

## EEG-BASED COGNITIVE LOAD INDICATORS IN CAD MODELLING TASKS OF VARYING COMPLEXITY

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### ABSTRACT

As an initial step towards a better understanding of cognitive load in computer-aided design (CAD), the herein presented study investigated cognitive load imposed on 24 mechanical engineers during two CAD modelling tasks of intentionally different complexity levels. The cognitive load has been rarely studied in the CAD context, which resulted in the lack of understanding if and how the EEG-based indicators available from the literature reflect the changes in cognitive load imposed on engineering designers in CAD activities. Therefore, cognitive load was measured and analysed using three EEG-based indicators to explore insights that might be obtained from them. The initial analysis revealed different cognitive load results from the employed indicators for the same EEG data. In addition, the study implies that the cognitive load results obtained through the used indicators are only partially coherent with the CAD modelling task complexity. Hence, the results imply that the chosen EEG-based indicator matters when measuring and analysing cognitive load in CAD modelling tasks and that its adjustment for CAD context might be needed.

**Keywords:** Computer Aided Design (CAD), Cognitive load, Electroencephalography, Complexity, Design cognition

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## 1 INTRODUCTION

Computer-aided design (CAD) systems, consisting of CAD software and interaction tools (such as a mouse and a keyboard), are regularly employed in the contemporary engineering design process for creating, recreating, reviewing, and modifying digital versions of design representations (McMahon, 2015). These CAD activities are visual (information is presented visually), virtual (they are situated in virtual environments of CAD and engineering designers' minds), and cognitively complex in nature (Ullman, 2002). The cognitive complexity of CAD activities arises from the characteristics of design tasks and the use of CAD systems (Robertson et al., 1991). Therefore, it is assumed that the execution of design activities supported by CAD systems imposes high demands (i.e. cognitive load) on the engineering designers' cognitive system.

Cognitive load is the multidimensional construct resulting from complex relationships among the three main elements: a subject performing a task, the task, and the working environment (Sweller et al., 2011). The characteristics of these elements; engineering designer (e.g. cognitive abilities and prior knowledge), the design task (e.g. the intrinsic task complexity defined by the number of interacting information elements and the way of presenting the task instructions), and the working environment (e.g. characteristics of the CAD environment) present the potential factors influencing the cognitive load levels in CAD activities. Identifying the influencing factors may pave the way to affecting the allocation of engineering designers' limited information-processing cognitive resources for enhanced CAD performance (Ullman, 2002).

The reliable measurement, analysis, and interpretation of cognitive load are the prerequisites to identifying influencing factors and potentially controlling the cognitive resources' allocation through manipulation. Previous studies primarily measured and analysed the overall cognitive load (within the experimental tasks) using the subjective assessment (e.g. self-rated scales and post-task interviews) and the performance measurement (e.g. the number of errors and task completion time) methods. However, more than these methods is needed to detect and explain the effects of various influencing factors on cognitive load. Incorporating psychophysiological measurement methods is the suggested approach to continuous measurement of cognitive load that may offer additional insights regarding the influencing factors and provide cognitive feedback for affecting engineering design performance in real time (Gevins and Smith, 2003).

Electroencephalography (EEG) is a neuroimaging method used to measure cognitive load in various tasks and activities across the fields (Antonenko et al., 2010). At the same time, EEG proved suitable and valuable for studying design cognition due to its non-invasiveness and high temporal resolution (Sivanathan et al., 2015). However, EEG has rarely been used for measuring and studying cognitive load in engineering design (Balters et al., 2022). Consequently, it is yet to be explored what insights about cognitive load EEG might offer and how to obtain them.

As an initial step towards a better understanding of cognitive load in CAD, the herein presented study investigated cognitive load imposed on 24 mechanical engineers during two CAD modelling tasks of intentionally different complexity levels. Cognitive load was measured and analysed using three EEG-based indicators available from the literature to explore insights that might be obtained from them.

The following section presents the related cognitive load studies in engineering design and the EEG-based indicators the literature already uses. Section 3 explains the research methodology. Then, the obtained results are presented in Section 4 and discussed with the study's limitations in Section 5. Finally, the conclusions and avenues for future work are summarised in Section 6.

