EPiC Series in Built Environment
Volume 5, 2024, Pages 894–902
Proceedings of 60th Annual Associated Schools of Construction International Conference

Experimental Analysis of Cognitive Load Risks in Employing Active Back-Support Exoskeleton in Construction

Akinwale Okunola and Abiola Akanmu, Ph.D.
Virginia Tech
Blacksburg, Virginia

Houtan Jebelli, Ph.D.
University of Illinois Urbana-Champaign,
Urbana, Illinois

There is a growing interest in utilizing active back-support exoskeletons to address work-related musculoskeletal disorders in various industries, including construction. However, the unique characteristics of construction sites may impede the biomechanical advantages of active back-support exoskeletons by increasing users' cognitive load. This research focuses on assessing the impact of active back-support exoskeletons on cognitive load during a construction framing task. An experimental study, involving sixteen participants performing a simulated carpentry framing task with and without active back-support exoskeletons across six subtasks, was conducted. Participants' brain activities were captured using Electroencephalography for the two experimental conditions. The differences between the conditions were analyzed using paired t-tests. The findings indicate that the use of active back-support exoskeletons significantly heightens cognitive load during measuring, assembly, nailing, and installing subtasks. These results emphasize the importance of developing adaptive active back-support exoskeletons tailored to the construction industry's specific needs, considering the distinct challenges of construction environments. Additionally, this study contributes to construction stakeholders' understanding of the psychological risks associated with active back-support exoskeletons use on construction sites.

Key Words: Active back-support exoskeletons, Construction framing task, Cognitive load, Electroencephalography, Power spectrum density

Introduction

Musculoskeletal issues remain a concern in the construction industry due to the physically demanding nature of the work. The back bears the brunt of about 50% of these issues (BLS, 2020). Back-support exoskeletons have emerged as a potential solution to alleviate strain on the musculoskeletal system (Kim et al., 2019; Ogunseiju, Gonsalves, Akanmu, & Nnaji, 2021), garnering interest from construction industry stakeholders keen on enhancing safety and productivity (Kim et al., 2019). However, researchers have unearthed unexpected challenges associated with exoskeleton use, including perceived pressure, added weight, thermal discomfort, catch and snag risks, and movement

restrictions, all contributing to increased cognitive load (Giustetto et al., 2021; Kim et al., 2019; Liu et al., 2021; Ogunseiju et al., 2021; Picchiotti, Weston, Knapik, Dufour, & Marras, 2019).
High cognitive load, characterized by intense mental effort, can lead to mental fatigue and a decline in situational awareness, elevating the risk of falls with potentially dire consequences (Marchand, De Graaf, & Jarrassé, 2021). Zhu, Johnson, Chang, and Mehta (2020) noted that sustained high cognitive load may negate the biomechanical benefits of exoskeletons and increase the likelihood of errors. Construction tasks, encompassing both physical and mental components, demand efficient cognitive functioning for activities like carpentry framing, involving measuring, assembly, and installation. An increase in cognitive load may impede overall work efficiency and productivity.

While researchers have utilized wearable sensors, such as Electroencephalography (EEG), to evaluate cognitive load in various construction tasks like bolt and nut fastening and assembly tasks (Chen, Taylor, & Comu, 2017), research has predominantly focused on the benefits of exoskeletons rather than assessing the associated cognitive load risks. Considering the unstructured environment of construction sites that inherently increases cognitive load, deploying active back-support exoskeletons without empirical research on their cognitive effects poses a potential hazard. Thus, this study aims to assess the cognitive load effects of exoskeletons in carpentry framing tasks, shedding light on the psychological risks associated with their use in construction settings.

