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Cognitive load assessment of active back-support exoskeletons in construction: A case study on construction framing

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ABSTRACT

Active back-support exoskeleton has emerged as a potential solution for mitigating work-related musculoskeletal disorders within the construction industry. Nevertheless, research has unveiled unintended consequences associated with its usage, most notably increased cognitive load. Elevated cognitive load has been shown to deplete working memory, potentially impeding task performance and situational awareness. Despite the susceptibility of exoskeleton users to increased cognitive load, there has been limited empirical evaluation of this risk while performing construction tasks. This study evaluates the cognitive load associated with using an active back-support exoskeleton while performing construction tasks. An experiment was conducted to capture brain activity using an Electroencephalogram, both with and without the use of an active back-support exoskeleton. A construction framing task involving six subtasks was considered as a case study. The participants' cognitive load was assessed for the tested conditions and subtasks through the alpha band of the Electroencephalogram signals. The study identified the most sensitive Electroencephalogram channels for evaluating cognitive load when using exoskeletons. Statistical tests, including a one-way repeated measure ANOVA, paired *t*-test, and Spearman Rank were conducted to make inferences about the collected data. The results revealed that using an active back-support exoskeleton while performing the carpentry framing task increased the cognitive load of the participants, as indicated by four out of five significant Electroencephalogram channels. Selected channels in the frontal and occipital lobes emerged as the most influential channels in assessing cognitive load. Additionally, the study explores the relationships among Electroencephalogram channels, revealing strong correlations between selected channels in the frontal lobe and between channels in the occipital and frontal lobes. These findings enhance understanding of how specific brain regions respond to the use of active back support exoskeletons during construction tasks. By identifying which brain regions are most affected, this study contributes to optimizing exoskeleton designs to better manage cognitive load, potentially improving both the ergonomic effectiveness and safety of these devices in construction environments.

1. Introduction

The rising prevalence of work-related musculoskeletal disorders (WMSDs) within the construction industry presents challenges to productivity [1], as well as safety and health concerns [2,3]. The emergence of active back-support exoskeletons (aBSE), also referred to as wearable robots [4], has sparked considerable interest as a potential remedy for WMSDs across various industrial sectors [5–7]. Prior research has demonstrated the potential of aBSE to reduce muscle exertion and joint hyperextension during manual handling tasks [8–10]. However, there have been reports of unintended consequences associated with exoskeleton usage, and increased cognitive load [11,12]. Cognitive load can be defined as the mental capacity and effort required to process information or execute mental tasks [13]. Elevated cognitive load could deplete working memory [14], potentially impeding task performance and situational awareness [15,16]. Fox, Aranko [17] noted that exoskeleton users may become preoccupied with the device, diverting their attention from the primary work tasks. Other exoskeleton-related factors that may shift users' focus away from the tasks include physical discomfort [18,19], restrictions on mobility [20,21], an elevated sense of fall risk because of the exoskeleton's weight [22,23], potential entanglement hazards [24], and issues related to anthropometric fit due

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to the diversity in human body sizes and proportions [25,26]. These unintended consequences could significantly contribute to the increased cognitive load of exoskeleton users, justifying the need to be investigated.

Researchers have explored the use of wearable sensors such as Electroencephalograms to measure cognitive load [27,28]. Electroencephalogram (EEG) is a neuroimaging technique that records electrical activity in the brain through electrodes placed on the scalp [29]. EEG detects and measures brain waves, including alpha, theta, gamma, and beta brain waves, which represent different frequency bands associated with various cognitive states [30]. As such, changes in these brain waves captured by EEG can provide insights into cognitive load [31]. Antonenko, Paas [28] identified the alpha wave as the most dominant in a normal human being. Positive correlations have been reported between the alpha wave and cognitive load during everyday tasks (e.g., driving [32] and visual mental work [33]) and construction-related tasks (e.g., general construction work [27] and human-robot interaction during bricklaying [34]). For example, Huang, Jung [32] showed the efficacy of the alpha band in assessing cognitive load during driving simulation tasks, where the band power increased as the demand for attention became more prominent. Additionally, Kumar and Kumar [33] demonstrated the capability of alpha band power in evaluating cognitive load during visual mental tasks, where complexity resulted in increased values of the alpha band power. In the context of construction applications, Chen, Taylor [27] assessed the effect of cognitive load on task allocation in the construction industry using the alpha band and demonstrated an increase in cognitive load. Shayesteh and Jebelli [34] also assessed the cognitive load associated with masonry work during human-robot interaction. The results indicated increased cognitive load while interacting with an autonomous robot compared to a semi-autonomous one, as reflected in a higher alpha band. Despite the potential consequences of cognitive load associated with exoskeleton use and the opportunities offered by EEG to quantify cognitive load, there remains limited research on the cognitive burden of using exoskeletons, particularly in the context of construction tasks. Exploring cognitive load in the context of construction is crucial due to the unique characteristics of construction tasks, which often involve repetitive, awkward postures and dynamic physical demands. These tasks require significant mental effort to manage and adapt to varying physical conditions and safety requirements. Understanding how these tasks influence cognitive load could inform the design of exoskeletons that not only address physical strain but also minimize cognitive burden. This knowledge gap underscores the need for efforts to monitor cognitive load, potentially through redesigning exoskeletons with integrated devices for measuring users' cognitive loads. Understanding the most sensitive brain regions during the use of active back-support exoskeletons could be valuable in this context.

This study aims to achieve two primary objectives: 1) assess the cognitive load associated with the use of aBSE in construction work, and 2) identify the most sensitive brain regions, represented by brain channels, essential for evaluating cognitive load and investigate the interrelationships among these channels during exoskeleton use while performing construction tasks. The objectives are achieved through a focus on carpentry framing tasks, chosen due to the high incidence of WMSDs among carpenters. According to the United States Bureau of Labor and Statistics [35], carpenters are 1.08 times more likely to suffer from back-related disorders compared to other construction trades, indicating their potential suitability as beneficiaries of aBSEs. The paper is structured to begin with an introduction, followed by a background section discussing related studies. The subsequent section describes the methods employed for assessing an aBSE, followed by the presentation of the results. The discussion section interprets the findings, and finally, the conclusion and suggestions for future studies are provided. This study contributes empirical evidence on the cognitive load risks of using exoskeletons for construction tasks, addressing the current knowledge gap in the effects of aBSE usage. Also, it provides a quantitative measure of the cognitive load imposed by the exoskeleton which helps understand the mental demand placed on exoskeleton users. The most sensitive EEG channels for cognitive load assessment could facilitate the development of adaptive exoskeletons capable of evaluating user's cognitive status and providing feedback such as increasing the level of augmentation or adjusting task complexity to reduce cognitive strain. This capability would also enable safety engineers to monitor and mitigate cognitive load risks, thereby preventing accidents on construction sites. The demonstrated correlations among the EEG channels highlight the most strongly related channels, which should be examined in conducting brain-exoskeleton interaction studies.