## 2 RELATED WORK AND RESEARCH GAP

The previous studies of cognitive load in engineering design intended to compare its levels during various design activities or tasks based on their type, methods and tools used to perform them, and characteristics of the subjects performing them. For example, Jia et al. (2021) found differences in the level of the imposed cognitive load among the several *types of design activities* (problem understanding, idea generation, idea evaluation, and self-rating). Furthermore, Majdic et al. (2017) suggested that cognitive load arises with *task difficulty* (defined by its complexity and structuredness) and differs between *novice and advanced engineering students*. Barrella et al. (2019) reported on differences in cognitive load imposed on engineering undergraduate students when using different *methods* to solve sustainability-related design tasks. Similarly, Shealy et al. (2020) found differences when using different *techniques* for concept generation. Furthermore, Maier et al. (2014) suggested

that the *type of representation* used to communicate design information affects the cognitive load. In addition, [Nguyen et al. \(2018\)](#) and [Nolte and McComb \(2021\)](#) reported on the relationship between cognitive load and *stress* experienced by engineering designers during design activities. These studies imply potential factors that influence cognitive load and some effects of the cognitive load on engineering designers' performance in design activities. However, none of the studies within the available sample focused on studying cognitive load in CAD activities.

## 2.1 EEG-based cognitive load indicators

Previous studies across domains have persistently reported on the sensitivity of brain activity in alpha (8-13 Hz) and theta (4-7 Hz) frequency bands to different cognitive demands imposed by the experimental tasks ([Gevins and Smith, 2003](#)). In particular, an increase in theta band power and a decrease in alpha band power have been noticed when performing more difficult tasks associated with higher cognitive load ([Klimesch et al., 2005](#)). The power of a frequency band (POW) is calculated as the squared amplitude of the EEG signal in the particular range and interpreted as the contribution of that band to the overall signal's power. Three indicators often used to measure cognitive load through alpha and theta POW changes are described below.

Event-related desynchronisation (ERD) or event-related synchronisation (ERS) reflects the percentual decrease or increase in the POW during the experimental task compared with a baseline interval ([Antonenko et al., 2010](#)). The previous studies using the ERD/ERS indicator often observed higher theta ERS and alpha ERD with increasing task complexity and the associated cognitive load (e.g. [Zhu et al., 2021](#)). It has been calculated according to the following equation:

$$\text{ERS/ERD} = \frac{\text{POW}_{\text{baseline}} - \text{POW}_{\text{task}}}{\text{POW}_{\text{baseline}}} \cdot 100. \quad (1)$$

Similarly, task-related power (TRP) reflects a decrease or increase in the POW during the experimental task compared to the baseline. Values above one reflect POW increases from the baseline to the task, whereas values below one reflect POW decreases ([Pfurtscheller and Lopes da Silva, 1999](#)). An increase in theta TRP and a decrease in alpha TRP have been associated with higher levels of cognitive load in previous studies (e.g. [Jia et al., 2021](#)). The following equation has been used to calculate TRP:

$$\text{TRP} = \frac{\text{POW}_{\text{task}}}{\text{POW}_{\text{baseline}}}. \quad (2)$$

The cognitive load index (CLI) is the ratio between the average theta band POW in the frontal and alpha band POW in the parietal and occipital cortical areas ([Holm et al., 2009](#)). The larger value of the CLI indicates a higher cognitive load (e.g. [Dan and Reiner, 2017](#)). CLI is usually calculated using the following equation:

$$\text{CLI} = \frac{\text{POW}_{\text{task (frontal theta)}}}{\text{POW}_{\text{task (rear alpha)}}}. \quad (3)$$

