Studying the Effects of Back-Support Exoskeletons on Workers' Cognitive Load during Material Handling Tasks

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ABSTRACT

Exoskeletons, also known as wearable robots, are being studied as a potential solution to reduce the risk of work-related musculoskeletal disorders (WMSDs) in construction. The exoskeletons can help enhance workers' postures and provide lift support, reducing the muscular demands on workers while executing construction tasks. Despite the potential of exoskeletons in reducing the risk of WMSDs, there is a lack of understanding about the potential effects of exoskeletons on workers' psychological states. This lack of knowledge raises concerns that exoskeletons may lead to psychological risks, such as cognitive overload, among workers. To bridge this gap, this study aims to assess the impact of back-support exoskeletons (BSE) on workers' cognitive load during material lifting tasks. To accomplish this, a physiologically based cognitive load assessment framework was developed. This framework used wearable biosensors to capture the physiological signals of workers and applied Autoencoder and Ensemble Learning techniques to train a machine learning classifier based on the signals to estimate cognitive load levels of workers while wearing the exoskeleton. Results showed that using BSE increased workers' cognitive load by 33% compared to not using it during material handling tasks. The findings can aid in the design and implementation of exoskeletons in the construction industry.

INTRODUCTION

Workers in physically demanding industries, especially construction, face a high risk of work-related musculoskeletal disorders (WMSDs) due to the nature of their work. Specifically, construction tasks often require workers to engage in repetitive movements, maintain awkward postures, and perform heavy lifting, which can increase the biomechanical strain on the worker's musculoskeletal system and cause WMSDs (Antwi-Afari et al. 2017). These disorders will further cause functional impairments, productivity loss, and, in severe cases, permanent disability (Passmore et al. 2019). Studies have estimated that WMSDs in the construction industry result in over $400 million in workers' compensation claims annually (Bhattacharya 2014). In addition, the incidence rate of back-related WMSDs in the construction sector is nearly twice that of all industries (Luckhaupt et al. 2019). Although the Occupational Safety and Health Administration (OSHA) and the National Institute for Occupational Safety and Health (NIOSH) have recommended general ergonomic practices to reduce the risk of WMSDs among workers (Dale et al. 2016), several physically intensive tasks still require workers to perform repetitive movements and maintain awkward postures, leading to WMSDs. As such, there is a critical need for continued research of effective solutions to mitigate the risk of WMSDs in the construction industry.

Recent advancements in mechatronics and sensing techniques have led to the emergence of wearable robots, also called exoskeletons, as a promising solution for reducing the risk of WMSDs (Kim et al. 2019). Exoskeletons can be classified as active or passive: an active exoskeleton uses actuators, such as electric motors and hydraulics, to provide active force assistance to the human body; In contrast, a passive exoskeleton utilizes materials, springs, or dampers to store energy from human movements and provide physical support and assistance as needed, without the use of actuators. During physically demanding construction tasks, both types of exoskeletons can help prevent WMSDs by optimally distributing the load exerted on the worker's body, correcting workers' awkward postures, and providing lift support (Kim et al. 2019). For instance, Cho et al. reported that the use of an exoskeleton could correct the awkward postures of workers by maintaining the waist bending angles and shoulder twisting angles within the safe angles while performing the material-lifting construction tasks (Cho et al. 2018). These supports and assistances will reduce the physical strain on the body and biomechanical strain on workers' musculoskeletal systems (Kim et al. 2019). Given these findings, exoskeletons have the potential to reduce the risk of WMSEs among construction workers.

Despite the potential of exoskeletons, the limited knowledge regarding their impacts on workers' psychological states hinders their widespread use in the construction industry. The current body of knowledge fails to provide a comprehensive understanding of the impacts of exoskeletons on the cognitive load of workers, which may lead to decreased productivity and mental health risks for workers wearing exoskeletons. Some studies have suggested that exoskeletons can reduce cognitive load by reducing workers' physical demands and allowing workers to focus more on the task (Yang et al. 2023). However, other studies have argued that the use of exoskeletons may actually increase the cognitive load on workers due to the manual operation of the device. During the worker-exoskeleton interaction, workers are required need to input settings constantly to enable the exoskeleton to adjust suitable assistance for various movements, such as squatting, walking, lifting, or stooping (Weisberg and Reeves 2013), which will impose additional cognitive load on workers. This increased cognitive load may result in human errors at work and, in the long run, may adversely affect the mental health of workers, causing anxiety and depression (Mizuno et al. 2011). Therefore, it is necessary to conduct cognitive load assessments of workers using exoskeletons to better understand the impact of the exoskeletons on workers' cognitive load and ensure their psychological safety. Unfortunately, few studies have been conducted to assess the cognitive load levels of workers while wearing exoskeletons to perform construction tasks.