2. Background

2.1. Cognitive load associated with using exoskeletons

Researchers have explored the impacts of exoskeletons on users' cognitive load across various activities that involved manual material handling [11,36–38] and gait rehabilitation [39,40]. For manual material handling tasks, Zhu, Weston [11] examined the cognitive load associated with using a passive back-support exoskeleton (Laevo) for lifting and lowering tasks under two conditions, with and without mental arithmetic tasks. The study revealed that the biomechanical advantages garnered without the mental task were substantially reduced when the mental task was introduced. Schroeter, Kähler [36] evaluated the cognitive load of using an active shoulder-support exoskeleton (Lucy) for an overhead task that involved scaffolding installation. Using the exoskeleton resulted in a higher cognitive load, leading to reduced concentration, information processing, and an increase in errors. Similarly, Tyagi, Mukherjee [37] assessed the neurophysiological effects of an upper body passive exoskeleton (Eksovest) for overhead tasks (reaching and pointing) with concurrent mental demand tasks. The activation of the motor cortex was higher during the exoskeleton use, signifying an increase in cognitive load. Also, Govaerts, De Bock [38] examined the impact of mental fatigue on work productivity while using a passive back-support exoskeleton (Laevo) for manual material handling tasks, such as repetitive lifting and lowering subtasks. The study demonstrated reduced performance when participants were mentally fatigued during exoskeleton use. Conversely, for assessing users' cognitive load associated with using exoskeletons for gait rehabilitation, Gupta, McKindles [39] analyzed the relationship between cognitive load and gait performance during exoskeleton-augmented training. This was assessed by asking participants to walk on the treadmill while using a powered ankle exoskeleton. The study revealed that the exoskeleton competed with the available mental space, decreasing the participants' focus on the training. Additionally, Zhu, Johnson [40] assessed neuroergonomics metrics to evaluate exoskeleton use during gait rehabilitation. The study indicated that training with an exoskeleton potentially increases the cognitive load negatively impacting gait training performance. As such, it is not an underestimate that using exoskeletons, especially for mentally demanding tasks, can impact the user's cognitive load. Therefore, it is critical to understand the extent of this load and how it could inform investigations into suitable control measures, given the consequences of variations in cognitive load on work performance.

Cognitive Load Theory provides a framework for understanding the cognitive implications of using aBSEs in construction tasks. Cognitive Load Theory posits that the human brain has a limited capacity for processing information [48], and cognitive load refers to the mental effort required to perform a task [13]. Cognitive load is influenced by the task's complexity, the user's experience, and the cognitive resources needed to operate tools or machinery. Several factors contribute to increased cognitive load when using exoskeletons. Firstly, there is an initial learning curve and adaptation phase where users expend additional mental resources to understand exoskeleton's functions and controls [18,19]. Secondly, operating an exoskeleton demands increased attention and coordination, requiring users to adjust their movements [24]. Thirdly, users must process and integrate feedback and other inputs from the exoskeleton, which adds to the cognitive burden. Moreover, the complexity of tasks performed while wearing an exoskeleton, especially when multitasking, could influence cognitive load. Prolonged use could also lead to mental fatigue, reducing cognitive capacity over time [17]. Thus, by integrating Cognitive Load Theory principles, this study aims to assess the cognitive load associated with using aBSE in construction work. It will identify the most sensitive brain regions essential for evaluating cognitive load and explore their interrelationships during exoskeleton use.

2.2. Cognitive load evaluation techniques

Over the years, studies have proposed assessing cognitive load via subjective and objective measures. Subjective measures have been quantified using questionnaires such as the Rating Scale Mental Effort (RMSE) [41], Subjective Workload Assessment Test (SWAT) [42], and National Aeronautics and Space Administration Task Load Index (NASA TLX) [43]. For instance, RMSE was implemented to assess the mental workload of participants engaged in a driving task involving three typical maneuvers (Lin and Cai [41]. Similarly, Jeong, Baek [42] compared the mental workload of two driving methods, i.e., using a joystick and a steering wheel, using SWAT as a subjective measure to appraise participants' cognitive status. More recently, and with the emergence of visual technologies Atici-Ulusu, Ikiz [43] adopted the NASA TLX to examine the cognitive load effects of using augmented reality glasses during the operation of automobiles. However, such techniques of cognitive load assessment have been criticized because of their lack of continuous measurement [41], their inability to offer real-time quantifications of cognitive workload [41], and their susceptibility to bias inherent in self-evaluation [13].

The need for objective assessments encouraged researchers to explore objective measures, such as using EEG to evaluate cognitive load through brain activity [44]. EEG records electrical signals from the cerebral cortex, providing insights into the cognitive status through Power Spectral Density (PSD). Cognitive status has been examined over five major brain waves with different frequency bands, including delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), beta (13–30 Hz), and gamma ($>$ 30 Hz) [45]. Distinctly, the alpha brainwave band power has been recognized as the most dominant in a normal human being [28]. Studies have demonstrated relationships between the PSD of the alpha frequency band (8–12 Hz) and cognitive tasks, such as human-robot interaction tasks [34], human–computer interaction [33,46], driving [32], and general construction work [27]. For instance, Shayesteh and Jebelli [34] investigated the cognitive loads of workers in a human-robot interaction task involving bricklaying. The results indicated increased alpha band PSD in specific channels (F3, F4, T7, and T8) demonstrating higher cognitive load when working with an autonomous robot compared to a semi-autonomous one. Kumar and Kumar [33] assessed cognitive load during a human–computer interaction experiment, finding an increase in alpha band PSD in channels (T7 and T8) as the task difficulty increased. Janssen and Kirschner [47] evaluated cognitive load during a human–computer interaction activity that involved retention in short memory tasks. The study revealed an increase in alpha band PSD in channels T7, T8, FC5, and FC6. Furthermore, Huang, Jung [32] observed changes in the PSD of five of the major brainwaves during driving simulation tasks, with the alpha band exhibiting the highest PSD for channels in the occipital (O1 and O2) and temporal (T7 and T8) brain regions. Chen, Taylor [27] used EEG to measure cognitive load in construction workers demonstrating the feasibility of assessing mental workload via channels FP1, FP2, TP9, and TP10 using four of the frequency bands including alpha to inform proper task allocation. The results demonstrated the potential of all the examined channels, with FP1 showing a higher level of correlation with mental workload.

3. Research gap and significance

Despite the potential for increased cognitive load among aBSE users in the construction industry due to unintended consequences, there is a limited body of knowledge on this topic. Moreover, the existing evidence highlighting to the significance of the alpha band in understanding cognitive load status has not been adequately applied to the study of exoskeletons. This lack of understanding hinders the development of strategies to mitigate cognitive load, potentially impeding the widespread adoption of aBSEs in the construction industry. Addressing this gap could improve the occupational safety and health of construction workers. Therefore, the objective of this study is two-fold: firstly, to evaluate the cognitive load associated with using aBSE in construction activities, and secondly, to identify the brain channels most responsive to assessing cognitive load. Additionally, the study aims to explore the interconnections among these channels while engaging in construction tasks with exoskeletons.

4. Method

This section describes the approach adopted to achieve the objectives of this study. This includes the participants, experimental design, instrument and data collection, data processing, and data analysis (Fig. 1).