## 2.2 Research gaps and research questions

Previous studies employed different methods and measures when studying cognitive load in engineering design, such as NASA Task Load Index (TLX) questionnaire (e.g. [Nolte and McComb, 2021](#)), eye tracking (e.g. [Maier et al., 2014](#)), functional near-infrared spectroscopy (e.g. [Shealy et al., 2020](#)), and EEG (e.g. [Jia et al., 2021](#)). In addition, the studies that used EEG often relied on the cognitive load indicators associated with the used EEG device (e.g. [Barrella et al., 2019](#) and [Majdic et al., 2017](#)). Alternatively, scholars used one of the indicators previously reported in the cognitive psychology literature (e.g. [Jia et al., 2021](#)), usually without explaining their choice. The literature review highlighted several cognitive load indicators based on changes in brain activation captured by EEG; they build upon the decrease and increase of POW in alpha and theta frequency bands. The previous literature further argued that EEG-based indicators of cognitive load might depend on the characteristics of the task and the subjects ([Antonenko et al., 2010](#)). However, the cognitive load has been rarely studied in the CAD context, which resulted in the lack of understanding if and how the suggested EEG-based indicators reflect the changes in cognitive load imposed on engineering designers in CAD activities.

Therefore, the herein presented study aims to answer the following research question:

*How to measure and analyse cognitive load in CAD modelling tasks using EEG-based indicators?*

### 3 RESEARCH METHODOLOGY

#### 3.1 Participants

The study recruited 24 mechanical engineers (2 female and 22 male) to participate in the experimental study. They ranged in age from 25 to 31 years. All the participants were right-handed, had normal or corrected-to-normal vision, and did not report any neurological disorder. Furthermore, all the participants were familiar with the basics of CAD modelling in SolidWorks®. On a scale from one (*non-existent*) to five (*advanced*), the participants self-rated their CAD modelling proficiency with a median (Med) of three and a median absolute deviation (MAD) of one. The same result (Med = 3 and MAD = 1) was obtained for the frequency of using CAD software to generate 3D models and technical documentation, where one stood for *never* and five for *every day*. The participants' professional working experience ranged from 11 to 77 months, with Med = 27 and MAD = 1.

#### 3.2 CAD modelling tasks

The study included two CAD modelling tasks of intentionally different complexity levels, defined by the overall geometric complexity of the used components (presented in Figure 1) and the complexity of their CAD models. The selection of the components was driven by the premise that the higher number of interacting elements a task contains, the higher the cognitive load it imposes on the engineering designer's cognitive system (Antonenko et al., 2010). Interaction elements in the context of the CAD modelling tasks refer to the design characteristics (e.g. form and dimensions) of the components to be modelled. These characteristics were presented in the technical drawings, interpreted and perceived from them, and generated in a CAD environment using the CAD system.

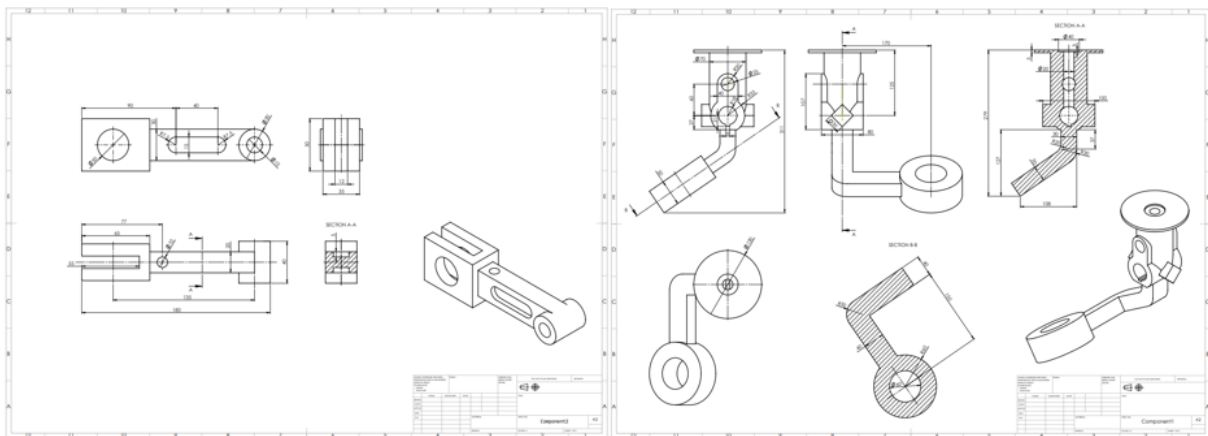


Figure 1. Low-complexity component (left) and high-complexity component (right)