Background

Contributions of Exoskeleton to Cognitive Load

Studies have highlighted the potential benefits of exoskeletons in mitigating work-related musculoskeletal disorders (WMSDs) by reducing muscle activation (Walter, Stutzig, & Siebert, 2023) and perceived discomfort (Huysamen et al., 2018). However, the use of exoskeletons has also revealed unintended consequences, including an increased cognitive load on users. These consequences manifest as perceived discomfort in various body parts (Giustetto et al., 2021), movement restrictions (Ogunseiju et al., 2021), catch and snag risks (Kim et al., 2019), thermal discomfort (Liu et al., 2021), and uneven load distribution (Picchiotti et al., 2019). For instance, Giustetto et al. (2021) investigated the effectiveness of passive back-support exoskeletons (Laevo) in manual material handling tasks, revealing discomfort in the chest region. Ogunseiju et al. (2021) assessed the suitability of passive back-support exoskeletons (Laevo) for construction flooring tasks, highlighting biomechanical advantages but also restrictions in movements. Kim et al. (2019) explored the potential and barriers to exoskeleton use in construction, with stakeholders expressing concerns about catch and snag risks on construction sites. Liu et al. (2021) studied thermal comfort with a passive back-support exoskeleton (Mile bot) during lifting tasks, indicating participants experienced thermal discomfort in hot conditions. Picchiotti et al. (2019) assessed spine biomechanical loading using passive exoskeletons (FLx and V22) in manual material handling tasks, revealing uneven load distribution. These studies highlight the need to examine cognitive load contributions of exoskeletons during construction work.

Electroencephalography for Assessing Cognitive Load

In addition to physical assessments, cognitive load has been studied using wearable sensors across various mental tasks (Castro-Meneses, Kruger, & Doherty, 2020; Cummins, Broughton, & Finnigan, 2008; Keskin, Ooms, Dogru, & De Maeyer, 2020; Schapkin, Raggatz, Hillmert, & Böckelmann, 2020). Theta band power in EEG power spectral density (PSD) has been identified as a sensitive indicator of cognitive load. For instance, Schapkin et al. (2020) evaluated cognitive load during reaction tasks, showing a strong correlation between high cognitive load conditions and elevated theta band PSD. Keskin et al. (2020) assessed cognitive load in map reading tasks, revealing an increase in theta band PSD with higher difficulty levels. Cummins et al. (2008) studied cognitive load in word recognition tasks for amnestic mild cognitive impaired participants, showing lower theta band PSD compared to controls. Castro-Meneses et al. (2020) validated theta band power as a measure of cognitive load in a multimedia task. Researchers have also investigated the cognition of exoskeleton users (Swerdloff and Hargrove, 2022; Di Marco et al., 2023). For example, Swerdloff and Hargrove (2022) employed EEG to measure the cognitive load of exoskeleton users in various states, including sitting, standing, and walking on a treadmill. Their findings indicate a higher cognitive load while walking on the treadmill. Similarly, Di Marco et al. (2023) examined the cognitive load effects before and after training individuals to use a movement-aided exoskeleton using EEG. The study revealed an increase in the cognitive load for the exoskeleton users after the training. Despite evidence of cognitive load impact of exoskeletons and opportunities offered by EEG, there is a lack of studies examining the cognitive load of exoskeleton users, particularly in construction framing tasks. Given the potential cognitive load triggers and the weight of active back-support exoskeletons, this study aims to evaluate the cognitive load during a simulated construction carpentry task.

Methods

This section presents the method employed in the evaluation of cognitive load while using active back-support exoskeleton as shown in Figure 1. These include the participants, active back-support exoskeleton, experimental design and procedure, EEG, signal processing, and data analysis.

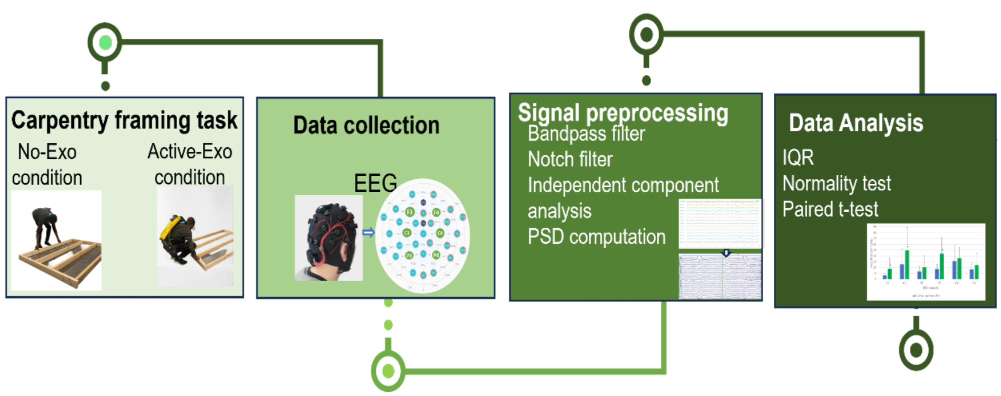


Figure 1. Methodology overview

Participants

Sixteen male students with limited or no prior experience in constructing frames were recruited from Virginia Tech University to participate in this study in accordance with the approval of the institution review boards (IRB: 19-796). Although some of the participants had previous exposure to exoskeletons, their encounters were limited to experimental settings, and they did not have regular usage experience. The participants have no history of mental or musculoskeletal disorders in the past 6 months that could affect the outcomes of the study's results. The demographics of the participants in terms of means and standard deviation of age, weight, and height are as follows: 30 years ± 4 years, 72 kg ± 7.5kg, and 173cm ± 5.5cm, respectively.