4.1. Participants

Sixteen male graduate students of Virginia Tech were recruited to participate in this study. The number of participants was selected based on a priori sample size computation, which provides a minimum power of 80 % with an effect size (f) and alpha (α) of 0.5 and 0.05, respectively [49]. This yields a sample size of 12 participants, which is the minimum required for this study. All computations were performed using G*Power 3.1.9.7. Similar sample sizes have been employed in related studies [50–52]. Although some participants had previous exposure to exoskeletons, their encounters were limited to experimental settings, and they did not have regular usage experience. The participants reported no health issues about their mental state that could have hampered their performance and the biomechanical benefits of the exoskeleton. Following the approval of the Virginia Tech Institutional Regulation Board (IRB: 19-796), the experiment details were provided to the participants before they gave their consent. The demographic information of the participants (age, weight, and height) was calculated and the average age is 30 years with a standard deviation (SD) $\pm$4 years, the average weight is 72 kg with an SD $\pm$ 7.5 kg, and the average height is 173 cm with an SD $\pm$ 5.5 cm.

4.2. Experimental design and Procedure

The experiment requires that participants perform carpentry framing tasks under two conditions: without aBSE (No Exo) and with aBSE (Active Exo) (Fig. 2a and 2b, respectively). The order of these conditions (i.e., No Exo and Active Exo) was randomized for different participants to reduce bias of familiarity with the task. The framing task was divided into six subtasks, which were performed sequentially: measuring, assembly, nailing, lifting, moving, and installing (Fig. 2c). Although the experiment was conducted in a laboratory setting, the sequence was designed to represent realistic carpentry framing work by including the key subtasks required to execute an actual framing task. The duration of each experimental condition did not exceed five minutes to mitigate the potential influence of fatigue [53]. Also, the participants were allowed to rest for 30 min after completing the first experimental condition (No Exo) before proceeding to the second condition (Active Exo) [53].

During the experiment, brain activity was captured using an EEG. The participants were asked to construct a wooden frame that would facilitate drywall installation using materials such as timber, nail gun, and measuring tape. The timber consists of members of various lengths,

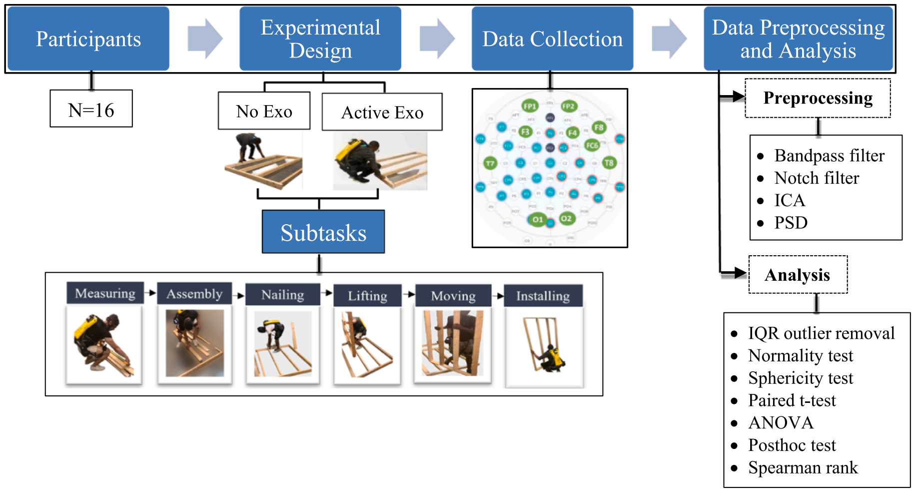

Fig. 1. Overview of the methodology.

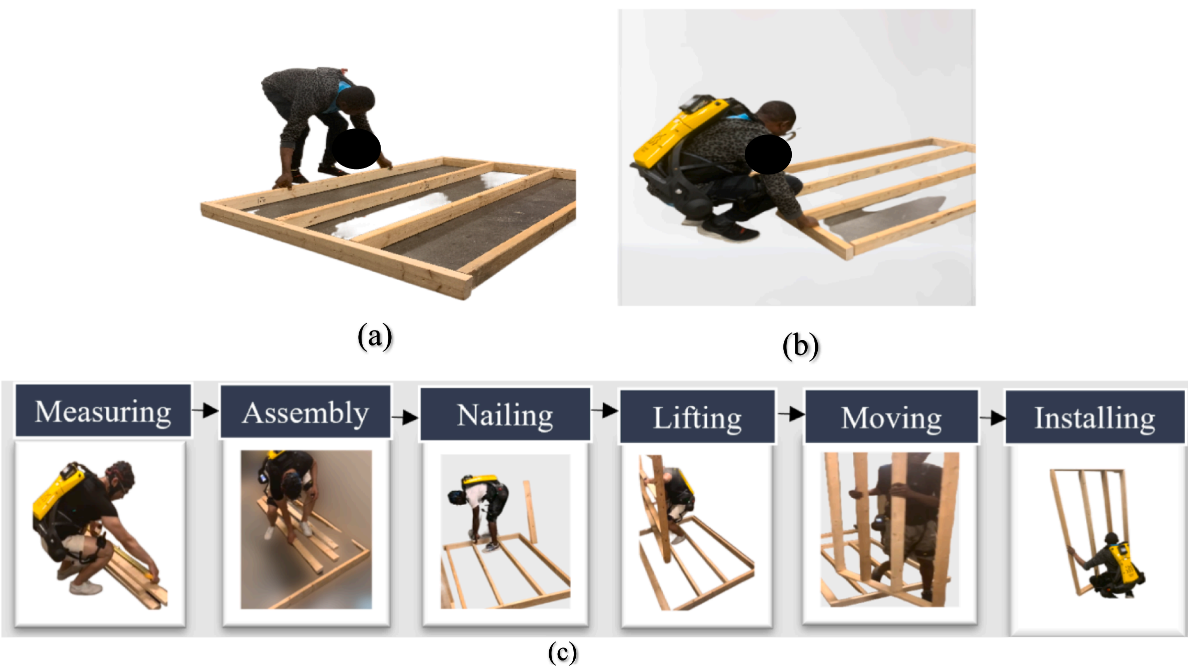

Fig. 2. Simulated framing task: (a) No Exo, (b) Active Exo, and (c) Subtasks.

such as 1.2 m, 1.8 m, 1 m, and 1.5 m, with equal cross-sectional area of 100 mm × 25 mm. Before commencing the experiment, the participants were shown a model of the frame they were expected to build, which is a 1.2 m by 1.8 m frame, as shown in Fig. 2. Subsequently, the participants were introduced to the aBSE used for the experiment and were trained on how the device works. Also, the framing task was demonstrated to the participants, and they were allowed to practice the task according to the sequences until they were fully familiar with it. This helps to reduce the effects of the task difficulty during the experiment.

The experiment commenced after the participants understood the workings of the aBSE and how the task should be performed. The participants commenced the first subtask by measuring the timber members required to construct the frame. This subtask is expected to place a mental demand on the participants, as they are expected to select the right plank out of a pile of planks for the subtask. The next subtask includes assembling and arranging the timber planks according to the model in Fig. 2. Subsequently, the participants were expected to nail the assembled frame at each joint using the nail gun. The nail gun was not activated to ensure the safety of the participants. Before commencing the lifting subtask, the prepared model was placed on the assembled frame, which was lifted by the participants and manually moved to the upper floor for installation. The weight of the frame is approximately 20 kg, which is within the range of the permitted manual lifting regulation as provided by the National Institute for Occupational Safety and Health lifting equation [54].

