Cognitive Load and Fall Risk Dynamics in Human-Exoskeleton Interaction for Construction Workers

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Abstract. Exoskeleton is increasingly perceived as an ergonomic solution to work-related musculoskeletal disorders. However, their use could lead to unintended consequences for users, such as increased cognitive workload and elevated fall risk on construction sites. This study examined the relationship between cognitive load and fall risk metrics among exoskeleton users. Sixteen participants were engaged in simulated construction framing tasks performed with and without an exoskeleton. Electroencephalography sensors and pressure insoles were employed to capture participants' brain activity and foot plantar pressure distribution, respectively. Paired t-test was used to compute the statistical significance between the with and without exoskeleton conditions for fall risk and cognitive load. Spearman correlation test was used to examine the relationship between the power spectral density of electroencephalography data, indicative of cognitive load, and pressure-time integral metric of foot plantar pressure distribution among exoskeleton users. The findings revealed moderate relationships in two directions (direct and indirect relationship). Elevated cognitive load, as indicated by increased power spectral density values in the parietal lobe and occipital lobe directly correlates with fall risk metrics at the toe region. Conversely, an indirect relationship was observed in the frontal lobe and occipital lobe which inversely correlates with the heel foot region. By highlighting the relationship between cognitive load and fall risk metrics, this study underscores the importance of integrating cognitive factors into strategies aimed at mitigating fall risk among exoskeleton users on construction sites.

Keywords: Cognitive load · Fall risk · Active back-support exoskeleton

1 Introduction

The prevalence of work-related musculoskeletal disorders (WMSDs) in the construction industry is a concern. WMSDs are often triggered by the physically demanding nature of construction tasks, which require workers to assume abnormal postures such as squatting, twisting, stooping, and bending [1]. The back is the most affected body part, accounting for 43% of the total WMSDs experienced by workers.

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Exoskeletons are increasingly recognized as a potential solution to mitigate the risks of WMSDs. These external wearable devices enhance the body's strength during physically demanding tasks [2, 3]. Specifically, active back support exoskeletons (aBSEs), which augment the body's musculoskeletal system using an electrical power source, are seen as an effective means to reduce muscle contraction and range of motion, thereby decreasing muscle fatigue [2, 3]. However, misalignment between the human body and exoskeletons often results in restricted mobility, instability, reduced attention span, and uneven load distribution [4, 5]. These may increase cognitive load, potentially introducing fall hazards on construction sites.

Assessing and monitoring these risks while using exoskeletons on construction sites could inform mitigation measures. Although studies have demonstrated the potential of electroencephalogram (EEG) for quantifying cognitive load [6] and pressure insoles for assessing fall risks [7], the use of multiple wearable devices could be intrusive. This may affect worker acceptance of exoskeletons, thereby preventing them from reaping the intended benefits [3]. Understanding the relationship between metrics of cognitive load and fall risk could reveal how these variables influence each other. This insight could determine whether one metric can reliably predict the other, potentially enabling the substitution of one measurement device for another.

While studies have assessed cognitive load using EEG and fall risk using pressure insoles during various tasks, few have explored these metrics in the context of aBSEs for construction tasks. Specifically, research on the relationship between cognitive load and fall risk in this setting remains limited. Therefore, this study aims to investigate the relationship between cognitive load and fall risk during the use of aBSE in construction-related tasks. Given the rising incidence of back-related disorders in construction activities like carpentry framing, this study uses simulated framing work as a case study. Understanding the relationships between cognitive load and fall risk could inform the development of predictive models that could substitute one set of metrics for another, potentially reducing the need for multiple intrusive monitoring devices. This could also lead to better mitigation strategies and design improvements for exoskeletons, enhancing their overall effectiveness and worker acceptance.

2 Background

Active back support exoskeletons have been shown to reduce muscle activity, range of motion, and perceived discomfort during various manual material handling tasks [2, 8]. However, their use may introduce risks, which may not only reduce the biomechanical effects of the device due to high cognitive load but also potentially trigger fall hazards on construction sites. These risks could arise from the biomechanical misalignment between the exoskeletons' degrees of freedom and the body [9, 10]. Common triggers of these risks include mobility restriction [11], depletion of mental capacity [9], increased perceived pressure [8], reduced stability [12], and uneven distribution of loads [5]. For example, Ogunseiju, Gonsalves [11] identified movement restriction while using exoskeleton for flooring tasks. Zhu, Weston [9] reported decreased mental capacity with the use of exoskeleton during lifting tasks, which also impacts biomechanical efficacy. Okunola, Akanmu [8] highlighted increased discomfort due to perceived pressure while using exoskeletons for flooring work. Gonzalez, Stegall [12] found that exoskeleton users exhibited instability when navigating a beam. Picchiotti, Weston [5] showed uneven distribution of loads across muscles during manual material handling tasks. Experiencing these triggers could exacerbate the risks of high cognitive load and increased fall risk while using aBSEs.