Active Back-Support Exoskeleton

The active back-support exoskeleton adopted for this study is CrayX, obtained from German Bionic. The exoskeleton is designed to reduce the muscle activation of the back with three major modes of assistive operations, such as lifting, placing, and walking. The exoskeleton weighs approximately 8 kg. The exoskeleton consists of two motors powered by a 40-volt battery that help supply the required torque to the body of the user. As indicated in Figure 2a, the exoskeleton consists of different straps, such as the chest strap, thigh strap, waist strap, and shoulder strap, all of which support the anthropometric fitness of the exoskeleton for the users.

Experimental Design and Procedure

The study employed a repeated measure design to assess how cognitive load influences the performance of individuals engaging in a construction carpentry framing task while using an active back support exoskeleton. In this design, the same group of participants carried out the framing task both with and without the active back-support exoskeleton, as illustrated in Figure 2a and 2b. The independent variables encompass the exoskeleton conditions (No-Exo and Active-Exo). The dependent variables consist of the PSD values, EEG channels, and subtasks. The framing task comprises of six distinct subtasks, representing the sequential steps of the experiment: measuring, assembly, nailing, lifting, moving, and installing. The experiment initiation involves briefing the participants on the details of the study, including explanations of the instruments used—such as the active back-support exoskeleton, EEG, timber planks, nail gun, and measuring tape. The measuring subtask begins with participants measuring the required timber log from the provided set of timber planks. Subsequently, they assembled the timber planks to create the frame, as depicted in Figure 2. The assembled frame was then fastened together using the provided nail gun, with the frame weighing 20kg—within the recommended maximum manual material handling weight of 23kg according to the revised NIOSH lifting formula (Waters, Putz-Anderson, & Garg, 1994). Following assembly, the frame was lifted and manually moved to the upper floor through the staircase, where it was ultimately installed. Throughout the experiment, an EEG sensor captured the cognitive status of participants under the two experimental conditions.

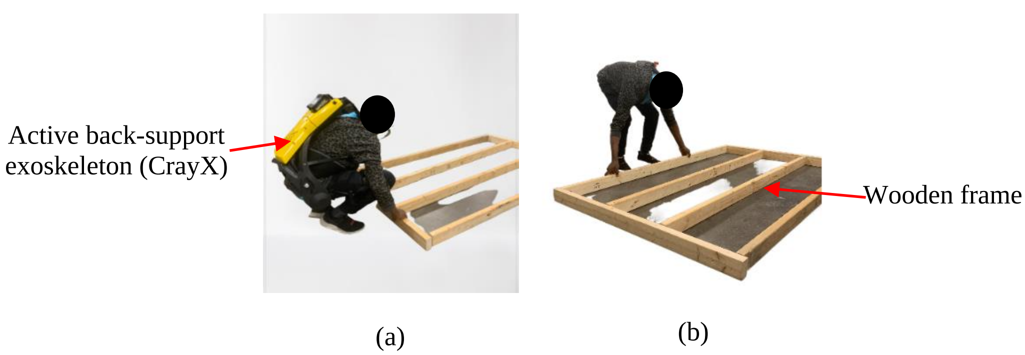


Figure 2. Simulated framing task: (a) No-Exo condition, (b) Active-Exo condition.