4.3. Instruments and data collection

4.3.1. Active Back-Support exoskeleton

CrayX, an active back-support exoskeleton manufactured by German Bionic, was used for this study. The device weighs 7.5 kg and has a lifting support of 33 kg. The aBSE has three working modes: lifting, walking, and bending. Support provided during each mode can be adjusted from 0 to 100 %. The device is powered by a rechargeable 40-volt battery, which, can last about 6 to 8 h. The aBSE consists of a backpack housing an electrical panel, motors, and strap pads (Fig. 3). The motors are located on both sides of the pelvis. The strap pads help attach the device to the body's thigh, chest, shoulder, and waist regions.

4.3.2. Electroencephalography

An EEG sensor was adopted in this study to capture the electrical activity in the brain. The brain's electrical activity was used to analyze the cognitive load of the users of the aBSE. The EEG device used in the study is a 32-channel Epoc Flex manufactured by Emotiv (Fig. 4a). The EEG device was placed on the surface of the scalp to target the cerebral cortex of the brain, which has the greatest EEG electrical conductivity [31]. The cerebral cortex can be divided into four major parts (Fig. 4b), namely, the frontal lobe, temporal lobe, parietal lobe, and occipital lobe, which are represented by different EEG channels based on international 10–20 systems, as shown in Fig. 4c [56]. EEG signals are usually described according to the different rhythmic activities of the brain over which data are recorded. They are grouped into five waves according to the frequency bands they occur: delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), beta (13–30 Hz), and gamma (> 30 Hz) [57]. The delta frequency band is related to deep sleep and unconsciousness, and theta frequencies describe drowsiness and early stages of sleep [33,45]. However, the alpha frequency band denotes the relaxed state and conscious thinking; the beta frequency range aligns with active cognitive processing and attentive operations; and the gamma frequency band encompasses intense mental engagement and the processing of information [33]. Since EEG infers cognitive load directly from the central nervous system via the brain, studies identified a significant correlation between the alpha band and cognitive load [58,59]. Specifically, alpha band frequency around the frontal lobe, temporary lobe, and occipital lobe has been adopted to measure cognitive load because of its high conductivity [32–34,60]. The frontal lobe aids in decision-making on how to construct the frame and controls the movements of the body to execute the task. The temporal lobe enables understanding and memorization of the verbal instructions on how to construct the frame, and visual recognition of the frame, while the occipital lobe supports the processing of the visual information [61]. The relationship between the alpha band and cognitive load is directly proportional, i.e., the higher the mean PSD of the alpha band, the higher the cognitive load [33]. Drawing from past studies as explained in the background [27,32–34,62], this study focused on the alpha band of the frontal lobe channels (F3, F4, F8, FP2, FP1, and FC6), the temporal lobe (T7 and T8), and the occipital lobe of the brain (O1 and O2) to assess the cognitive status of aBSE users while working on construction framing task. The brain regions and channels are shown in Fig. 4b and 4c, respectively.

4.3.3. Data preprocessing

EEG data is prone to artifacts, especially when the task involves a lot of body movement, which could affect the data quality [65]. Since carpentry framing is a physically demanding task involving repetitive body movements, artifacts could compromise the EEG data. Artifacts generated while capturing EEG data can be categorized into intrinsic and extrinsic artifacts [66]. The body generates intrinsic artifacts during data collection, and these include eye blinking, facial muscle movements, and cardiac pulse [66]. The extrinsic artifacts are generated from external sources such as electromagnetic interference, electrode popping, environmental noise, and wiring noise [66]. To eliminate the extrinsic artifacts, the raw EEG data was fed into the EEGLAB tool [65], and a bandpass filter with a frequency range of 0.5 Hz to 60 Hz was adopted to cut off unwanted frequencies that could affect the outcome of the study [67]. This was followed by applying a notch filter at a narrow frequency of 60 Hz to remove the noise from the electrode wires.

Independent component analysis was adopted within the EEGLAB toolbox to eradicate the intrinsic artifacts. This was conducted by passing the data through independent component analysis (ICA), which decomposed the data into 32 components. Moreover, intrinsic artifacts such as eye blinking and muscle movement were manually removed and pruned using the ICA label features After preprocessing the data, the mean PSD of the alpha frequency range for each subtask was computed using Welch's algorithm as illustrated by Eqs. (1) and (2) [27,68,69]. Adopted from Chiu, Lu [69], Welch's method of evaluating PSD for each N-point time series in the m^{th} segment can be expressed as:

$$P_{x_m,M}(f) = \frac{1}{N}\left|\sum_{n=0}^{N-1} x_m(n)e^{-\frac{j2\pi nk}{N}}\right|^2 \quad (1)$$

The PSD for the entire series can be expressed as:

$$P_w(f) = \frac{1}{M}\sum_{m=0}^{M-1} P_{x_m,M}(f) \quad (2)$$

Where, P_x = Power spectral density; M = Number of segments; m = Segment index; N = Length of each segment; n = Sample index; k = Normalizing constant; and f = Frequency variable.

4.4. Data analysis

After EEG data preprocessing and ensuring the collected data was of high quality, the data was analyzed to assess the cognitive load associated with using aBSE for the carpentry framing task. The PSD values from the alpha frequency band, computed from Eqs. (1) and (2), were examined for possible outliers within the data distribution. Tukey's range test was used to identify the outliers, which were computed using the interquartile range (IQR) to define the lower limit (Q1 − 1.5 * IQR) and upper limit (Q3 + 1.5 * IQR) to remove any possible outliers [70,71] – Q1 and Q3 are the first and third quartiles of the data. The normality and sphericity of the PSD data were tested using the d'Agostino-Pearson test and the Mauchly test, respectively, to determine which statistical analysis tools to consider. The PSD data met the normality and sphericity assumptions. Thus, a paired *t*-test was conducted to examine the experimental condition within each subtask. Furthermore, one-way repeated measure ANOVA was conducted to determine the most sensitive channels for cognitive load assessment using an aBSE. This was further corroborated by exploring the relationship among the EEG channels using Spearman correlation after the dataset showed no linearity. Bar graphs and tables were used to illustrate the analysis conducted. All statistical analysis was computed using Microsoft Excel and JMP Pro 17.0.0.