To bridge the current knowledge gap, this study proposed a physiologically-based cognitive load assessment framework and applied the framework to evaluate the impact of exoskeletons on the cognitive load levels of workers. Specifically, the proposed framework utilized wearable sensors to capture workers' physiological signals, which were processed to remove artifacts and extract informative features. Based on the extracted features, an ensemble learning technique was employed to train a robust machine learning (ML) classifier, which was able to assess the cognitive load levels of workers. During the worker-exoskeleton interaction, this proposed physiologically-based framework could continuously, non-intrusively, and robustly assess workers' cognitive load levels. The authors applied the proposed framework to a material handling task. Fourteen subjects were recruited to perform the task while wearing and not wearing the back-support exoskeleton (BSE), one of the most commonly used commercial exoskeletons in construction (Kermavnar et al. 2021). The proposed framework assessed the workers' cognitive load during task execution with and without the BSE. The comparison results between the two scenarios revealed the impact of the BSE on workers' cognitive load, contributing to a better understanding of the impact of exoskeletons on workers' psychological safety. Furthermore, the findings of the study should aid the implementation of exoskeletons in the field, thereby facilitating the establishment of a reliable human-technological collaborative workplace in construction.

METHODOLOGY

To evaluate the impact of the BSE on workers' cognitive load levels, the authors developed a physiologically-based framework that could assess workers' cognitive load based on their EEG and EDA signals. Figure 1 shows the overall structure of the framework, which is comprised of three steps. In the first step, the authors implemented several signal denoising techniques (Figure 1-A) to reduce artifacts in signals, obtaining high-quality EEG and EDA signals. To eliminate flicker and generation-recombination noises in EDA signals, the authors applied a 0.5Hz-45Hz bandpass filtering method. Next, the authors used the blind-source separation (BSS) method to reject EEG-specific ocular and facial movement artifacts (Liu et al. 2021c). The authors also utilized the discrete wavelet transforms adaptive predictor filtering technique to remove motion artifacts in EDA and EEG signals (Liu et al. 2021a).

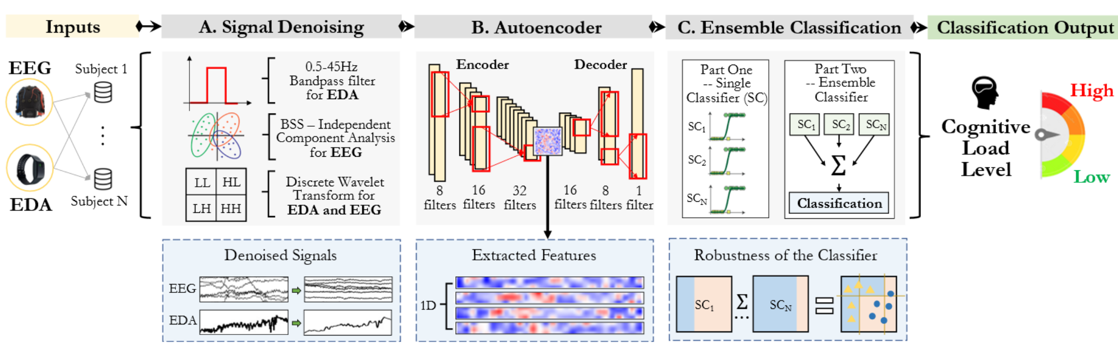

Figure 1. Overview of the physiologically-based cognitive load assessment framework.

