Detection of Cognitive Loads during Exoskeleton Use for Construction Flooring Work

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ABSTRACT

Active back-support exoskeletons are increasingly being perceived as potential solutions to the ergonomic risks of construction work. However, users of exoskeletons are susceptible to increased cognitive load could thwart the benefits of the device. Using self-reported cognitive load and electroencephalogram (EEG) data, this study investigated the detection of the cognitive load of users of an active back-support exoskeleton. EEG data and perceived ratings of cognitive load from participants performing flooring tasks are trained with several classifiers. The performance of the best classifier, Ensemble, improved using synthetic minority oversampling technique. This study contributes to existing knowledge by providing evidence of the extent to which cognitive load can be detected from the brain activity of exoskeleton users. The study also advances knowledge of the extent to which synthetic data could enhance the detection of cognitive load. Therefore, the study opens doors for improving exoskeleton designs to better support human cognition and performance.

INTRODUCTION

Wearable robots, in the form of back-support exoskeletons, have the potential to reduce work-related musculoskeletal disorders in the construction industry. These exoskeletons can augment a user's body and provide support while performing physically demanding tasks that are associated with abnormal postures, forceful exertion, bending or twisting of the back, and repetitive movements (CDCP 2023). Active back-support exoskeletons, in particular, are effective in reducing the risk of back-related disorders by reducing the load on the user's back muscles and joints. These devices can be particularly useful for construction workers who perform repetitive or strenuous tasks, such as lifting heavy loads or operating power tools, which can increase the risk of developing back-related disorders.

Despite the potential of active back-support exoskeletons to reduce back disorders, there are several concerns associated with the use of the device in the work environment that can increase the cognitive load of a user. These concerns stem from difficulty working in confined spaces (Jebelli, Hwang et al. 2018), fall risks due to the additional weight of the device (Capitani, Bianchi et al. 2021), pressure or discomfort to body parts (Ogunseiju, Gonsalves et al. 2021), restrictions in movement (Ogunseiju, Gonsalves et al. 2021), catch and snag risks (Okpala, Nnaji et al. 2022), thermal discomfort (Liu, Li et al. 2021) and difficulty adjusting to fit (Fox, Aranko et al. 2019). Furthermore, unequal loading and balancing of body parts due to exoskeleton use can cause users to be more aware of the device and the task they are performing, leading to an increase in cognitive load (Fox, Aranko et al. 2019). Prolonged increases in cognitive load can result in distraction, emotional distress, anxiety, and stress, which can negatively impact a worker's overall well-being and performance Zhu, Weston et al. (2021).

Electroencephalogram (EEG) signals can help infer physiological and psychological states which can enhance detection of cognitive load. EEG produces electrical signals which represent brain activity in response to external and internal stimuli (Jebelli, Hwang et al. 2018). By detecting the cognitive load of users of exoskeletons, adjustments can be made to the device to optimize performance and reduce the risk of cognitive overload. This could also inform the contextual use of the device, length of usage, and appropriate training to support the users. Therefore, the objective of the study is to investigate the extent to which cognitive loads of users of active back-support exoskeletons can be recognized from EEG data. Supervised machine learning algorithms are employed for the detection. The ability of the Synthetic Minority Oversampling Technique to enhance the performance of the machine learning models is presented. The results of this study highlight the potential of supervised learning classifiers in facilitating the adaptation of exoskeleton designs to users' cognitive loads. Given the increasing rate of back-related disorders associated with construction activities such as flooring, this study used simulated flooring work as a case study.