5. Results

In this section, the impact of the two experimental conditions on cognitive load is reported using the alpha band PSD across carpentry framing subtasks: measuring, assembling, nailing, lifting, moving, and

Fig. 3. Active back-support exoskeleton (Cray X) ().
Source: [55]

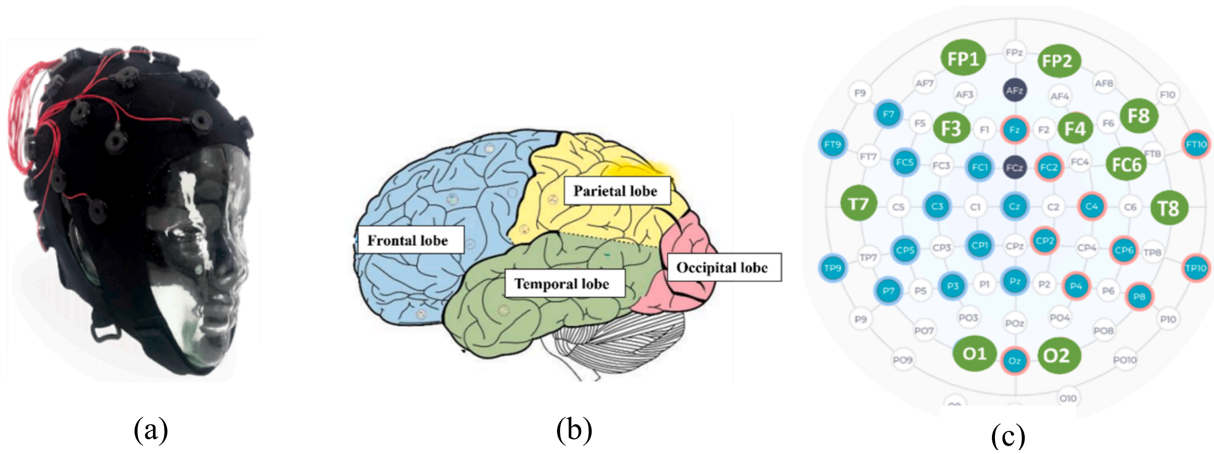

Fig. 4. (a) 32-channel EEG, ; (b) Cerebral cortex of the brain, Source: and (c) EEG channel location. Source: .
Source: [63][64][63]

installing. Also, the results of comparing the EEG channels and the relationship between the channels in the exoskeleton condition are reported. Bar graphs and tables are used to illustrate the results, including the statistical significance (p-value < 0.05).

5.1. Comparison of No-Exoskeleton and exoskeleton conditions

Results of the paired t-test revealed the differences between the cognitive load of the two experimental conditions within each subtask and across the carpentry task. Fig. 5 presents the results of the comparison of the cognitive load of the two experimental conditions for the measuring subtask. The results indicated statistically significant ($p < 0.05$) higher PSD in the Active Exo condition across frontal lobe channels F3, F8, and FC6 with percentage increments of 166 %, 127 %, and 57 %, respectively, and a temporal lobe channel T7 with percentage increment of 137 %. However, for comparing the cognitive load of the two experimental conditions for the assembly subtask shown in Fig. 6, only the Active Exo condition in frontal lobe channel F3 has a significantly high PSD with a percentage increment of 103 %. Conversely, a temporal lobe channel T8 shows a significant ($p < 0.05$) increase in PSD, with a percentage increase of 62 % in the No Exo condition (Fig. 6). For the nailing subtask, the results presented in Fig. 7 indicate that frontal lobe channel F3 shows a significant ($p < 0.05$) increment of 153 % in the Active Exo condition. Conversely, another frontal lobe channel FP2 shows an increment of 61 % in the No Exo condition compared to the Active Exo condition. The lifting subtask shows no statistical significance across all the channels (Fig. 8). Additionally, for the moving subtask, Fig. 9 shows statistical significance across frontal lobe channels FP1, F3, and F8, which indicates an increment of 175 %, 150 %, and 79 %, respectively, in the PSD of the Active Exo condition. In the No Exo condition, the reverse is the case for frontal lobe channel FC6, where

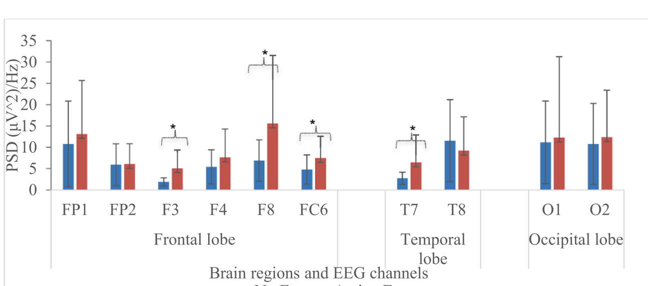

Fig. 5. Power spectrum comparison for an alpha frequency band in frame measuring subtask. ("*" = significant at p-value < 0.05).

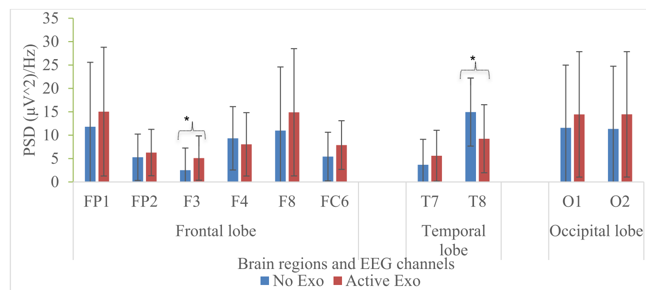

Fig. 6. Power spectrum comparison for alpha frequency band in frame assembly subtask.("*" = significant at p-value < 0.05).

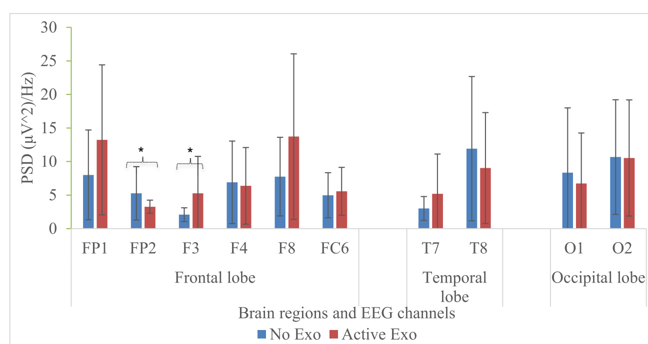

Fig. 7. Power spectrum comparison for alpha frequency band in nailing subtask ("*" = significant at p-value < 0.05).

there is an increase of 51 % compared to the Active Exo condition. Lastly, in the installation subtask, there is no statistical significance across the channels (Fig. 10). A summary of the PSDs of exoskeleton conditions across the EEG channels for the entire carpentry subtask is presented in Fig. 11. The paired t-test shows that five channels are statistically significant ($p < 0.05$). The results indicate higher PSD values in the Active Exo condition of frontal lobe channels FP1, F3, and F8 with percentage increases of 57.3 %, 23.3 %, and 129.5 %, respectively. A similar increase was observed in occipital lobe channel O2 with a percentage increase of 55 %.

5.2. Comparison of EEG channels in the exoskeleton condition

Figs. 12-17 show the results of the comparisons of the EEG channels,

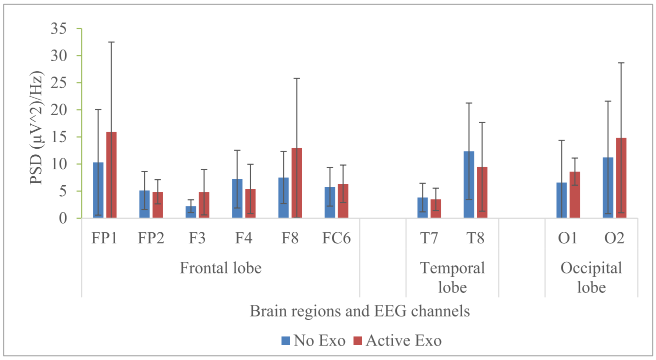

Fig. 8. Power spectrum comparison for alpha frequency band in frame lifting subtask.