Over the years, cognitive load and fall risks have been assessed using metrics such as gamma band power of EEG [6, 13] and pressure-time integral of foot plantar pressure distribution [7, 14, 15] in various contexts. For instance, Fitzgibbon, Pope [13] explored cognitive load assessment, finding increased gamma power correlating with increased cognitive load across brain regions, including the frontal lobe (FP1, FP2, F3, and F4), parietal lobe (P3 and P4), and occipital (O1 and O2) lobes during cognitive tasks. Chen, Taylor [6] assessed cognitive load associated with different construction tasks using EEG, demonstrating higher gamma band activity in the frontal lobe regions (FP1 and FP2) correlating with increased cognitive load. In the context of fall risk assessment, Antwi-Afari and Li [7] used pressure-time integral metric of foot plantar pressure distribution in four regions (heel, arch, metatarsal, and toe) to identify potential fall hazards. Yan, Ou [14] investigated fall risk in older adults and established relationships between higher-pressure time integral values and increased risk of fall. Mickle, Munro [15] differentiated fall risk levels in elderly populations using pressure-time integral metrics, highlighting higher values associated with increased fall risk.

Considering the aforementioned factors that contribute to cognitive load and fall risks, this study aims to evaluate the relationship between these variables in the context of using aBSEs during construction tasks.

3 Methods

The approach used to conduct this study is shown in Fig. 1, including the experimental design and procedure, data collection method, as well as data preprocessing and analysis techniques.

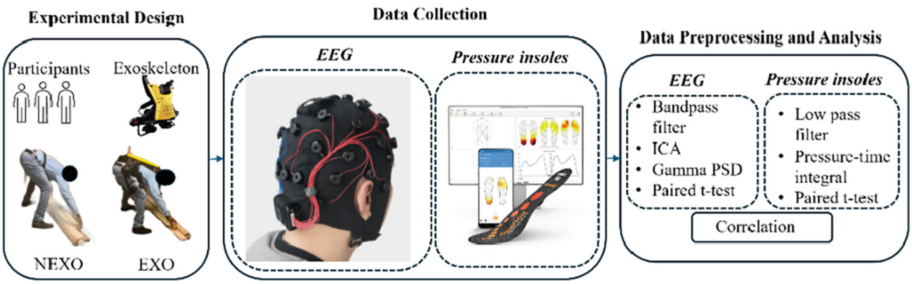

Fig. 1. Methodology overview. Source: [16–18]

3.1 Experimental Design, and Procedure

Participants. A sample of 16 healthy male graduate students was recruited from Virginia Tech to participate in this study. The participants had a mean age, weight, height, and body mass index of 30 $\pm$ 4 years, 72 $\pm$ 7.5 kg, 173 $\pm$ 5.5 cm, and 23.98 $\pm$ 1.9 kg/m^2, respectively. Participants provided their informed consent following the approved procedures of the Virginia Tech Institutional Review Board for conducting this study.

Exoskeletons. Cray X active back-support exoskeleton, manufactured by German Bionic (see Fig. 2a), was used for this study. The exoskeleton weighs approximately 7.5 kg and has a lifting capacity of 30 kg, as stated by the manufacturer. It supplies support to the body through two motors located on the protruded sides, powered by a 40-V battery.

Simulated Framing Task. The participants engaged in a simulated framing task, performed under two conditions: with and without the exoskeleton (i.e., NEXO and EXO). Thirty-minute break intervals were allowed to mitigate fatigue. Materials provided for the framing tasks included logs of timber, a nail gun, and a model of a prepared frame. Participants were familiarized with the exoskeleton's operating procedure and given time to practice and adapt to its usage. Additionally, the step-by-step process of constructing the frame was demonstrated to the participants to minimize intermittent questions, which could introduce noise to the EEG signal. The experiment began with participants measuring the timber logs required for constructing the frame using the provided measuring tape. Subsequently, the timber logs were assembled to form the frame, with dimensions of 1.2 m by 1.8 m and cross-sectional area of 100 mm $\times$ 25 mm. The assembled frame, weighing approximately 20 kg, was fastened together using the provided nail gun. Finally, participants manually lifted the frame and moved it to an upper floor via the staircase for final installation. Throughout the experiment, participants wore EEG and pressure insole sensors.