BACKGROUND

According to Zhu, Weston et al. (2021), the presence of physical risks or environmental and situational disturbances will neuro-cognitively burden users of exoskeletons and could ultimately reduce the benefits associated with the device. Recently, studies have explored the physical risks associated with exoskeletons (Huysamen, de Looze et al. 2018, von Glinski, Yilmaz et al. 2019, Kim, Nussbaum et al. 2021, Linnenberg and Weidner 2022). For example, Huysamen, de Looze et al. (2018) assessed the perceived pressure, contact pressure, and subjective usability of an active back-support exoskeleton for dynamic lifting and lowering handling tasks. The results showed that the participants experienced pressure on the back and thigh while using the device. Additionally, there was strong contact pressure on the upper leg, and this caused a restriction in their movement. von Glinski, Yilmaz et al. (2019) evaluated discomfort while using the HAL active back-support exoskeleton for repetitive lifting tasks. The participants reported discomfort due to pressure in the low back area. Linnenberg and Weidner (2022) examined fatigue, distress pain, and arms drop while using four exoskeletons, including an active exoskeleton, for an overhead task. The participants experienced fatigue and pain in the upper arm due to the weight and anthropometric fit of the devices. The exoskeletons also interfered with their arms which could have caused a restriction in blood flow, leading to fatigue. Kim, Nussbaum et al. (2021) assessed the usability and perceived rate of exertion of an active back-support exoskeleton for lifting tasks. The participants perceived a higher rate of exertion while using the exoskeleton. There were also usability issues related to the weight of the device. The aforementioned risks could negatively impact worker's cognitive load.

Over the years, researchers have demonstrated the efficacy of machine learning for classifying cognitive loads from EEG data. For instance, Liu, Habibnezhad et al. (2021) assessed cognitive load for brick-laying activity involving human-robot collaboration. The authors classified cognitive load using EEG data collected from participants (n=14) with different levels of cognitive load. The data was labeled using the results of the NASA-Task Load Index (NASA

TLX), and a 9-point rating scale (RS9). Multilayer perceptron (MLP) Neural Network was the best-performing classifier with an accuracy of 81.9%. Using Multi-Attribute Task Battery (MATB)-II task, Salaken, Hettiarachchi et al. (2020) classified cognitive load using EEG data of five participants (n=5). The task was simulated in two different stages, representing low, medium, and high cognitive loads. NASA TLX was also employed for labeling the EEG data. A classification accuracy of 95% was achieved with the Random Forest classifier. Zarjam, Epps et al. (2015) investigated the detection of cognitive load levels during a human-computer interaction-related task involving n=12 participants. The participants' EEG data was labeled using levels of cognitive tasks ranging from level 1 to level 7 (i.e., very low to extremely high). MLP structure of artificial neural network performed best with an accuracy of 98.8%. Despite the risks of increased cognitive loads, scarce studies are exploring the use of machine learning frameworks for automated detection of cognitive loads during exoskeleton-use for construction-related tasks.

METHOD

This study classified the cognitive load of the users of an active back-support exoskeleton for simulated construction flooring work. Both subjective and objective evaluation approaches, using NASA TLX and EEG brain signals respectively, were employed in this study. EEG data are processed, labeled with NASA TLX data, and classified using machine learning algorithms to predict the cognitive loads of users of an active exoskeleton. Figure 1 presents an overview of the methodology.

