policies of the sponsor.

References

Chang, C.Y., Hsu, S.H., Pion-Tonachini, L. & Jung, T.P. (2019). Evaluation of artifact subspace reconstruction for automatic artifact components removal in multi-channel EEG recordings. *IEEE Transactions on Biomedical Engineering, 67*(4), 1114-1121. https://doi.org/ggbrpc

Chen, Y., Fang, W., Guo, B. & Bao, H. (2022). The moderation effects of task attributes and cognitive fatigue on post-interruption task performance in a concurrent multitasking environment. *Applied Ergonomics, 102*, 103764. https://doi.org/10.1016/j.apergo.2022.103764

Chen, C., Li, K., Wu, Q., Wang, H., Qian, Z. & Sudlow, G. (2013). EEG-based detection and evaluation of fatigue caused by watching 3DTV. *Displays, 34*(2), 81-88. https://doi.org/10.1016/j.displa.2013.01.002

Chen, J., Taylor, J.E. & Comu, S. (2017). Assessing task mental workload in construction projects: A novel electroencephalography approach. *Journal of Construction Engineering and Management, 143*(8), 04017053. https://doi.org/10.1061/(ASCE)CO.1943-7862.0001345

Delorme, A. & Makeig, S. (2004). EEGLAB: An open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *Journal of Neuroscience Methods, 134*(1), 9-21. https://doi.org/bqr2f2

Eoh, H.J., Chung, M.K. & Kim, S.H. (2005). Electroencephalographic study of drowsiness in simulated driving with sleep deprivation. *International Journal of Industrial Ergonomics, 35*(4), 307-320. https://doi.org/b257w7

Gao, Z., Li, S., Cai, Q., Dang, W., Yang, Y., Mu, C. & Hui, P. (2019). Relative wavelet entropy complex network for improving EEG-based fatigue driving classification. *IEEE Transactions on Instrumentation and Measurement, 68*(7), 2491-2497. https://doi.org/qjkj

Gu, J. & Guo, F. (2022). How fatigue affects the safety behaviour intentions of construction workers an empirical study in Hunan, China. *Safety Science, 149*, 105684. https://doi.org/10.1016/j.ssci.2022.105684

Jap, B.T., Lal, S., Fischer, P. & Bekiaris, E. (2009). Using EEG spectral components to assess algorithms for detecting fatigue. *Expert Systems with Applications, 36*(2), 2352-2359. https://doi.org/fbf6zd

Jebelli, H., Hwang, S. & Lee, S. (2018). EEG signal-processing framework to obtain high-quality brain waves from an off-the-shelf wearable EEG device. *Journal of Computing in Civil Engineering, 32*(1), 04017070. https://doi.org/10.1061/(ASCE)CP.1943-5487.0000719

Kar, S., Bhagat, M. & Routray, A. (2010). EEG signal analysis for the assessment and quantification of driver's fatigue. *Transportation Research Part F: Traffic Psychology and Behaviour, 13*(5), 297-306. https://doi.org/10.1016/j.trf.2010.06.006

Li, X., Chen, P., Yu, X. & Jiang, N. (2022). Analysis of the relationship between motor imagery and age-related fatigue for CNN classification of the EEG data. *Frontiers in Aging Neuroscience, 14*, 909571. https://doi.org/qjkk

Li, J., Li, H., Umer, W., Wang, H., Xing, X., Zhao, S. & Hou, J. (2020). Identification and classification of construction equipment operators' cognitive 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/gg53gh

Li, G., Li, B., Wang, G., Zhang, J. & Wang, J. (2017). A new method for human cognitive fatigue detection with several EEG channels. *Journal of Medical and Biological Engineering, 37*(2), 240-247. https://doi.org/10.1007/s40846-017-0224-6

Mbto. (n.d.). Smarting S. https://bit.ly/4rWX5JB

Melo, H.M., Nascimento, L.M. & Takase, E. (2017). Mental fatigue and heart rate variability (HRV): The time-on-task effect. *Psychology and Neuroscience, 10*(4), 428-436. https://doi.org/10.1037/pne0000110

Muñoz-de-Escalona, E., Cañas, J.J. & Noriega, P. (2020). Inconsistencies between cognitive fatigue measures under compensatory control theories. *Psicológica Journal, 41*(2), 103-126. https://doi.org/qjkm

National Safety Council (NSC). (2018). Fatigue in safety-critical industries: Impact, risks and recommendations. https://bit.ly/4rWQoHz

Noghabaei, M., Han, K. & Albert, A. (2021). Feasibility study to identify brain activity and eye-tracking features for assessing hazard recognition using consumer-grade wearables in an immersive virtual environment. *Journal of Construction Engineering and Management, 147*(9), 04021104. https://doi.org/10.1061/(ASCE)CO.1943-7862.0002130

Pergher, V., Vanbilsen, N. & Van Hulle, M. (2021). The effect of cognitive fatigue and gender on working memory performance during repeated practice by young and older adults. *Neural Plasticity, 2021*(1), 6612805. https://doi.org/10.1155/2021/6612805

Richman, J.S. & Moorman, J.R. (2000). Physiological time-series analysis using approximate entropy and sample entropy. *American Journal of Physiology-Heart and Circulatory Physiology, 278*(6), H2039-H2049. https://doi.org/10.1152/ajpheart.2000.278.6.H2039