Using the denoised EEG and EDA signals, in the second step, the authors utilized the autoencoder technique to extract informative EEG and EDA features capable of classifying workers' cognitive load levels. As depicted in Figure 1-B, the first three 1-D convolutional layers (with 8, 16, and 32 filters, respectively) were connected to form an encoder network of the autoencoder that can extract features from EEG and EDA signals. The subsequent three transposed 1-D convolutional layers (with 16, 8, and 1 filter, respectively) were used to generate a decoder network that can assess the quality of the features extracted from the encoder. The applied autoencoder can automatically extract informative features, enhancing the accuracy of ML classifiers trained in the next step in cognitive load assessment (Li et al. 2015).

After feature extraction, the outputs were used to train a robust ML classifier to assess the cognitive load levels of workers. The ML training process employed in this study consisted of two parts (Figure 1-C). Firstly, the extracted features were divided into N subsets to train a set of single ML classifiers. Secondly, an ensemble rule was proposed to systematically combine these single classifiers to generate an ensemble ML classifier. This process was designed to address the non-stationary issues inherent in physiological signals (Liu et al. 2021a), allowing the ML classifier to accurately evaluate the cognitive load levels of various workers. Once the final ensemble ML classifier was obtained, it could be applied for the measurement of workers' cognitive load levels while performing construction tasks, with and without wearing exoskeletons. Notably, the signal denoising and autoencoder techniques applied in the proposed framework were developed by the authors in their previous work, the detailed information on their implementations can be found in (Liu et al. 2021c, 2022;). For the rest of this section, the authors will explain the third step of the framework, which involves training single classifiers and developing an ensemble rule to generate the ensemble classifier for cognitive load assessment.

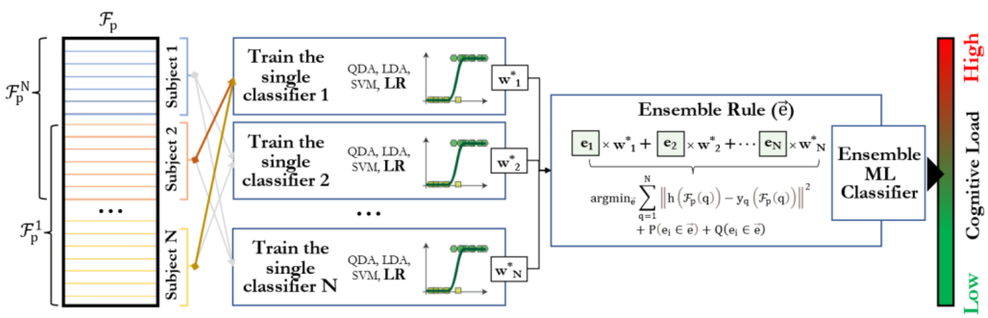

Figure 2. Procedure of generating the ensemble ML classifier for cognitive load assessment.

Figure 2 visualizes the details of the third step in the framework. As shown, after extracting informative features, $\mathcal{F}_p$, from denoised EEG and EDA signals collected from all workers using the signal denoising and autoencoder techniques, the features were divided into N subsets to generate a set $S = \{\mathcal{F}_p^1, \dots, \mathcal{F}_p^N\}$, where each $\mathcal{F}_p^i$ $(i = 1, \dots N)$ represents the features extracted from EEG and EDA signals collected from all workers except worker i (Figure 2). Each $\mathcal{F}_p^i$ was then utilized to train a single ML classifier. In this study, the selected single ML classifiers were from widely-accepted supervised learning techniques, such as Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), Support Vector Machine (SVM) with Gaussian Kernel, and Logistic Regression (LR) with Gaussian Kernel. As demonstrated in (Lotte et al. 2018), all these single ML classifiers were effective and computationally efficient in assessing the cognitive load levels based on physiological signals. For simplicity, the authors introduced Logistic Regression with Gaussian Kernel as an example of the selected ML classifiers. Equation (1) presents its corresponding objective function:

$$\mathrm{Objective_{LR}}: \mathrm{argmin}_w \ \frac{1}{n}\sum_{j=1}^{n} \log\left(1 + \exp(-y_j[(K_j w)_j])\right) + \frac{\beta}{2} w^T K_j w \quad (1)$$