The number of surfaces the components consist of was used as a proxy to determine the level of the overall geometric complexity, as suggested by Johnson et al. (2018). The low-complexity (LC) component (shown in Figure 1 on the left) consisted of 33 surfaces, while the high-complexity (HC) component (shown in Figure 1 on the right) consisted of 49 surfaces. Furthermore, the number of features needed to generate CAD models served as a proxy to determine the components' CAD model complexity (Johnson et al., 2018). The LC component's CAD model consisted of 7 features, while the HC component's consisted of 11 features. Since the literature does not prescribe the absolute scale of the design component and CAD model complexity, the complexity levels were defined relatively for the study purposes. Therefore, generating a CAD model of the HC component (HC task) involves the simultaneous processing of more interrelating information elements than CAD modelling the LC component (LC task). Consequently, performing the HC task imposes a higher cognitive load than the LC task, which can be solved by processing a sequence of fewer information elements with fewer references to one another.

#### 3.3 Experimental procedure

The experimental procedure started with signing a consent. In the second step, the participants filled out the questionnaire related to demographics, educational background, and CAD experience and proficiency. Then, the participants proceeded to the CAD modelling tasks. Each task was divided into

three main parts: (1) perception and interpretation of the component from the technical drawing, (2) cognitive division of the presented component into CAD features, and (3) generation of a 3D CAD model of the presented component. In the first step, the component was presented with the orthographic projection (three main views) in the technical drawing, while the isometric projection accompanied it in the second and third steps. The tasks were restricted in time; the participants had two minutes for the first part, one minute for the second part, and 15 minutes for the third part of the tasks. One-half of the participants (HC-LC group) first solved the HC task and proceeded to the LC task. The order of the tasks was the opposite for the other half of the participants (LC-HC group). The division into the groups with the reversed task sequence was motivated by the goal of controlling the potential influence of the previous CAD modelling task (not necessarily related to the complexity) on cognitive load levels. In addition, the division enables the analysis of the task sequence as the between-subject variable in the conducted experiment, which has often been neglected in previous studies. Before and after each task, the participants were asked to stare at the cross presented in the middle of the screen for two minutes, which served as the baseline. After the second task, the semi-structured interview was conducted to understand better the factors that influenced the cognitive load the participants experienced during the execution of the tasks. Finally, the participants were asked to solve the Purdue Spatial Visualization Test (PSVT) to test their spatial abilities.

### 3.4 Experimental setup

The experimental protocol was run using the iMotions® platform to present the stimuli (technical drawings and instructions) and synchronise the gathered data. The stimuli were presented on the monitor screen (1920 x 1080 pixels; 60 Hz) powered by a high-performance computer. The CAD models were generated in SolidWorks® using the same monitor screen, mouse, and keyboard (see Figure 2 on the right). Using the dedicated keyboard key, participants switched between the stimuli (including the technical drawings) and the SolidWorks® window. The screen was captured during the entire duration of the experiment. In addition, the participant's face and the produced sound were captured with the video camera. EEG data were gathered with a 14-channel Emotiv EPOC+ device wirelessly connected to the high-performance computer. The locations from which the continuous brain activity was captured through the sensors were: AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4 (according to the international 10-20 system).