3.2 Data Collection Instruments

The data collection instruments employed in this study are described below.

Electroencephalogram. A 32-channel EEG was employed to record the electrical brain activities of the participants. This data was used to assess participants' cognitive load from the cerebral cortex i.e., the outer layer of the brain. The cerebral cortex is divided into four regions: frontal, temporal, parietal, and occipital regions [4]. The EEG channels are arranged following the 10–20 system, which corresponds to the cerebral cortex regions as shown in Fig. 2b. EEG signals, from the channels, are typically expressed in the frequency domain across five major frequency bands: delta (0.1 Hz to 3.9 Hz), theta (4 to 8 Hz), alpha (8 to 13 Hz), beta (14 to 30 Hz), and gamma band (30 to 60 Hz), from deep sleep and continuous attention to high mental activity and sensory information processing [4]. The PSD of the gamma band has been identified as a suitable measure for computing cognitive load during construction tasks [6]. Consequently, this study focuses on the gamma band to assess cognitive load due to the exoskeleton use. Additionally, this study considered the EEG channels at the frontal lobe (FP1, FP2, F3, and F4), parietal lobe (P3 and P4), and occipital lobe (O1 and O2) [6, 13].

Pressure Insoles. Opengo pressure insoles, manufactured by Moticon, were used to capture foot plantar pressure data. The pressure insoles are designed for both feet and comprise 16 sensors each, distributed across various foot regions, including the toe, metatarsal, arch, and heel, as illustrated in Fig. 2c. These sensors are arranged such that sensors 1–4 correspond to the heel region, sensors 5–8 to the arch, sensors 9–13 to the metatarsal region, and sensors 14–16 to the toe region.

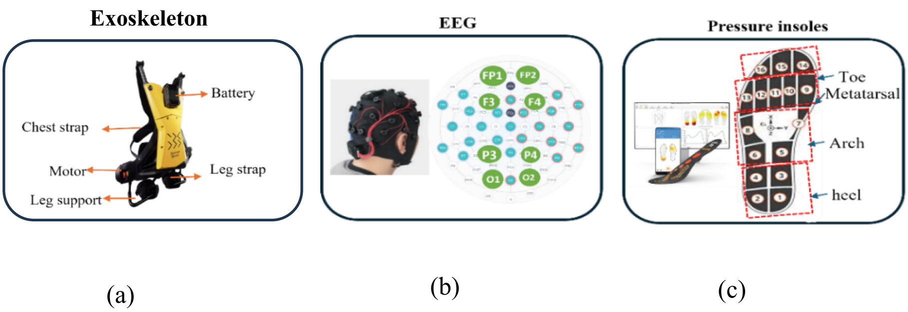

Fig. 2. (a) Exoskeleton; (b) EEG; (c) pressure insoles. Source: [16–18]

3.3 Data Preprocessing

Sensing data could be susceptible to artifacts from the body or external environment, which could lead to false results [19]. Therefore, it is important to preprocess the data before proceeding with the analysis. The EEG data was subjected to a bandpass filter with a frequency band of 0.5–65 Hz to remove artifacts from the external environment source [19]. A notch filter was applied at a frequency of 60 Hz to remove electrode noise [19]. Artifacts generated through body movement were removed using independent component analysis [19]. Regarding the pressure insole data, a 12th-order Butterworth low pass filter with an 8 Hz c was applied to remove the artifacts [20].

Power spectral density of the gamma frequency band (30–60 Hz) was computed from the filtered EEG data using the Welch algorithm [6], as shown in Eqs. 1 and 2, for the NEXO and EXO conditions. Similarly, pressure time-integral was computed for the filtered foot plantar pressure data to represent the fall risk metric using Eq. 3 for the NEXO and EXO conditions. All computed data were further screened with a Tukey range test using the interquartile range (IQR) to remove outliers that could skew the results [20]. The lower and upper limits were defined as (Q1 - 1.5 * IQR) and (Q3 + 1.5 * IQR), respectively. The filtering process and computations were done with MATLAB 2023R and Microsoft Excel.

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

The PSD for the entire series can be expressed as:

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

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.

$$Pressure - Time\ Integral = \sum_{t=0}^{N} Pi\ X\ dt \tag{3}$$

where Pi represents the pressure value at i-th sensor; N represents the number of sensors and dt represents the time interval.