Where the parameter n means the number of feature vectors in $\mathcal{F}_p^i$, and w represents the objective parameters of the classifier that need to be trained using the input feature vectors. y_i

denotes the label (i.e., cognitive load level) of the input j^{th} feature vector, K represents the Gaussian Kernel, and K_j indicates applying the kernel trick to the j^{th} feature vector. $\frac{\beta}{2} w^T K_i w$ is the l_2-regularization for this kernelized Logistic Regression classifier, and β is the hyperparameter that needs to be tuned during the training process. Using each $\mathcal{F}_p^i$ ($i \in \{1, \dots, 14\}$), a single classifier was trained to generate the optimal object parameters w_i^*. In total, 14 single classifiers were trained in this study, and their corresponding optimal object parameters w_i^* ($i = 1, \dots, 14$) were fed into the developed ensemble rule (Figure 2) to produce the ensemble classifier.

Equations (2) to (5) formulate the ensemble rule developed in the third step of the framework. In Equations (2), $\vec{e}$ represents the objective parameters of the ensemble rule that need to be optimized. e_i ($i = 1, \dots, 14$) $\in \vec{e}$ is an element in $\vec{e}$. $h\left(\mathcal{F}_p(q)\right)$ is the classification output of the ensemble model $h(\cdot)$ expressed in Equation (3). w_i^* ($i = 1, \dots, 14$) in Equation (3) indicates the optimal parameters of each single ML classifier obtained from Equation (1). In addition, the variable of Equation (3), $\mathcal{F}_p(q)$, is the q^{th} feature vector in $\mathcal{F}_p$ extracted from the EEG and EDA signals collected from all workers, and y_q is the true label of the $\mathcal{F}_p(q)$. Furthermore, $P(e_i \in \vec{e})$ indicates the $l_2 - l_1$ regularization function formulated based on the Elastic Net algorithm, and $Q(e_i \in \vec{e})$ is an additional regularization function formulated according to the study reported in (Ijaz et al. 2021). α_1, α_2, and α_3 are hyperparameters that need to be tuned in this study. By optimizing the ensemble rule, the ensemble parameters, $\vec{e}$, were obtained, which would systematically combine all 14 single classifiers (w_i^* ($i = 1, \dots, 14$)) to generate the final ensemble classifier (refer to Figure 2). As demonstrated in (Fazli et al. 2009), this ensemble classifier was able to have a robust performance in assessing the cognitive load levels of workers based on their physiological signals with non-stationary issues.

$$\mathrm{argmin}_{\vec{e}} \sum_{q=1}^{N} \left\| h\left(\mathcal{F}_p(q)\right) - y_q\left(\mathcal{F}_p(q)\right) \right\|_2^2 + P(e_i \in \vec{e}) + Q(e_i \in \vec{e}) \quad (2)$$

$$h\left(\mathcal{F}_p(q)\right) = \sum_{i=1}^{14} e_i\, w_i^*(\mathcal{F}_p(q)) \quad (3)$$

$$P(e_i \in \vec{e}) = \alpha_1 \sum_{i=1}^{14} \|e_i\|_2 + \alpha_2 \sum_{i=1}^{14} \|e_i\|_1 \quad (4)$$

$$Q(e_i \in \vec{e}) = \alpha_3 \sum_{i \neq l=1}^{14} |e_i e_l| \quad (5)$$

CASE STUDY

The objective of the case study is to evaluate the efficacy of the proposed physiologically-based framework in assessing cognitive load levels, and subsequently apply the framework to evaluate the impact of exoskeletons on cognitive load levels of workers during construction tasks. To this end, the authors conducted a two-stage material handling task. In the first stage, the authors collected the physiological signals (EEG and EDA) from human subjects performing the material lifting task with and without exoskeletons (BSE). The collected signals were used to train and validate the developed framework's capability to assess the cognitive load levels of workers. In the second stage, the authors utilized the validated framework to determine the cognitive load levels of workers during the same material handling task under two scenarios:

with and without exoskeletons. This allowed for an assessment of the impact of the exoskeleton on the cognitive load of workers. More details of the case study will be provided below.