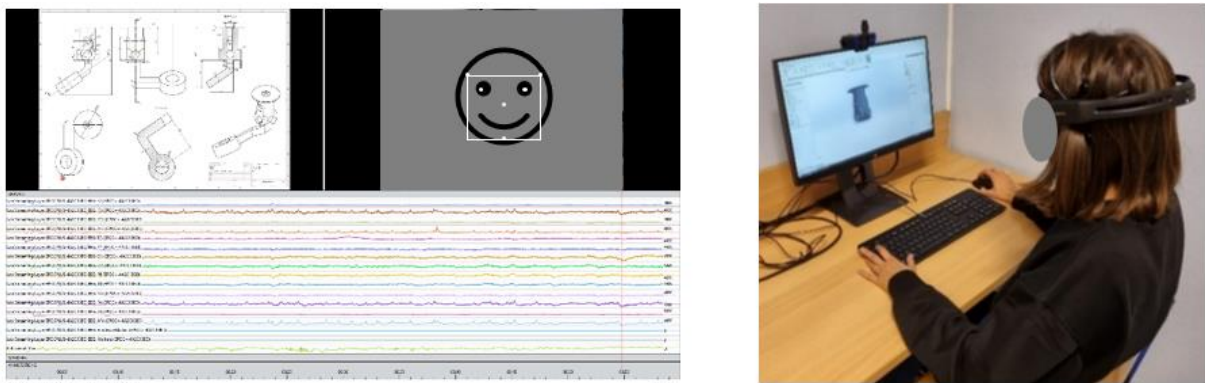


Figure 2. Experimental setup

### 3.5 EEG data pre-processing

Gathered raw EEG data were pre-processed in MATLAB® employing the EEGLAB toolbox (Delorme and Makeig, 2004) and advising the pipelines described by Li *et al.* (2021) and Jia *et al.* (2021). The pre-processing started with removing the DC offset characteristic for the Emotiv EPOC+ devices with the infinite impulse response (IIR) filter. The frequencies outside the 4-45 Hz range were removed with the finite impulse response (FIR) filter in the second step. After that, muscle artefacts were removed with the blind source separation (BSS) technique based on canonical correlation analysis (CCA; De Clercq *et al.*, 2006). The filtering parameters were set as follows: window length of 2.5 s, window shift of 1.2 s, and removal of the four least correlated components. The filtering was followed by removing the windows (length of 3 s, shift of 1/128 s) with an amplitude exceeding the threshold value. The threshold was calculated for each participant individually as a value of three standard

deviations greater than the mean ( $M$ ) of the entire epoch across the channels. In this way, any 3 s long epoch of the EEG data with the  $M$  amplitude higher than the calculated threshold was discarded. The FIR filter divided EEG data into theta (4-7 Hz) and alpha (8-13 Hz) sub-frequency bands in the next step. After the threshold was applied, the POW of EEG signals was calculated as the mean ( $M$ ) of the squared values of microvolts ( $\mu V^2$ ).

### 3.6 Data analysis

Analysis of the gathered EEG data focused on calculating and comparing the cognitive load from three EEG-based indicators: ERD/ERS (according to Equation 1), TRP (according to Equation 2), and CLI (according to Equation 3). The ERD/ERS and TRP were calculated for each participant and CAD modelling task considering all the channels for both the alpha and the theta frequency band. The CLI was calculated as a ratio between the average theta POW in the frontal cortical area (included channels: AF3, AF4, F3, F4, F7, F8) and the average alpha POW in the rear cortical area (included channels: P7, P8, T7, T8, O1, O2) for each participant and both tasks. The obtained cognitive load results were then compared qualitatively and quantitatively using the R language. Descriptive statistics included the calculation of  $M$  or  $Med$  to measure the central tendency and  $SD$  or  $MAD$  as a measure of variability in the alpha and theta ERD/ERS, alpha and theta TRP, and CLI across the participants.  $M$  and  $SD$  were used to describe normally distributed data, while  $Med$  and  $MAD$  described data with non-normal distribution. Once obtained, the values were compared between the HC and the LC task (the within-subject variable of complexity) using inferential statistics. Alpha and theta ERD/ERS, alpha and theta TRP, and CLI were first compared between the LC and the HC task of all the participants cumulatively. After that, alpha and theta ERD/ERS, alpha and theta TRP, and CLI were compared between the LC and the HC task only when performed as the first in order. In the further comparison, the same values were compared between the LC and the HC task of each group (between the HC-LC and the LC-HC group), depending on the sequence of performing the CAD modelling tasks (the between-subject variable). Differences in the obtained values were compared using the paired t-test when the assumptions of normality (tested by Shapiro-Wilk test;  $p < 0.05$ ) and equity of variances (tested by Levene test;  $p < 0.05$ ) were confirmed. When the normality assumption was violated, Wilcoxon signed-rank test was employed instead. Furthermore, the effect size of the differences in the ERD/ERS, TRP, and CLI among the LC and the HC task was calculated with Cohen's  $d$  as the number of standard deviations between the means of the compared variables. Significant differences ( $p$ -value) and large effect sizes ( $d$ -value) are presented in box plots within Section 4. Finally, the results provided by each EEG-based indicator were compared quantitatively to answer the research questions.