3.4 Statistical Analysis

The computed metrics, the power spectral density and pressure-time integral, underwent further analysis to determine statistically significant differences and the relationship between them. The metrics were subjected to a Shapiro-Wilks normality test to determine the appropriate statistical method. Having passed the normality test ($p > 0.05$), a paired t-test was employed for each metric to compare the NEXO and EXO conditions, providing insights into the cognitive load and fall risk impact of using exoskeletons. Cohen's d was reported to estimate the effect sizes for the paired t-test results. Spearman rank correlation test was used to understand the relationship between cognitive load and fall risk. The results are illustrated through bar graphs and a table. All statistical analyses were conducted using JMP Pro 17.0 and Microsoft Excel.

4 Results

This section presents the results of the statistical analysis conducted to understand the impact of exoskeleton on the cognitive load, fall risk, and the relationship between the measures.

4.1 Cognitive Load Evaluation

Results of the paired t-test reveal statistical differences across the brain regions. As depicted in Fig. 3, channel F4 exhibits a higher PSD value ($t(15) = -2.38$, $P = 0.03$, $d = -0.61$) while using the exoskeleton compared to all other channels of the frontal lobe. Similarly, in the parietal lobe, channel P3 also shows statistical significance ($t(15) = -3.20$, $P = 0.03$, $d = -.83$), indicating a higher cognitive load while using the exoskeleton. While other channels show no statistical difference, substantial increases are observed across all channels except F3.

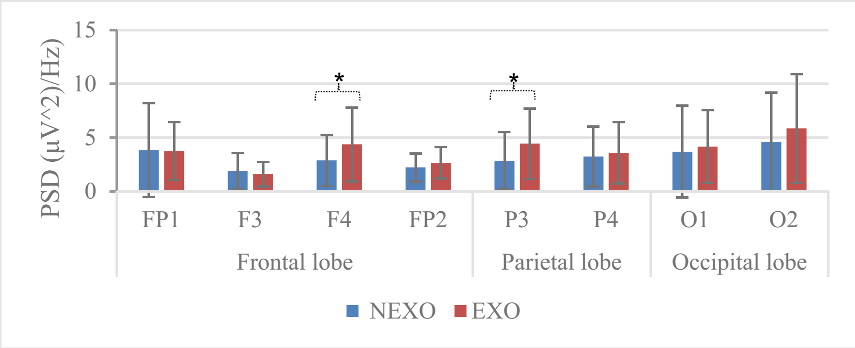

Fig. 3. Cognitive load assessment ("*" = significant at p-value < 0.05).

4.2 Fall Risk Assessment

Figure 4 reveals the pressure-time integral results assessing fall risk across the foot regions. The paired t-test results indicate that only the arch foot regions show significant differences (t (84) = 1.96, P = 0.02, d = 0.21), with the use of the exoskeleton increasing the pressure-integral value. Furthermore, while other foot regions demonstrate an increase in the pressure-integral value, the difference is not statistically significant.

4.3 Relationship Between Fall Risk and Cognitive Load Risk

Table 1 illustrates the relationship between fall risk and cognitive load measures analyzed during carpentry framing tasks with an exoskeleton. According to Schober, Boer [21], a correlation coefficient ranging from 0.00 to 0.09 signifies a negligible relationship, 0.10 to 0.39 indicates a weak relationship, 0.40 to 0.69 denotes a moderate relationship, 0.7 to 0.89 represents a strong relationship, and 0.9 to 1 signifies a very strong correlation. From Table 1, moderate relationships were observed in the following pairs: heel and FP2 (−0.62), and heel and O1 (−0.68); however, these relationships are inversely proportional, suggesting that the heel region instability indirectly affects cognitive load due to reasoning and visual perspectives. Moderate relationships, as indicated by the correlation coefficient in Table 1, were also observed in the following pairs: toe and P3

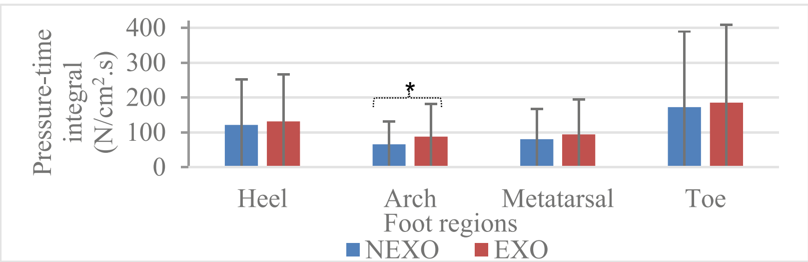

Fig. 4. Fall risk assessment ("*" = significant at p-value < 0.05).