A total of fourteen subjects were recruited to participate in the case study, with a mean age of 25.1 years (standard deviation: 1.4 years), a mean weight of 155 lbs. (standard deviation: 22.2 lbs.), and a mean height of 5' 9" (standard deviation: 2.80 inches). All subjects were in good health and had not worked a night shift prior to their participation in the study (Liu et al. 2021b). The material lifting task was conducted under two scenarios. In the first scenario, each subject was required to perform the task without using an exoskeleton (Figure 3-A). The task involved lifting a 25-pound bag of cement from a material unloading area, carrying the material for a distance of 33 feet, and placing it in a designated material staging area. Each subject was required to complete 20 rounds of the task in this scenario. In the second scenario, the same task was performed, but with the added requirement of wearing the Cray X back-support exoskeleton (Figure 3-B). During the task, subjects were instructed to manually adjust the settings of the BSE in the human-exoskeleton interface (Figure 3-C) to enable the BSE to generate the appropriate assistances to support subjects in completing the task. These settings included lower back posture support for lifting and bending actions as well as hip-assistance force for walking actions. Subjects needed to frequently adjust these settings, as they constantly changed their actions while performing the task. Additionally, each subject needed to perform 20 rounds of the task in the second scenario. The total duration of each scenario for each subject was 15 minutes.

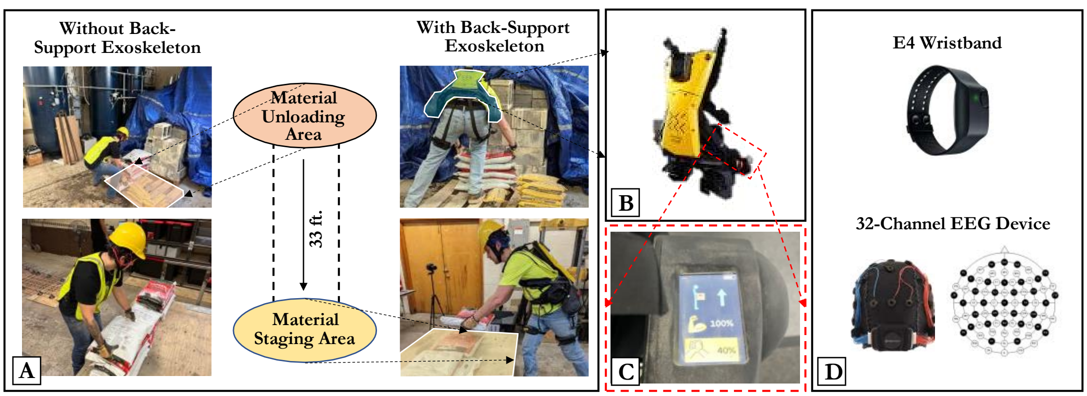

Figure 3. Details of the designed case study.

During the material handling task in each scenario, the E4 wristband (Figure 3-D) and the 32-channel EEG headset (Figure 3-D) were utilized to collect EDA signals from subjects with a sampling rate of 4Hz and EEG signals from subjects with a sampling rate of 128Hz, respectively. The data collection process for each subject lasted 15 minutes for each scenario (2 in total). Then, the collected EDA signals were upsampled to 64Hz, and the collected EEG signals were downsampled to 64Hz to ensure the compatibility with the data processing step in the proposed framework. After completing each round in each scenario, subjects were required to evaluate their cognitive load levels by filling out the widely-accepted cognitive load assessment questionnaire, NASA-TLX (Hart 2006). The NASA-TLX generated a score ranging from 0 to 100 based on each subject's self-evaluation, with scores over 67 considered high cognitive load, scores under 34 considered low cognitive load, and scores between 34 and 67 considered medium cognitive load, as per the study reported in (Liu et al. 2021b). The authors labeled the collected EDA and EEG signals as low, medium, and high levels of cognitive load based on the

NASA-TLX score for each subject. These labeled signals were used to construct the dataset for training the proposed physiologically-based cognitive load assessment framework. Specifically, the dataset consisted of labeled signal data points collected from 14 subjects. For each subject, a total of 3,801,600 data points were stored in a matrix format with dimensions of 33 rows and 115,300 columns. The first 32 rows represented the EEG signals collected from the 32-channel EEG device, and the last row indicated the collected EDA signals. Each column in the matrix corresponded to a specific time point, representing an interval of $\frac{1}{64}$ second. The data matrices for all 14 subjects were concatenated vertically, row-wise. In addition, to validate the performance of the proposed framework, a 5-fold cross-validation process was conducted, and the validation results will be presented in the next section.