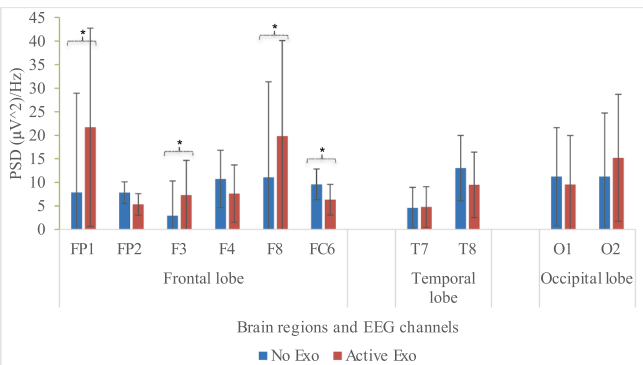

Fig. 9. Power spectrum comparison for alpha frequency band in moving subtask. ("*" = significant at *p*-value < 0.05).

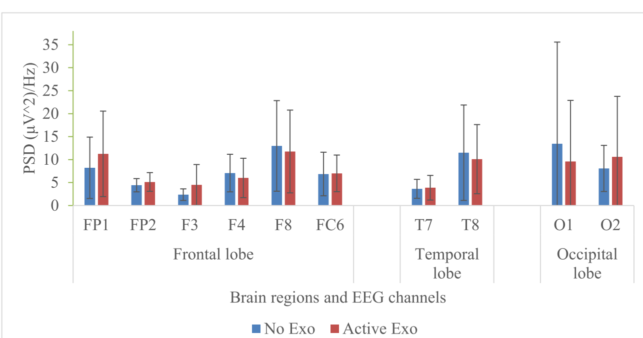

Fig. 10. Power spectrum comparison for alpha frequency band in frame installation subtask.

using one-way repeated measure ANOVA, to identify the most sensitive channels in the Active Exo condition. Fig. 12 illustrates the results of the frame measuring subtask and reveals a statistically significant difference ($p < 0.05$) among the EEG channels, with channel F8 showing the highest sensitivity to cognitive load as indicated by the post-hoc test. Fig. 13 shows the results of the frame assembly subtask depicting a significant difference ($p < 0.05$) between the channels, with the post hoc analysis revealing frontal lobe channels FP1 and F8 as the most sensitive channels. Fig. 14 gives the detailed results of the nailing subtask and indicates statistical significance ($p < 0.05$), with the post-hoc test revealing frontal lobe channel F8 as the most sensitive channel to cognitive load evaluation. Figs. 15 and 16 illustrate the results of the frame lifting and moving subtasks, respectively, with frontal lobe channel FP1 showing the highest sensitivity in both subtasks. Fig. 17 shows the results of the frame installation subtask indicating statistical

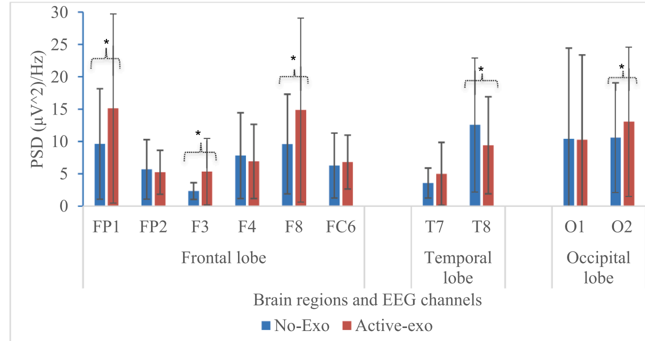

Fig. 11. Overall power spectrum comparison for alpha frequency band for carpentry framing task. ("*" = significant at *p*-value < 0.05).

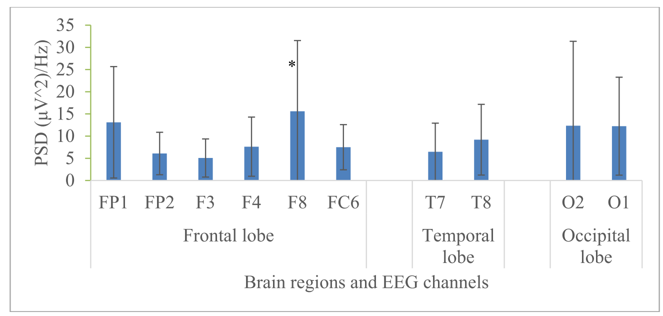

Fig. 12. Power spectrum comparison for alpha frequency band for frame measuring subtask in Active Exo condition. ("*" = significant at *p*-value < 0.05).

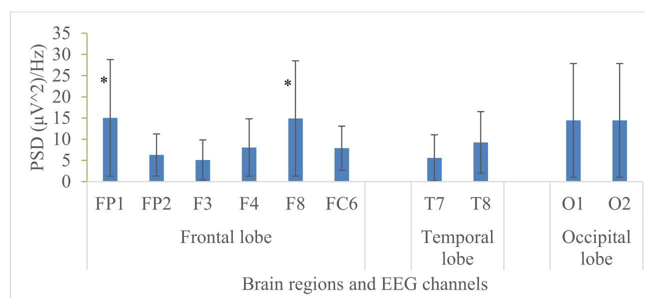

Fig. 13. Power spectrum comparison for alpha frequency band for frame assembly subtask in Active Exo condition. ("*" = significant at *p*-value < 0.05).

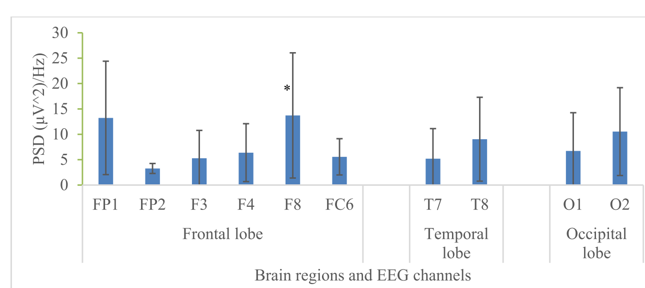

Fig. 14. Power spectrum comparison for alpha frequency band for frame nailing subtask in Active Exo condition. ("*" = significant at *p*-value < 0.05).

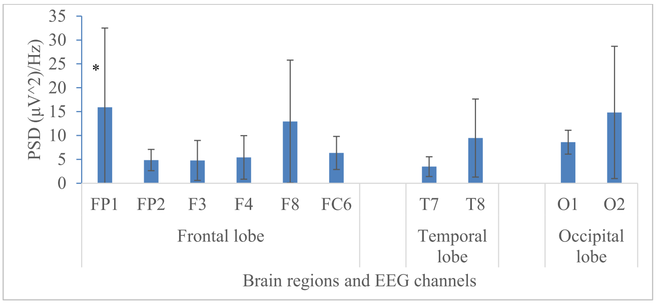

Fig. 15. Power spectrum comparison for alpha frequency band for frame lifting subtask in Active Exo condition. ("*" = significant at *p*-value < 0.05).