(0.4), and toe and O1 (0.41), which are direct. Other relationships exhibit either weak or negligible correlations.

Table 1. Relationship between fall risk and cognitive load risk (Blue: Moderate correlation, ρ = ± 0.4 to ± 0.69; Yellow: Weak correlation, ρ = ± 0.1 to ±0.39; and White: Negligible correlation, ρ = ± 0 to ±0.09).

	Brain regions	**Frontal lobe**				**Temporal lobe**		**Occipital lobe**	
	EEG channels	**FP1**	**FP2**	**F3**	**F4**	**P3**	**P4**	**O1**	**O2**
Foot regions	**Heel**	0.035	-0.62	-0.2	-0.36	0.03	-0.14	-0.68	0.1
	Arch	0.11	-0.16	-0.26	-0.19	0.16	-0.33	-0.15	0.03
	Metatarsal	-0.18	0.33	0.12	-0.12	0.13	-0.23	0.17	-0.15
	Toe	0.19	0.17	0.33	0.37	0.4	0.37	0.41	0.13

5 Discussion

This study evaluates the relationship between cognitive load and falls during exoskeleton use for framing tasks. The frontal lobe, particularly channel F4, is associated with higher-order cognitive functions such as decision-making, problem-solving, and attention [4]. The increased activity in F4 suggests that workers may require additional cognitive resources to use the exoskeleton, which could lead to mental fatigue over time. The parietal lobe, and specifically channel P3, is involved in integrating sensory information and spatial awareness [4]. The significant increase in cognitive load in this region indicates that workers may experience heightened demands on their sensory processing and spatial awareness when using the exoskeleton. The significant increase in pressure-integral value in the arch foot region suggests that using the exoskeleton places additional strain on this area. This could be due to the weight of the exoskeleton and the abnormal postures assumed during the framing tasks [20]. This could potentially increase the risk of discomfort and injury in the arch foot region, which may elevate the risk of fall. The arch of the foot is crucial for shock absorption and weight distribution [22], so increased pressure in the region could lead to long-term injuries.

The inverse relationship between heel instability and cognitive load in channels FP2 and O1 suggests that as heel instability increases, cognitive load related to reasoning and visual processing decreases. This could imply that workers are subconsciously prioritizing physical stability over cognitive tasks when experiencing heel instability. The direct relationship between toe instability and cognitive load in channels P3 and O1 indicates that toe instability directly increases the cognitive load related to sensory and visual processing. This suggests that workers must devote more cognitive resources to maintaining stability when toe regions are unstable.

The participants' high cognitive load and increased fall risk highlight potential safety concerns with using aBSEs in the construction industry, underscoring the need for improved exoskeleton designs capable of withstanding the demands of construction tasks. Also, the established relationship between cognitive load and fall risk shows their combined value in assessing the risks associated with aBSE use. These findings could inform explorations of machine learning models to monitor these risks on construction sites and guide the design of enhanced aBSEs that better mitigate these challenges.

6 Conclusion, Limitations, and Future Work

While active back-support exoskeletons have demonstrated efficacy in reducing physical strain, their implementation in construction settings may introduce unintended consequences, including heightened cognitive load and increased fall risk for workers. Wearable devices such as electroencephalogram and pressure insoles are instrumental in assessing these risks, yet their concurrent use may be intrusive, potentially impacting worker acceptance and hindering the realization of intended benefits. Understanding the feasibility of substituting one measurement device for another is crucial for optimizing monitoring strategies in construction contexts. This study investigates the impact and correlation between fall risk and cognitive load during the use of the exoskeleton in framing tasks. By analyzing pressure-time integral and gamma power spectral density, the findings reveal that exoskeleton use may elevate fall risk and cognitive load. Moderate relationships, both direct and indirect, between these metrics indicate a correlation between fall risk and cognitive load.

However, this study was conducted in a laboratory with novice participants, which may limit its applicability to real-world construction sites with experienced workers. Future research would replicate similar studies on actual construction sites to enhance generalizability and applicability. Despite these limitations, this study provides insights into the effects of using exoskeletons for construction work. The identified relationship between the metrics provides insights that could inform risk assessments and enhance safety guidelines associated with exoskeleton deployment on construction sites. This study informs construction stakeholders of the potential risks associated with adopting aBSEs and emphasizes the importance of implementing precautionary measures. It underscores the need for mitigation strategies through adaptive aBSEs, which future research should prioritize.

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