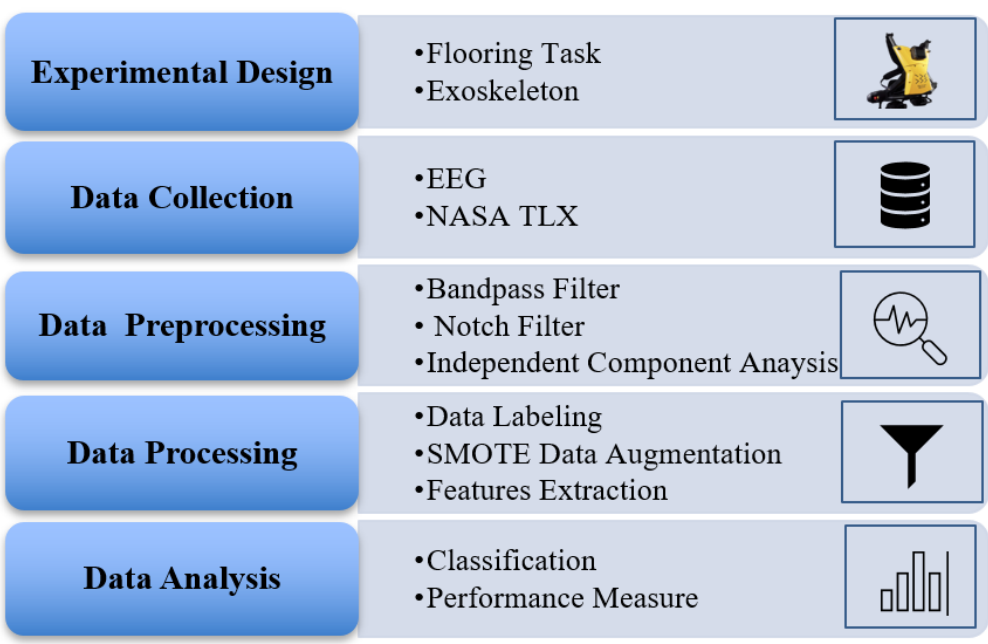

Figure 1. Overview of methodology.

Experimental Design. An experiment, involving a simulated flooring task, was conducted with participants (n=8) wearing an active back-support exoskeleton (Figure 2) and an EEG device (Figure 3). The participants are students from construction-related programs at Virginia

Tech. The mean and standard deviation of the participant's demographic information are age: 30 ± 6 years, weight: 79.8kg ± 15.8, and height: 1.84m ± 0.1. The experiment was conducted with the approval of the Virginia Tech Institutional Regulation Board (IRB: 19-796). The flooring task consists of lifting, placing, and installing subtasks. The participants were asked to lift six stacks of timber tiles with each stack totaling twenty timber tiles, place the tiles beside each of the bays, and install the tiles in the bays (Figure 4). This process is performed in six cycles, i.e., six lifting cycles, six placing cycles, and six installation cycles. Before commencing the study, the participants were given orientations on how the exoskeleton works and how to adapt the devices to their preferences. The participants had the opportunity to practice and be comfortable with the device before commencing the experiment. The EEG device was used to record the participants' brain signals. This was captured across the 14 channels of the device at a frequency of 256Hz. At the end of the study, the participants provided ratings of their cognitive load, via the NASA TLX questionnaire, on a scale of 0 to 20 where '0' represents very low and '20' represents very high.

Figure 2. Cray X Exoskeleton

Figure 3. EEG

Figure 4. Wooden frame (left) and installation of timber floor tiles (right)

Data Collection

Electroencephalography. EEG is a non-invasive technique for collecting and studying the electrical activity of the brain through electrodes attached to various portions of the scalp (Cohen 2017). The brain, which controls the central nervous system, produces electrical signals of brain waves at different frequencies such as delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-13Hz), beta (13-30Hz), and gamma (>30Hz) (Hwang, Jebelli et al. 2018). According to Hwang et al. (2018), the delta band is produced during deep sleep, the beta band corresponds to powered thinking, alertness, concentration, and attentional processing, and the gamma band involves high mental activity and information processing. The EEG device used in this study is a 14-channel EPOCx by EMOTIV.

NASA TLX. The participants completed the NASA-TLX questionnaire to provide subjective ratings on their cognitive workload while performing the task. The questionnaire was used to capture five subscales of the NASA TLX i.e., mental demand, physical demand, performance, effort, and frustration, which were employed to compute the cognitive load of the participants. Mental demand (MD) measures how much brain activity such as looking, thinking, and remembering is needed while using the exoskeleton. Physical demand (PD) measures the participants' level of exertion while performing the task. Performance (P) measures how successful the participants felt while executing the task. Effort (E) on the other hand, measures how difficult the participants must work to seek and understand how to use the exoskeleton for the task, and Frustration (F) measures how irritated discouraged, or stressed learners feel when interacting with an exoskeleton to perform the flooring task (Shayesteh and Jebelli 2022).