After the training and validation process, the framework could continuously assess the cognitive load levels of workers. The authors then applied the framework again to each scenario for an additional 20 rounds of the material handling task. During these rounds, the proposed framework continuously assessed the cognitive load levels of each subject while performing the material handling task with and without the BSE. By comparing the cognitive load assessments between these two scenarios, the impacts of the BSE on the cognitive load of subjects were evaluated. The comparison results will be presented in the next section.

RESULTS AND DISCUSSION

As introduced in the previous section, the collected and labeled physiological signals-based dataset was used to train and validate the ability of the proposed framework to assess the cognitive load levels of subjects. Table 1 presents the performance of the framework, showing the validation accuracy of both the single and corresponding ensemble ML classifiers. The single ML classifiers included LDA, QDA, SVM with Gaussian Kernel, and LR with Gaussian Kernel. Each ensemble ML classifier was generated by combining 14 corresponding single classifiers using the optimized ensemble parameters obtained from Equation (2). All reported accuracies were averaged from all 14 subjects. As shown in Table 1, all single and ensemble classifiers achieved validation accuracy over 75% (the baseline accuracy was 33%). In addition, the accuracy of each ensemble classifier was improved by at least 2.0% compared to that of the corresponding single ML classifier. Notably, the ensemble LR classifier achieved the largest improvement in validation accuracy, with a value of 6.1%. This ensemble classifier also achieved the highest validation accuracy of 88.2% (optimal performance) in measuring the cognitive load levels of workers. Such an accuracy is competitive with existing studies reported in (Thorvald et al. 2019).

To further evaluate the capability of the optimal ensemble ML classifier (LR with Gaussian) in cognitive load assessment, the authors reported its validation accuracy for each subject in Figure 4. The optimal ensemble classifier demonstrated a stable and robust performance across all 14 subjects, with a standard deviation of 1.44% in the validation accuracy. In comparison, the standard deviation in the validation accuracy of the corresponding single classifier was 6.5%. This stability suggested that the ensemble ML classifier in the proposed framework could robustly assess cognitive load levels for all 14 subjects. In summary, these results demonstrate that the ensemble ML classifier was effectively trained using the applied dataset. The proposed framework could be applied to accurately measure workers' cognitive load levels while performing construction tasks, with or without wearing the BSE.

Table 1. Validation accuracy of the proposed framework in cognitive load assessment.

ML Algorithm	Validation Accuracy (single classifier)	Validation Accuracy (ensemble classifier)	Improvement
QDA	77.4%	82.6%	5.2%
LDA	75.7%	78.2%	2.5%
SVM with Gaussian	83.8%	85.8%	2.0%
LR with Gaussian	82.1%	**(88.2%)**	6.1%

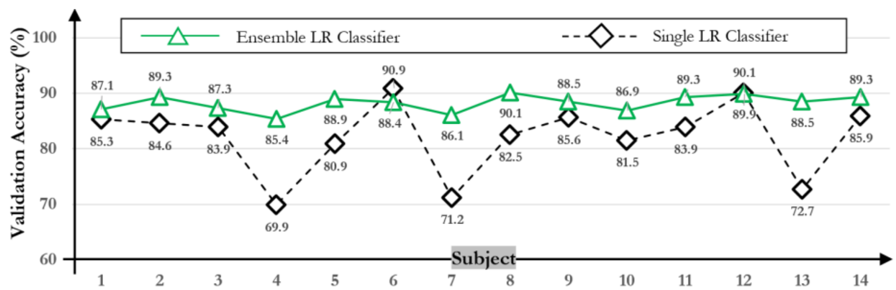

Figure 4. Performance of the ensemble classifier for cognitive load assessment per subject.