Electroencephalography

A non-invasive 32-channel EEG obtained from Emotiv was adopted in this study to capture the electrical activity in the brain (Figure 3b and 3c). The EEG records the electrical activity from the cerebral cortex part of the brain, which was used to evaluate the cognitive status of the exoskeleton users. The cerebral cortex comprises of four major parts: the frontal lobe, parietal lobe, occipital lobe, and temporal lobe. The frontal lobe houses the front EEG channels and captures cognition, memory, and decision-making. The parietal lobe, represented by parietal channels, specifically captures sensory information processing (Jawabri and Sharma 2019). The occipital lobe processes visual information, and the temporal lobe handles sensory input (Jawabri and Sharma 2019). EEG channels are laid out according to a 10-20 system to capture electrical activity in all the parts of the cerebral cortex. The EEG measures brain activity across five major frequency ranges, such as delta, alpha, theta, beta, and gamma, all of which represent different cognitive states (Chen et al., 2017). Specifically, the theta frequency range represents the state of drowsiness and resource allocation. This have been used to evaluate cognitive load during mentally demanding tasks. An increase in theta band power corresponds to a higher cognitive load (Castro-Meneses et al., 2020). Significantly, EEG channels around the frontal lobe (F3 and F4), central sulcus (C3 and C4), and parietal lobe (P3 and P7) have been used to assess cognitive load during mentally demanding activities within the theta frequency range (Puma, Matton, Paubel, Raufaste, & El-Yagoubi, 2018).

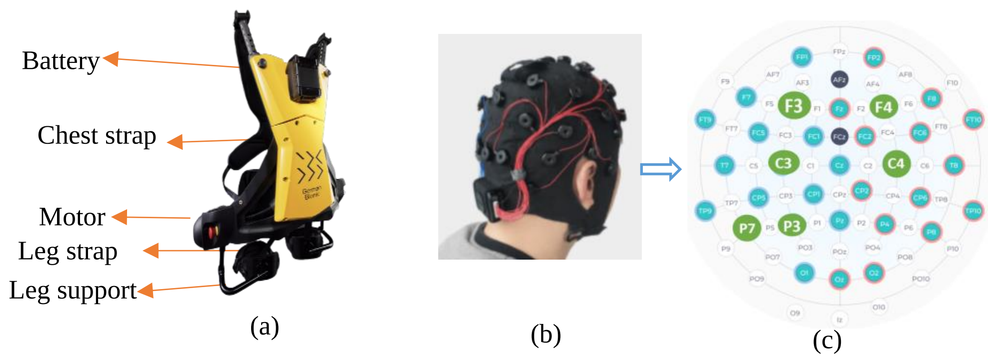


Figure 3. Instrument and data collection: (a) CrayX (Source: German-Bionic, 2023) (b) 32- channel EEG sensor (c) EEG channel selection (Source: Emotiv, 2023).

Signal Preprocessing

EEG signals are prone to noise, which could be triggered by body movement and the presence of electromagnetic waves in the environment (Tandle, Jog, D'cunha, & Chheta, 2015). Given the dynamic nature of the experimental task in this study, which involved physical labor and body movement, it is important to denoise the EEG signal before proceeding with the analysis. The first stage of denoising the EEG signal involved using a bandpass filter between a frequency of 0.5 to 60Hz to remove the frequency that could be affected by the noise from the environment (Murugappan, Murugappan, & Gerard, 2014). This was followed by the application of notch filter at the frequency of 60Hz to remove the wire noise from the channels. The last stage of denoising the signal involves the use of independent component analysis (ICA), which shows the heatmap of the brain of each component. At this stage, noises generated from the body, such as eye blinking and muscle movements, are removed using ICA label features. Following the denoising of the signal, the EEG data was sorted according to the subtasks using the recorded timestamped video captured during the experiment. The PSD of the considered channels were computed for the theta frequency range using Welch's algorithm. This was done for each of the subtasks. All signal processing and computation was done using the EEGLAB toolbox and MATLAB 2023Ra.

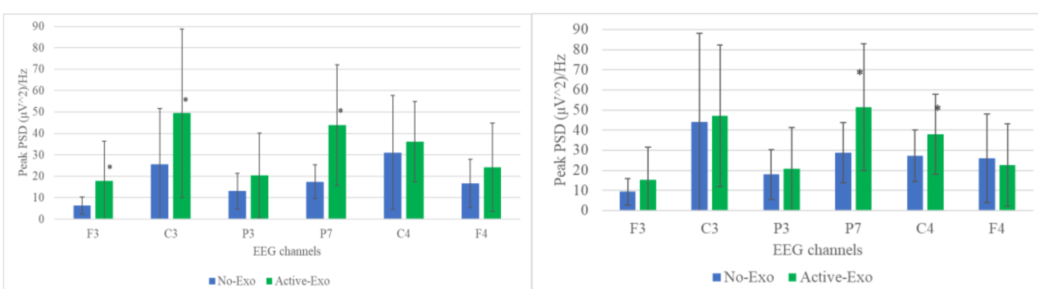
Data Analysis

Considering the continuous nature of the EEG signal, a parametric statistical analysis was used to compute the significant differences between the two experimental conditions. Prior to the statistical analysis computation, the data was screened using Tukey's range test, which uses interquartile range to define the lower limit (Q1 - 1.5 * IQR) and upper limit (Q3 + 1.5 * IQR) to remove any possible outliers. This was followed by computing a normality test using d'Agostino-Pearson test, before proceeding with paired t-test between the two experimental conditions for each of the subtasks. Also, the graphical representations of all the results are shown using bar graphs, while also indicating the statistical significance.