Data Preprocessing

Artifacts removal. EEG data are prone to artifact contamination, especially data obtained when subjects are exercising physical body movement in activities like construction work (Jebelli, Hwang et al. 2018). These artifacts significantly affect the quality of the signal. These artifacts can be classified as intrinsic and extrinsic artifacts (Jebelli, Hwang et al. 2018). The intrinsic artifacts are generated by subjects' bodies through eye movements, blinking, and muscle movement. In contrast, the extrinsic artifacts are generated by external factors such as wiring noise, environmental noise, and electrode popping. The study employed the framework developed by Jebelli, Hwang et al. (2018) to process the EEG signal obtained during the simulated task. EEGLAB was also used to remove the artifacts. The raw EEG data were fed into EEGLAB, and a channel location file developed by the authors was uploaded to map out and structure the EEG data. To remove the extrinsic artifacts, a bandpass filter was applied between frequencies of 0.5-65 Hz (Hwang, Jebelli et al. 2018). A notch filter was also applied at a frequency of 60 Hz to remove the noise from the electrode wire.

The intrinsic artifacts were removed using independent component analysis (ICA) (Hwang, Jebelli et al. 2018, Jeon and Cai 2021). The filtered EEG data was decomposed by ICA using the Extended Infomax method recommended by Delorme and Makeig (2004). The component was decomposed into 14 components and displayed using a scalp heat map. The components with intrinsic artifacts were removed using the ICA.

Data Processing

Features extraction. The choice of features for training machine learning classifiers is critical to improving the performance of classification models. Grounded in similar studies that classified cognitive load (Medeiros et al. 2021 and Liu et al. 2021), time and frequency domain features were extracted from the processed EEG data. The time domain features include the maximum value of the EEG amplitude (peak), location of maximum EEG amplitude (peak location), time between EEG signal peaks (peak to peak), skewness, mean amplitude, standard deviation, variance, kurtosis, and root mean squares. The frequency domain features are theta mean power, delta mean power, beta mean power, alpha mean power, and average peak among EEG frequency of the signal power. 196 features were extracted from the EEG data for the 14 channels.

Data Labeling. The aforementioned features were grouped into cognitive load levels based on the results of the feedback obtained from the participants via the NASA TLX questionnaire. NASA TLX has been leveraged for labeling cognitive load levels for machine learning classifications (Bilalpur, Kankanhalli et al. 2018, Liu, Habibnezhad et al. 2021). NASA TLX score of 0 to 50 was considered low, and a score of 51 to 100 was considered high (Bilalpur, Kankanhalli et al. 2018). Out of the eight participants, two participants had a low cognitive load and the remaining six participants had a high cognitive load. Their corresponding EEG data were labeled accordingly.

SMOTE data augmentation. The suitability of SMOTE data augmentation for data balancing has been established by previous studies (Jiang, Lu et al. 2016). Due to the imbalanced nature of the datasets, the SMOTE (Awada, Srour et al. 2021) was employed to balance the EEG data. For example in Table 1, the ratio of the raw dataset of the classes (i.e., High cognitive load:Low cognitive load) is 1:4. Additional datasets were generated with SMOTE algorithm to match the datasets of the minority class (i.e., low cognitive load) with the class with the higher datasets (i.e., the high cognitive load).

Table 1. Raw and SMOTE augmented data for each class.

Classes	Un-augmented data			SMOTE
	Raw Data	**Training Data (80%)**	**Testing Data (20%)**	**(Training data)**
High cognitive load	1356	1085	271	4488
Low cognitive load	5610	4488	1122	4488

Data Analysis

Classification. The labeled EEG data were split into training and testing using 80:20 ratios (see Table 1) (Wang, Xu et al. 2006). The training data (i.e., the raw and SMOTE augmented data) for both cognitive load levels were trained with several classifiers such as Support Vector Machine, Neural Networks, K-Nearest Neighbor, Discriminant, Tree, Kernel, Binary GLM Logistic Regression, and Ensemble, to determine the classifiers that would provide the best performance. MATLAB R2023a, installed on a machine with NVIDIA GeForce GTX 1060 GPU and 16GB memory, was employed for the prediction. Holdout and 5-fold cross-validation were employed to reduce the overfitting of machine learning models (Mahmoodzadeh, Mohammadi et al. 2020).