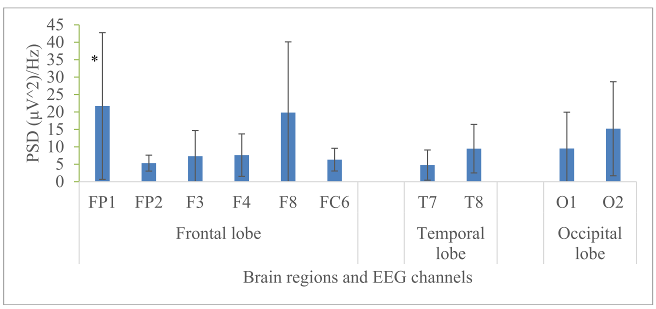

Fig. 16. Power spectrum comparison for alpha frequency band for frame moving subtask in Active Exo condition. ("*" = significant at *p*-value < 0.05).

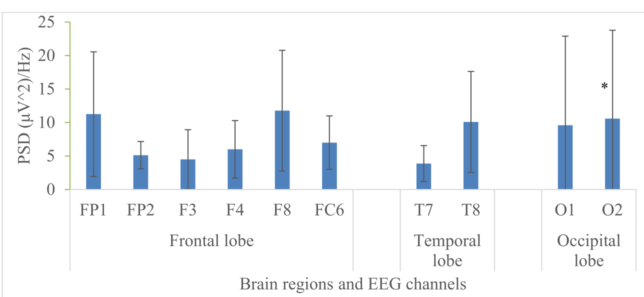

Fig. 17. Power spectrum comparison for alpha frequency band for frame installation subtask in Active Exo condition. ("*" = significant at *p*-value < 0.05).

differences ($p < 0.05$), with the post-hoc test revealing occipital lobe channel O2 as the most sensitive channel.

5.3. Relationship between the EEG channels

Table 1 illustrates the interrelationships among the EEG channels considered in evaluating cognitive load during the carpentry framing task. Following the classification by Schober, Boer [72], a correlation coefficient of 0.00 to 0.1 represents a negligible relationship, 0.10 to 0.39 represents a weak relationship 0.40 to 0.69 represents a moderate relationship, 0.7 to 0.89 represents a strong relationship, and 0.9 to 1 indicates a very strong correlation.

The results in Table 1 reveal strong relationships between pairs of frontal lobe channels (F4 and FC6; FP2 and FC6), and pairs of occipital and frontal lobe channels (O1 and FC6; O2 and FP1), which are statistically significant ($p < 0.05$) as indicated by bold coefficients. Moderate relationships are observed between pairs of frontal lobe channels (F4 and FC6; F3 and FP1; F8 and FC6; F8 and F4; FP2 and F4; FP2 and F8), pairs of temporal lobe channels (T8 and T7), and pairs of occipital lobe channels (O1 and O2). Similar relationships also exist between pairs of frontal and temporal lobe channels (F4 and T7; F4 and T8; F3 and T7; FC6 and T7; FC6 and T8; FP2 and T7; FP2 and T8; FP1 and T7; F3 and T8), pairs of temporal and occipital lobe channels (O1 and T7), and pairs of occipital and frontal lobe channels (O1 and FP1; O1 and F4; O1 and F8; O1 and FP2). These moderate relationships are statistically significant ($p < 0.05$) as indicated by the bold coefficients in Table 1. The remaining relationships are either weak or negligible, though some show statistical significance.

6. Discussion

This study evaluated the cognitive load imposed by aBSE used during a construction framing task via the alpha band. Additionally, this study examined the most sensitive EEG channels for evaluating cognitive load and the interrelationships among these channels during exoskeleton use. This section provides detailed interpretations of the results.

6.1. Comparison of No-Exoskeleton and exoskeleton conditions

In the analysis of the construction framing task across the six subtasks, notable findings reveal significantly higher PSD values for the Active Exo condition for frame measuring, assembling, nailing, and moving subtasks. However, for the case of frame lifting and installing subtasks, no significance was observed between the No Exo and Active Exo conditions. This indicates that using an aBSE substantially increases the cognitive burden on users within the examined task. This result is anticipated, given that using an aBSE introduces an additional element that the brain must conscientiously manage and preprocess, especially in an uncontrolled setting like a construction site. The elevated risk of catch and snag incidents, associated with the structure and weight of the

Table 1
Relationship between EEG channels in Active Exo condition (bold numbers are significant at p-value < 0.05) (Green: Strong correlation, ρ = 0.7 to 0.89; Yellow: Moderate correlation, ρ = 0.4 to 0.69; and Orange: Weak correlation, ρ = 0.1 to 0.39).

Brain Regions and EEG Channels		**Frontal lobe**						**Temporal lobe**		**Occipital lobe**	
		FP1	**FP2**	**F3**	**F4**	**F8**	**FC6**	**T7**	**T8**	**O1**	**O2**
Frontal lobe	**FP1**										
	FP2	0.1667									
	F3	**0.401**	**0.3562**								
	F4	−0.1179	**0.6475**	**0.3775**							
	F8	**0.2513**	**0.5984**	**0.3452**	**0.5841**						
	FC6	0.0601	**0.7137**	**0.3451**	**0.8694**	**0.5005**					
Temporal lobe	**T7**	**0.4529**	**0.6535**	**0.5536**	**0.4077**	**0.2334**	**0.4389**				
	T8	−0.1063	**0.4558**	**0.4576**	**0.6458**	**0.278**	**0.5172**	**0.419**			
Occipital lobe	**O1**	**0.4832**	**0.5493**	**0.2214**	**0.5176**	**0.4095**	**0.7115**	**0.4289**	0.1697		
	O2	**0.8264**	**0.3889**	**0.3698**	0.1519	**0.2495**	**0.3041**	**0.6494**	0.1372	**0.6495**	

aBSE, tends to increase the mental workload of aBSE users [24,73].

Notably, the moving and assembly subtasks exhibit the highest PSD values, indicating that participants experience heightened cognitive load during these activities. This aligns with expectations as both subtasks involve significant mental and physical demands and extensive body movements [74]. Participants are likely to exercise caution while navigating the task area, carrying the frame, and negotiating uneven surfaces, such as staircases, contributing to the augmented cognitive demand. Surprisingly, lifting and installing subtasks show no statistically significant differences in PSD values. This finding is noteworthy, considering these subtasks involve less movement than the other subtasks. This further suggests that using an exoskeleton during subtasks with limited movements may have a comparatively lower impact on cognitive load. A similar finding was reported by Wächtler, Kessler [14], who found that dynamic tasks impose a higher cognitive load compared to static tasks. Furthermore, Shayesteh and Jebelli [34] found that the cognitive load of humans collaborating with autonomous robots increase compared to those interacting with semi-autonomous robots during brick laying. As such, in the context of the carpentry framing task, which involves varying levels of kinetic movement contributing to the increased cognitive load for exoskeleton users, it is crucial to recognize that numerous construction tasks exhibit similar or higher levels of dynamism. Consequently, there is a need for exoskeleton designs to adapt effectively to these diverse and dynamic construction scenarios.

The result of the overall carpentry task shown in Fig. 11 reveals an increase in cognitive load in frontal lobe channels FP1, F3, and F8, and occipital lobe channel O2 among participants using the exoskeleton. This could be due to the task requirement to sustain working memory and process visual information, respectively. It can also be observed from Fig. 11 that the temporal lobe channel T8 exhibited a contrary trend. This could be due to the absence of time constraints in completing the carpentry task. Since participants were not under pressure to complete the task while utilizing the exoskeleton, the temporal lobe might not have been engaged. Conversely, increased activation of the temporal lobe during the carpentry task without the exoskeleton could be attributed to participants' familiarity with performing the task without an exoskeleton, motivating them to complete the task quickly. The findings regarding temporal lobe channel T8 in this study contradict those of Jensen, Gelfand [46], which focused on a short-term memory task. This discrepancy could arise from participants' efforts to actively maintain their short-term memory during task execution, a circumstance not replicated in this study.