Results

Cognitive Load Evaluation

Examining the cognitive load for both experimental conditions, namely the No-Exo and Active-Exo, across the six considered subtasks (measuring, assembly, nailing, lifting, moving, and installing), Figures 4a to 4f depict the PSD of theta frequency range. Starting with Figure 4a, which focuses on the measuring task, the results reveal an increased cognitive load when utilizing the aBSE across all considered channels. Notably, statistical significance ($P < 0.05$) is observed at channels F3, C3, and P7, with increases of 2.86, 1.93, and 2.51 times compared to the No-Exo condition. Figure 4b illustrates results for the assembly subtask. Channels P7 and C4 exhibit a significant ($P < 0.05$) increase of 2.79 and 2.39 times in the PSD value for the Active-Exo condition compared to the No-Exo condition. In Figure 4c, representing the nailing subtask, channels F3 and P7 of the Active-Exo condition displays a significant ($P < 0.05$) elevation of 2.59 and 1.79 times in PSD values compared to the No-Exo condition. Figures 4d and 4e, evaluating cognitive load during lifting and moving subtasks, show no statistically significant differences ($P > 0.05$) across all channels. Finally, Figure 4f illustrates the results of the installation subtask, revealing significant differences between the two experimental conditions. Specifically, in channels C3 and P7, the Active-Exo condition exhibits higher PSD values of 0.77 and 0.80 compared to the No-Exo condition.



(a) (b)

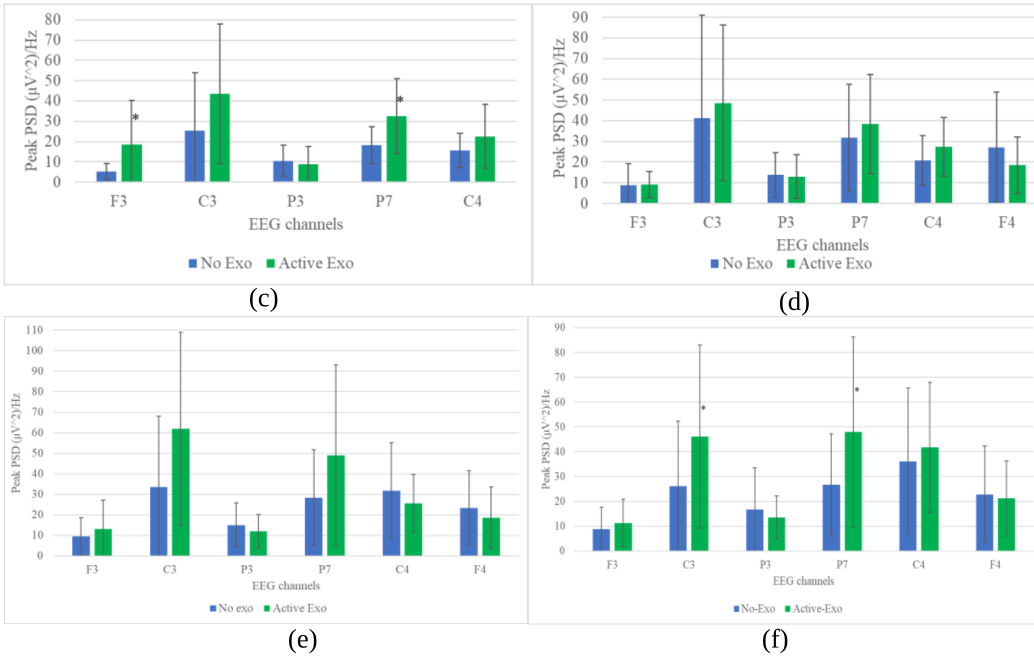


Figure 4. Theta frequency mean PSD: (a) measuring subtask, (b) assembly subtask, (c) nailing subtask, (d) lifting subtask, (e) moving subtask, and (f) installation subtask. (“*” = significant at p-value < 0.05)