Sharma, R., Pachori, R. & Acharya, U. (2014). Application of entropy measures on intrinsic mode functions for the automated identification of focal Electroencephalogram signals. *Entropy, 17*(2), 669-691. https://doi.org/10.3390/e17020669

Tehrani, B.M., Wang, J. & Truax, D. (2022). Assessment of cognitive fatigue using electroencephalography (EEG) and virtual reality (VR) for construction fall hazard prevention. *Engineering, Construction and Architectural Management, 29*(9), 3593-3616. https://doi.org/gm6dgq

Tran, Y., Craig, A., Craig, R., Chai, R. & Nguyen, H. (2020). The influence of cognitive fatigue on brain activity: Evidence from a systematic review with meta-analyses. *Psychophysiology, 57*(5), e13554. https://doi.org/10.1111/psyp.13554

Tyas, A.E., Dharma Wibawa, A. & Purnomo, M.H. (2020). Theta, Alpha and Beta activity in the occipital based on EEG signals for cognitive fatigue in high school students. In *2020 International Conference on Smart Technology and Applications (ICoSTA), 1-7*, IEEE. https://doi.org/10.1109/ICoSTA48221.2020.1570614141

Wang, D., Li, H. & Chen, J. (2019). Detecting and measuring construction workers' vigilance through hybrid kinematic-EEG signals. *Automation in Construction, 100*, 11-23. https://doi.org/qjkn

Wang, J., Wu, Y., Qu, H., & Xu, G. (2014). EEG-based fatigue driving detection using correlation dimension. *Journal of Vibroengineering, 16*(1), 407-413.

Wascher, E. & Getzmann, S. (2014). Rapid cognitive fatigue amplifies age-related attentional deficits. *Journal of Psychophysiology, 28*(3), 215-224. https://doi.org/10.1027/0269-8803/a000127

Xing, X., Zhong, B., Luo, H., Rose, T., Li, J. & Antwi-Afari, M. F. (2020). Effects of physical fatigue on the induction of cognitive 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

Xu, R., Zhang, C., He, F., Zhao, X., Qi, H., Zhou, P., Zhang, L. & Ming, D. (2018). How physical activities affect cognitive fatigue based on EEG energy, connectivity and complexity. *Frontiers in Neurology, 9*, 915. https://doi.org/10.3389/fneur.2018.00915

Zhang, Z., Xiang, T., Guo, H., Ma, L., Guan, Z. & Fang, Y. (2023). Impact of physical and cognitive 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

Zhang, H., Wang, J., Geng, X., Li, C. & Wang, S. (2021). Objective assessments of cognitive fatigue during a continuous long-term stress condition. *Frontiers in Human Neuroscience, 15*, 733426. https://doi.org/10.3389/fnhum.2021.733426

Zhao, C., Zhao, M., Liu, J. & Zheng, C. (2012). Electroencephalogram and electrocardiograph assessment of cognitive fatigue in a driving simulator. *Accident Analysis and Prevention, 45*, 83-90. https://doi.org/fxrbxv

Cite this article

Gugssa, M., Assafi, M.N., Wang, J., Pan, Z. & Chen, J. (2026, Jan.). Cognitive fatigue and task complexity: Ensuring worker safety in construction and engineering. *Professional Safety, 71*(1), 22-28.

Mikias Gugssa is a Ph.D. candidate and graduate research assistant at the Richard A. Rula School of Civil and Environmental Engineering at Mississippi State University. He holds an M.Sc. and a B.Sc. in Civil Engineering from Addis Ababa University, Ethiopia. His research focuses on integrating advanced technologies to enhance construction safety.

Mohammad Nafe Assafi is a Ph.D. student at the Richard A. Rula School of Civil and Environmental Engineering at Mississippi State University. He holds an M.Sc. in Civil Engineering from Mississippi State University and B.Sc. in Building Engineering and Construction Management from Khulna University of Engineering and Technology, Bangladesh. He is employed as a graduate research assistant within the Rula School. His research interests focus on safe human-robot interactions in construction using artificial intelligence and robotics.

Jun Wang, Ph.D., is an assistant professor in Richard A. Rula School of Civil and Environmental Engineering at Mississippi State University. She is the director of the Mississippi Transportation Research Center. Wang's research mainly focuses on smart construction, human-robot interaction, and the applications of automation and artificial intelligence in construction engineering and management. Wang received the National Science Foundation Faculty Early Career Development CAREER award in 2024. She holds a Ph.D. degree in Civil Engineering from McMaster University, Canada, and an M.Sc. and B.Sc. from Dalian University of Technology, China.

Zhujun Pan, Ph.D., is an associate professor in the Department of Kinesiology at Mississippi State University and codirector of the Cognitive Motor Control Laboratory. Her research focuses on cognitive motor control, motor function in older adults and Parkinson's disease patients, bimanual coordination and transfer of learning, and exercise intervention for special populations. Pan holds a Ph.D. in Kinesiology from Louisiana State University, an M.Sc. in Kinesiology from the Capital Institute of Physical Education, and a B.Sc. in Electronic Engineering from Southwest Jiaotong University, China.

Jingdao Chen, Ph.D., is an assistant professor in the Department of Computer Science and Engineering at Mississippi State University. Chen's research focuses on robotics, computer vision and machine learning, including construction robotics, disaster relief robotics, digital twins and Scan-to-BIM. Chen holds a Ph.D. in Robotics, an M.Sc. in Computer Science from Georgia Institute of Technology, and a B.Sc. in Electrical Engineering from Washington University in St. Louis.