Performance measures. The performance of the classifiers with the highest accuracy was evaluated using accuracy, precision, recall, and F1-score. Accuracy represents the number of correctly predicted instances of all classes out of the total number of data instances. Precision represents the proportion of positive class predictions that belong to the positive class. Low precision signifies that there are more false predictions than true predictions in a class. The recall represents the proportion of true positives across all class samples. Recall illustrates how accurately a model can predict true classes or the percentage of classes that are true. Low recall shows that there are more false negatives than true positives in a class. F1-score combines the effect of precision and recall. A high F1 score indicates high precision and recall values. The following parameters were determined to estimate these metrics: true positive, true negative, false positive, and false negative.

RESULTS

This section presents the extent to which cognitive loads of exoskeleton users can be recognized by comparing the performance of the raw and SMOTE-augmented EEG data. While the raw and SMOTE augmented data were trained on 9 classifiers, Ensemble emerged as the top-performing classifier. The performance of the classifier is described as follows:

Performance of the Ensemble classifier. Table 2 shows the overall performance of all the trained classifiers with Ensemble and Kernel having the highest and lowest accuracies respectively. Figures 5 and 6 show the accuracy, precision, recall, and F1-score of the raw and SMOTE augmented datasets of the Ensemble classifier in predicting the cognitive load levels during exoskeleton use. From Figure 5, an increase in the accuracy of the classifier was observed with the SMOTE augmented data for the high cognitive load class. With the SMOTE augmented data, the classifier achieved an accuracy of 99.55%, which is higher compared to the raw data with 98.35%. The SMOTE augmented data had higher values of precision, recall, and F1 score compared with the raw data i.e., about 3.09%, 4.46%, and 3.78% increase (respectively) was observed with the SMOTE augmented data. Similar increases were observed in the performance of the Ensemble classifier in predicting the low cognitive load class. From Figure 6, the use of the SMOTE augmented data resulted in an increase of about 1%, 0.16%, and 0.58% in the values of the precision, recall, and F1-score, respectively.

Table 2. Overall performance of trained classifiers

Classifiers	Accuracy	
	Original	SMOTE
Ensemble	98.35%	99.55%
Neural Network	98.26%	99.32%
SVM	98.24%	99.48%
Binary GLM Logistic Regression	96.93%	98.79%
KNN	96.86%	99.25%
Tree	95.85%	98.81%
Discriminant	94.17%	98.95%
Naïve Bayes	85.03%	97.46%
Kernel	84.60%	97.63%

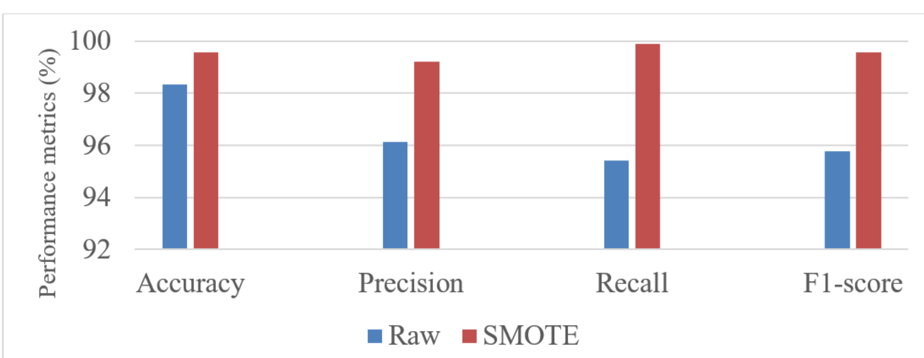

Figure 5. Comparison of performance of raw and SMOTE data for high cognitive load.