Discussion

This study evaluates the cognitive load of individuals engaged in construction carpentry framing tasks using an augmented reality-based smart exoskeleton. The assessment involves computing the mean theta power spectral density from wearable EEG data in two experimental conditions. Across the six subtasks (measuring, assembly, nailing, installation, lifting, and moving), results indicate a significant increase in cognitive load when using aBSE during measuring, assembly, nailing, and installation subtasks. However, the lifting and moving subtasks show no statistical significance, despite being the most demanding stages where the frame is relocated for installation. This lack of difference may be attributed to the inherently attention-demanding nature of these tasks in both experimental conditions. While scarce studies have explored cognitive load in human-robot relationships using theta-band power, Castro-Meneses et al. (2020) employed theta-band power to assess cognitive load in participants undertaking multimedia tasks with varying complexities, revealing significant differences similar to those observed in measuring, assembly, nailing, and installation subtasks.

Conclusion, Limitation, and Future Work

The dynamic and challenging working conditions inherent in construction sites may undermine the biomechanical advantages of employing active back support exoskeletons by amplifying users' cognitive load. This study assessed the impact of active back support exoskeletons on cognitive load during construction carpentry framing tasks, comparing Electroencephalography power spectral density between two experimental conditions, with and without active back support exoskeletons across six subtasks. The results reveal statistically significant increase in cognitive load among active back support exoskeleton users during the measuring, assembly, nailing, and installing subtasks.

While other subtasks also exhibited increased cognitive load, the differences did not reach statistical significance. It's crucial to acknowledge the study's limitations, conducted as a simulation in a controlled laboratory environment, which may not fully mirror the complexities of an uncontrolled construction site. Moreover, the participants, being inexperienced students without day-to-day construction involvement, may have influenced the results. Future research endeavors should shift towards real construction sites, involving experienced workers over extended periods to obtain a more comprehensive understanding of how cognitive load manifests among active back support exoskeleton users. This study, offering a scientific perspective, underscores the imperative of tailored active back support exoskeleton solutions for the construction industry, considering the unique challenges of the construction environment. Manufacturers of active back support exoskeleton can glean valuable insights into the necessity for adaptive designs that align with the specific demands of construction sites. Additionally, this research This research enhances construction stakeholders' understanding of psychological risks linked to active back support exoskeletons, promoting informed decision-making in the industry.

Acknowledgments

This study is based upon work supported by the National Science Foundation under Grant Nos. 2221166 and 2221167. Any opinions, findings, conclusions, or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

References

BLS. (2020). Injury and illness rate per 10,000 full-time workers Retrieved from https://data.bls.gov/pdq/SurveyOutputServlet

Castro-Meneses, L. J., Kruger, J.-L., & Doherty, S. (2020). Validating theta power as an objective measure of cognitive load in educational video. *Educational Technology Research and Development, 68*, 181-202. DOI:10.1007/s11423-019-09681-4

Chen, J., Taylor, J. E., & Comu, S. (2017). Assessing task mental workload in construction projects: A novel electroencephalography approach. *Journal of Construction Engineering and management, 143*(8), 04017053. DOI:10.1061/ASCEICO.1943-78620001345

Cummins, T. D., Broughton, M., & Finnigan, S. (2008). Theta oscillations are affected by amnestic mild cognitive impairment and cognitive load. *International Journal of Psychophysiology, 70*(1), 75-81.DOI:10.1016/j.ilpsycho.2008.06.002

Di Marco, R., Rubega, M., Lennon, O., Vianello, A., Masiero, S., Formaggio, E., & Del Felice, A. (2023). Exoskeleton Training Modulates Complexity in Movement Patterns and Cortical Activity in Able-Bodied Volunteers. *IEEE Transactions on Neural Systems and Rehabilitation Engineering.* DOI:10.1109/TNSRE.2023.3273819

Emotiv (2023). High-Density Saline EEG, Unlimited Research Flexibility. <https://www.emotiv.com/flex-saline/>. (September 25, 2023).