After obtaining the robust ensemble classifier, the authors leveraged the proposed framework to evaluate the impact of the BSE on the cognitive load levels of the subjects during the material handling task. As mentioned, the framework was applied to an additional 20 rounds of the designed task. During each round, the proposed framework assessed the cognitive load levels (low: 1, medium: 2, and high: 3) of each subject while they performed the task with and without wearing the BSE. Figure 5 illustrates the comparison results between these two scenarios. The red histogram in Figure 5 shows the cognitive load score of each of the 14 subjects while they performed the task with the BSE. The score of each subject was calculated by averaging the cognitive load levels (low: 1, medium: 2, and high: 3) assessed by the framework during the 20-round task. Higher values indicate higher levels. The blue histogram in the figure shows the cognitive load scores for all subjects while they performed the task without the BSE. On average for all subjects, the use of the BSE increased subjects' cognitive load score from 1.12 to 1.49, a 33% increase. The use of the BSE increased the cognitive load score for each subject during the task, with a minimum increase for the 13th subject (0.05) and a maximum increase for the 7th subject (0.8). These results provide plausible evidence that the use of BSE could increase the cognitive load imposed on subjects. The authors attributed this increase to the requirement for subjects to frequently adjust the BSE settings to support their actions during the task. Despite the increased cognitive load experienced by workers when using the BSE, the authors emphasize that the BSEs hold significant potential for reducing the musculoskeletal risks of workers during material handling tasks. This potential has been demonstrated in the authors' previous study and other related investigations (Liu et al. 2023; Zhu et al. 2021), where the BSE was capable of correcting workers' awkward postures of the trunk and knee, as well as reducing the load exerted on their backs and shoulders. These combined effects can lead to a notable reduction in the musculoskeletal risks faced by workers when performing physically demanding tasks.

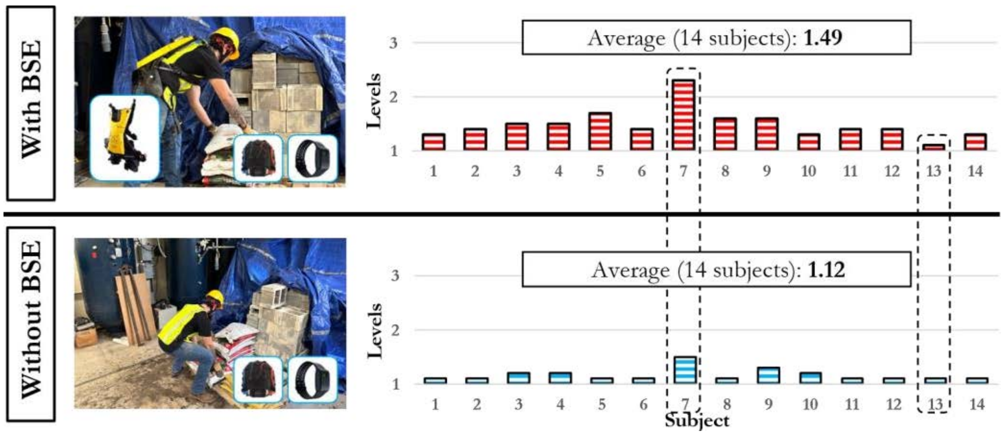

Figure 5. Cognitive load levels of subjects while performing the material handling task with and without using BSEs.

CONCLUSION

This study aimed to evaluate the impact of the back-support exoskeleton (BSE) on the cognitive load levels of workers when performing physically demanding tasks. To achieve this, the authors proposed a physiologically-based framework capable of utilizing artificial intelligence and physiological sensing techniques to evaluate workers' cognitive load levels from their EEG and EDA signals. The proposed framework was applied to a material handling task. During the task, the framework demonstrated robust performance in assessing subjects' cognitive load levels when subjects performed the tasks with and without the BSE. Upon the outcomes of the framework, the use of BSE would increase subjects' cognitive load levels during worker-exoskeleton interactions. The findings contributed to the understanding of the impact of the exoskeletons on the cognitive load levels of workers. Despite these promising findings, one limitation in the presented research requires further investigation in future studies. The current framework was evaluated based on a relatively limited sample of subjects participating in a specific construction task. As such, the efficiency of the proposed framework may be degraded when applied to a broader range of construction tasks and different workers. To address this potential limitation, future studies can recruit a larger sample size of subjects from different demographics. In addition, these studies can encompass various construction tasks, such as welding, bricklaying, and concrete pouring tasks. Conducting these studies will enable a more comprehensive evaluation of the framework's performance under diverse conditions. These efforts can improve the applicability and scalability of the framework in assessing the impact of BSEs on workers' cognitive load. This, in turn, will facilitate the safe and efficient implementation of exoskeletons in the construction industry.

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