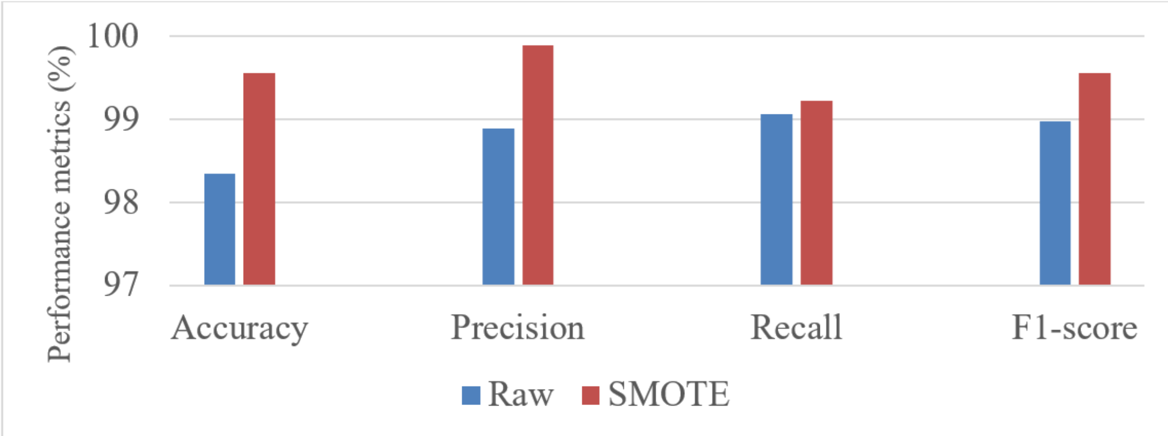

Figure 6. Comparison of performance of raw and SMOTE data for low cognitive load.

Confusion matrix. The confusion matrixes show the correctly and wrongly predicted classes. Figure 7 shows the confusion matrix for the prediction of the cognitive load classes (i.e., high cognitive load (HCL) and low cognitive load (LCL)) using the raw data. 96.1% of the total high cognitive load was correctly predicted as high cognitive load while 3.9% was misclassified as low cognitive load. Also, 98.9% of the total low cognitive load was correctly predicted as low cognitive load while 1.1% was wrongly predicted as high cognitive load. The confusion matrix that classifies the SMOTE augmented data into the cognitive load classes is shown in Figure 8. 99.2% of the total high cognitive loads were correctly predicted as high cognitive load while 0.80% was misclassified as low cognitive load. Moreover, 99.9% of the total low cognitive load was correctly predicted as low cognitive load while 0.1% was wrongly predicted as high cognitive load.