German-Bionic (2023). *CrayX* [Online]. Available: https://germanbionic.com/en/solutions/exoskeletons/crayx/ [Accessed December, 8 2023]

Giustetto, A., Vieira Dos Anjos, F., Gallo, F., Monferino, R., Cerone, G. L., Di Pardo, M., . . . Micheletti Cremasco, M. (2021). Investigating the effect of a passive trunk exoskeleton on local discomfort, perceived effort and spatial distribution of back muscles activity. *Ergonomics, 64*(11), 1379-1392. DOI:10.1080/000140139.2021.1928297

Huysamen, K., de Looze, M., Bosch, T., Ortiz, J., Toxiri, S., & O'Sullivan, L. W. (2018). Assessment of an active industrial exoskeleton to aid dynamic lifting and lowering manual handling tasks. *Applied Ergonomics*, *68*, 125-131. DOI:10.1016/j.apergo.2017.11.004

Jawabri, K. H., & Sharma, S. (2019). Physiology, cerebral cortex functions. https://europepmc.org/article/nbk/nbk538496#__NBK538496_dtls__

Keskin, M., Ooms, K., Dogru, A. O., & De Maeyer, P. (2020). Exploring the cognitive load of expert and novice map users using EEG and eye tracking. *ISPRS International Journal of Geo-Information*, *9*(7), 429. DOI:10.3390/ijgi9070429

Kim, S., Moore, A., Srinivasan, D., Akanmu, A., Barr, A., Harris-Adamson, C., . . . Nussbaum, M. A. (2019). Potential of exoskeleton technologies to enhance safety, health, and performance in construction: Industry perspectives and future research directions. *IISE Transactions on Occupational Ergonomics and Human Factors*, *7*(3-4), 185-191. DOI:10.1080/24725838.2018.1561557

Liu, Y., Li, X., Lai, J., Zhu, A., Zhang, X., Zheng, Z., . . . Chen, Z. (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. DOI:10.3390/ijerph18083889

Marchand, C., De Graaf, J. B., & Jarrassé, N. (2021). Measuring mental workload in assistive wearable devices: a review. *Journal of NeuroEngineering and Rehabilitation*, *18*(1), 1-15. DOI:10.1186/s12984-021-00953-w

Murugappan, M., Murugappan, S., & Gerard, C. (2014). *Wireless EEG signals based neuromarketing system using Fast Fourier Transform (FFT).* Paper presented at the 2014 IEEE 10th international colloquium on signal processing and its applications. DOI:10.1109/CSPA.2014.6805714

Ogunseiju, O., Gonsalves, N., Akanmu, A., & Nnaji, C. (2021). Subjective Evaluation of Passive Back-Support Exoskeleton for Flooring Work. *EPiC Series in Built Environment*, *2*, 10-17. https://6login.easychair.org/publications/download/P3d5

Picchiotti, M. T., Weston, E. B., Knapik, G. G., Dufour, J. S., & Marras, W. S. (2019). Impact of two postural assist exoskeletons on biomechanical loading of the lumbar spine. *Applied ergonomics*, *75*, 1-7. DOI:10.1016/j.apergo.2018.09.006

Puma, S., Matton, N., Paubel, P.-V., Raufaste, É., & El-Yagoubi, R. (2018). Using theta and alpha band power to assess cognitive workload in multitasking environments. *International Journal of Psychophysiology*, *123*, 111-120. DOI:10.1016/j.ijpsycho.2017.10.004

Schapkin, S., Raggatz, J., Hillmert, M., & Böckelmann, I. (2020). EEG correlates of cognitive load in a multiple choice reaction task. *Acta neurobiologiae experimentalis*, *80*(1), 76-89. DOI:10.21307/ane-2020-008

Swerdloff, M. M., & Hargrove, L. J. (2020, July). Quantifying cognitive load using EEG during ambulation and postural tasks*. In 2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC) (pp. 2849-2852). IEE*E DOI: 10.1109/EMBC44109.2020.9176264 .

Walter, T., Stutzig, N., & Siebert, T. (2023). Active exoskeleton reduces erector spinae muscle activity during lifting. *Frontiers in Bioengineering and Biotechnology, 11*, 1143926. DOI:10.3389/fbioe.2023.1143926

Waters, T. R., Putz-Anderson, V., & Garg, A. (1994). Applications manual for the revised NIOSH lifting equation. https://stacks.cdc.gov/view/cdc/5434

Zhu, Y., Johnson, C., Chang, S.-H. J., & Mehta, R. K. (2020). *Neuroergonomics metrics to evaluate Exoskeleton based Gait Rehabilitation.* Paper presented at the 2020 IEEE International Conference on Systems, Man, and Cybernetics (SMC). DOI:10.1109/SMC42975.2020.9283238