6.2. Spectral Power comparison for exoskeleton condition

In the Active Exo condition, frontal lobe channels F8 and FP1, and occipital lobe channel O2 exhibit the highest PSD, signifying their substantial contributions to the evaluation of cognitive load. The prominence of occipital lobe channel O2 is unexpected, however, the involvement of the frontal brain region channels—specifically frontal lobe channels F8 and FP1—is not surprising, given their roles in attention and working memory [75]. So, Wong [76] assert that frontal region channels activate during tasks requiring sustained attention and working memory, such as finger tapping, lexical decision-making, arithmetic, and mental rotation, which involve discriminating between closely related figures. Several subtasks in this study demanded sustained attention and memory, resembling the tasks mentioned. For instance, the measuring subtask required participants to select the correct timber log, measure it, and simultaneously keep track of the entire sequence of subtasks. The heightened sensitivity observed in the frontal lobe region can be attributed to the requisite sustained attention, a predominant aspect across the examined subtasks. Given the preeminence of the frontal lobe in the cerebral cortex, as indicated by the results, integrating frontal channels into EEG and exoskeletons may be considered for the development of an adaptive exoskeleton, providing real-time feedback and adjustments based on the cognitive status of exoskeleton users.

Activation of occipital channels results from triggers in the occipital lobe, known for processing visual information [28]. The sensitivity of the occipital lobe channel O2 suggests that carpentry framing activities are visually demanding and cognitively stimulating. While attention has been focused on the frontal lobe, the significant sensitivity of occipital channels indicates that participants maintained visual memory during framing tasks, particularly evident in the installation subtask, as depicted in Fig. 17. Although not the highest, substantial sensitivity in the occipital lobe is also observed in other subtasks, contributing valuable insights for brain-exoskeleton interaction studies aiming to develop adaptive exoskeletons capable of regulating users' cognitive load.

The predominance of frontal channels in indicating cognitive load has been established by Chen, Taylor [27] and Ismail and Karwowski [77] in their examinations of EEG's application for quantifying human cognitive load. These studies underscore the frontal lobe as a primary indicator. Additionally, Mapelli and Özkurt [78] emphasize the PSD of the occipital lobe, highlighting its heightened sensitivity in evaluating cognitive load during mental memory tasks.

6.3. Relationship between EEG channels

Considering the findings from previous studies outlined in the background, the selected channels were expected to exhibit close relationships, as detailed in Table 1. However, the surprising aspect was the order of strength in these relationships, revealing that occipital lobe channels had stronger connections with other brain regions compared to many frontal lobe channels. Notably, the dominance of the frontal and occipital lobes as the most sensitive channels in evaluating cognitive load is consistent with the results demonstrating the strongest relationships among the channels. This implies that participants not only engaged their frontal lobe for critical thinking, attention, and body movements but also activated their visual sensory functions during the carpentry task [79].

The direct assessment of human cognitions from the cerebral cortex involves the frontal lobe, temporal lobe, occipital lobe, and parietal lobe [56]. While each of these brain regions responds differently to the nature of mental workload tasks, this study indicates that performing the framing task with an aBSE predominantly activates the frontal and occipital regions, as depicted in Table 1 and Figs. 13 to 18. This alignment is justified by the substantial involvement of critical thinking, attention, and body movement in the framing task, sparking the frontal region. This insight is valuable for determining the group of EEG channels to be considered alongside the frontal region when investigating the cognitive load of exoskeleton users, potentially contributing to the development of enhanced exoskeletons through real-time cognitive load monitoring. The activation in the occipital region suggests that participants were visually engaged with the task, supported by the identification of occipital channels (O2) as among the most sensitive channels for cognitive load evaluation. Recognizing the importance of visual attention during the framing task, the strong correlations with other brain regions reveal that visual attention plays a crucial role in sustaining other aspects, such as critical thinking and body movement in various directions.

The observed strong relationships of frontal lobe channels with other channels in assessing cognitive load align with the findings of Shayesteh and Jebelli [34], where frontal lobe channels significantly contributed to evaluating cognitive workload in human-robot relationship tasks, akin to the human-exoskeleton relationship in this study. The relevance of occipital channels is also demonstrated in Cabañero, Hervás [80], where human–computer interaction tasks involving mobile phones and computers highlighted the significance of the occipital lobe among other regions in assessing cognitive load.

7. Conclusion, limitation, and future work

Active back-support exoskeletons have demonstrated their potential in reducing WMSDs in various industries. However, there are concerns about potential unintended consequences, particularly the prospect of increased cognitive load for users. This study investigates the impact of an active back-support exoskeleton on cognitive load within the context of a carpentry framing task. Brain activity in this study explains the cognitive load experienced by aBSE users. Notably, four out of five significant EEG channels suggest that aBSE elevates users' cognitive load, while one channel indicates otherwise. Among the various channels examined in the Active Exo condition, frontal lobe channels F8 and FP1 and occipital lobe channel O2 stand out for their high sensitivity in assessing cognitive load risk. Additionally, in exploring the relationships among the channels, pairs of frontal lobe channels, F4 and FC6, and FP2 and FC6, and pairs of occipital and frontal lobe channels, O1 and FC6, and O2 and FP1, demonstrate the strongest connections.

It is crucial to note that this study was conducted in a controlled laboratory environment with participants with limited experience in construction tasks, potentially influencing the results. Furthermore, all participants were male, which could limit the generalizability of the findings. Future research should involve diverse, experienced construction workers engaged in real-world tasks for a more accurate assessment. Assessing task difficulty could further elucidate how it influences cognitive load in exoskeleton users. Integrating aBSE and EEG technology for real-time cognitive load monitoring and adjustment could optimize user-exoskeleton coordination.

This study contributes empirical evidence regarding assessing cognitive load risks in construction tasks, filling a gap in knowledge regarding the effects of cognitive load on aBSE usage. The identified increase in cognitive load for exoskeleton users highlights the need for tailored designs capable of effectively managing cognitive load while reducing WMSDs. Refining ergonomic designs to align with user movement and preferences may alleviate cognitive load. The most sensitive EEG channels identified for cognitive load assessment could facilitate the development of adaptive exoskeletons capable of evaluating the user's cognitive status and providing real-time feedback. Furthermore, the demonstrated correlations among the EEG channels highlight those most strongly related, serving as valuable insights for brain-exoskeleton interaction studies.

CRediT authorship contribution statement

Abiola Akanmu: Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition. **Akinwale Okunola:** Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation. **Houtan Jebelli:** Supervision, Project administration, Methodology, Investigation, Funding acquisition. **Ashtarout Ammar:** Writing – review & editing, Visualization, Supervision. **Adedeji Afolabi:** Writing – review & editing, Visualization, Supervision, Investigation, Data curation.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: [Abiola Akanmu reports financial support was provided by National Science Foundation. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper].

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Data availability

Data will be made available on request.

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