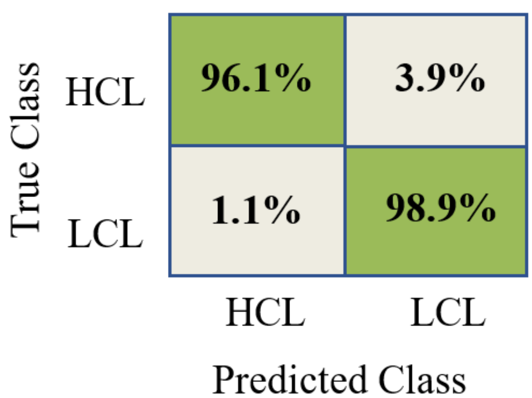

FIGURE 7. Confusion matrix for Raw Data

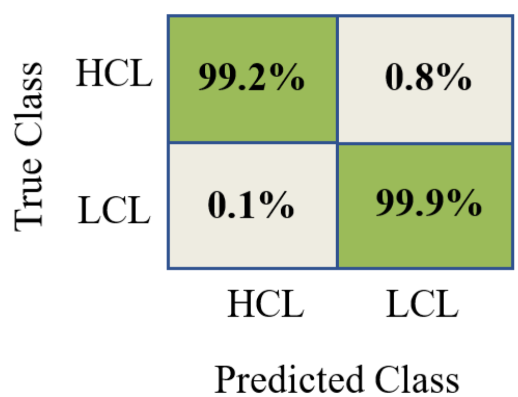

FIGURE 8. Confusion matrix for SMOTE data

CONCLUSION AND FUTURE WORK

Physical risks, such as discomfort to the body parts, anthropometric fit, additional weight, thermal discomfort, movement restrictions, and catch and snags, could trigger increases in cognitive load while using exoskeletons. A prolonged increase in cognitive load could undermine the benefits of exoskeletons. Thus, detection of cognitive load levels while using exoskeletons could inform contextual use or applications of the device, length of usage, and appropriate training to support the users. Moreover, this could also inform investigations into designs that are more adaptive to construction work and work environment. This study explored the use of machine learning for detecting cognitive loads of users of active back-support exoskeletons from EEG signals of their brain activity. EEG signals obtained from participants performing flooring tasks with an active back-support exoskeleton are trained using supervised learning classifiers. The study revealed the Ensemble classifier as the best-performing classifier. The performance of the resulting model improved when trained on the SMOTE augmented data, displaying the suitability of synthetic data obtained via SMOTE. The resulting model motivates the redesign of exoskeletons with EEG capabilities to better support human cognition and performance. This study contributes to the scarce literature on the potential of detecting cognitive load levels of users of exoskeletons from EEG data.

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REFERENCES

Awada, M., F. J. Srour, and I. M. Srour. (2021). “Data-driven machine learning approach to integrate field submittals in project scheduling.” *Journal of Management in Engineering* 37(1): 04020104.

Bilalpur, M., M. Kankanhalli, S. Winkler, and R. Subramanian. (2018). EEG-based evaluation of cognitive workload induced by acoustic parameters for data sonification. *Proceedings of the 20th ACM International Conference on Multimodal Interaction*.

Capitani, S. L., M. Bianchi, N. Secciani, M. Pagliai, E. Meli, and A. Ridolfi. (2021). “Model-based mechanical design of a passive lower-limb exoskeleton for assisting workers in shotcrete projection.” *Meccanica* 56: 195-210.

CDCP. (2023). “Exoskeletons in Construction: Will they reduce or create hazards?” Retrieved March 25, 2023, from https://blogs.cdc.gov/niosh-science-blog/2017/06/15/exoskeletons-in-construction/#:~:text=Musculoskeletal%20disorders%20(MSDs)%20are%20a,one%2Dthird%20of%20these%20injuries.

Cohen, M. X. (2017). “Where does EEG come from and what does it mean?” *Trends in neurosciences* 40(4): 208-218.

Delorme, A., and S. Makeig. (2004). “EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis.” *Journal of neuroscience methods* 134(1): 9-21.

Fox, S., O. Aranko, J. Heilala, and P. Vahala. (2019). “Exoskeletons: Comprehensive, comparative and critical analyses of their potential to improve manufacturing performance.” *Journal of Manufacturing Technology Management* 31(6): 1261-1280.

Huysamen, K., M. de Looze, T. Bosch, J. Ortiz, S. Toxiri, and L. W. O'Sullivan. (2018). "Assessment of an active industrial exoskeleton to aid dynamic lifting and lowering manual handling tasks." *Appl Ergon* 68: 125-131.
Hwang, S., H. Jebelli, B. Choi, M. Choi, and S. Lee. (2018). "Measuring workers' emotional state during construction tasks using wearable EEG." *Journal of Construction Engineering and Management* 144(7): 04018050.
Jebelli, H., S. Hwang, and S. Lee. (2018). "EEG signal-processing framework to obtain high-quality brain waves from an off-the-shelf wearable EEG device." *Journal of Computing in Civil Engineering* 32(1): 04017070.
Jeon, J., and H. Cai. (2021). "Classification of construction hazard-related perceptions using: Wearable electroencephalogram and virtual reality." *Automation in Construction* 132: 103975. 103975.
Jiang, K., J. Lu, and K. Xia. (2016). "A novel algorithm for imbalance data classification based on genetic algorithm improved SMOTE." *Arabian journal for science and engineering* 41: 3255-3266.
Kim, S., M. A. Nussbaum, M. Smets, and S. Ranganathan. (2021). "Effects of an arm-support exoskeleton on perceived work intensity and musculoskeletal discomfort: An 18-month field study in automotive assembly." *American Journal of Industrial Medicine* 64(11): 905-914.
Linnenberg, C., and R. Weidner. (2022). "Industrial exoskeletons for overhead work: Circumferential pressures on the upper arm caused by the physical human-machine-interface." *Applied Ergonomics* 101: 103706.
Liu, Y., M. Habibnezhad, and H. Jebelli. (2021). "Brainwave-driven human-robot collaboration in construction." *Automation in Construction* 124: 103556.
Liu, Y., X. Li, J. Lai, A. Zhu, X. Zhang, Z. Zheng, H. Zhu, Y. Shi, L. Wang, and Z. Chen. (2021). "The effects of a passive exoskeleton on human thermal responses in temperate and cold environments." *International Journal of Environmental Research and Public Health* 18(8): 3889.
Mahmoodzadeh, A., M. Mohammadi, A. Daraei, H. F. H. Ali, N. K. Al-Salihi, and R. M. D. Omer (2020). "Forecasting maximum surface settlement caused by urban tunneling." *Automation in Construction* 120: 103375.
Ogunseiju, O., N. Gonsalves, A. Akanmu, and C. Nnaji. (2021). "Subjective Evaluation of Passive Back-Support Exoskeleton for Flooring Work." *EPiC Series in Built Environment* 2: 10-17.
Okpala, I., C. Nnaji, O. Ogunseiju, and A. Akanmu. (2022). "Assessing the Role of Wearable Robotics in the Construction Industry: Potential Safety Benefits, Opportunities, and Implementation Barriers." *Automation and Robotics in the Architecture, Engineering, and Construction Industry*: 165-180.
Salaken, S. M., I. Hettiarachchi, L. Crameri, S. Hanoun, T. Nguyen, and S. Nahavandi. (2020). Evaluation of classification techniques for identifying cognitive load levels using EEG signals. *2020 IEEE International Systems Conference (*SysCon*)*, IEEE.
Shayesteh, S., and H. Jebelli. (2022). Investigating the Impact of Construction Robots Autonomy Level on Workers' Cognitive Load. *Proceedings of the Canadian Society of Civil Engineering Annual Conference 2021: CSCE21 General Track* Volume 1, Springer.
von Glinski, A., E. Yilmaz, S. Mrotzek, E. Marek, B. Jettkant, A. Brinkemper, C. Fisahn, T. A. Schildhauer, and J. Geßmann. (2019). "Effectiveness of an on-body lifting aid (HAL® for care support) to reduce lower back muscle activity during repetitive lifting tasks." *Journal of Clinical Neuroscience* 63: 249-255.

Wang, J., M. Xu, H. Wang, and J. Zhang. (2006). Classification of imbalanced data by using the SMOTE algorithm and locally linear embedding. *2006 8th International Conference on Signal Processing*, IEEE.

Zarjam, P., J. Epps, and N. H. Lovell. (2015). "Beyond subjective self-rating: EEG signal classification of cognitive workload." *IEEE Transactions on Autonomous Mental Development* **7**(4): 301-310.

Zhu, Y., E. B. Weston, R. K. Mehta, and W. S. Marras. (2021). "Neural and biomechanical tradeoffs associated with human-exoskeleton interactions." *Applied Ergonomics* 96: 103494.