## 4 RESULTS

The results reported in the following subsections are based on the sample of 21 participants since EEG data collected from three participants was excluded from the report due to the high EEG signal contamination.

### 4.1 ERD/ERS

Considering all the participants cumulatively (All in Figure 3), the average theta ERD/ERS was lower in the LC than in the HC task, while the alpha ERD/ERS showed the opposite behaviour. However, the results were contradictory when considering the first performed task of each group only; the average theta ERD/ERS was lower in the HC than the LC task, while the average alpha ERD/ERS was slightly lower in the LC than in the HC task.

Furthermore, the participants of the HC-LC group had both the average theta and the average alpha ERD/ERS lower in the LC than in the HC task. The difference between the tasks was significant in the latter case. Regarding the LC-HC group, the average theta ERD/ERS remained lower in the LC task. However, the results of the same group were the opposite in the alpha band; the average alpha ERS was significantly higher in the LC than in the HC task.

The average theta ERD/ERS was higher in the HC task when performed as the second task than the first in order (LC-HC group). Furthermore, alpha in the HC task changed significantly from the ERS when the HC was the first task to the ERD when it was the second task. On the contrary, the average theta ERD/ERS and the average alpha ERS were higher when the LC task was conducted as the first task than as the second in order.

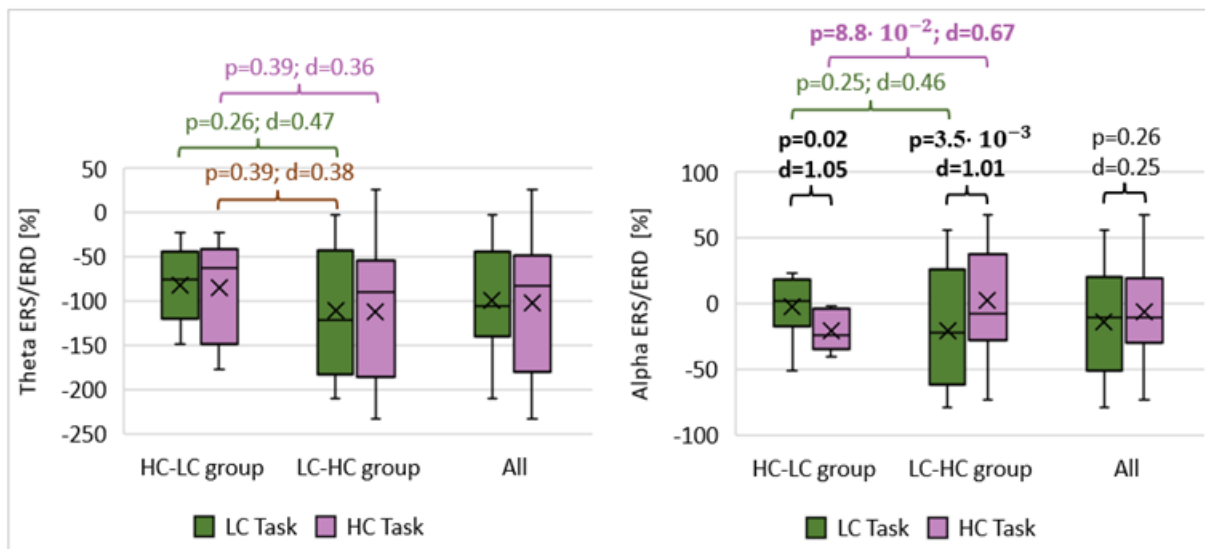


Figure 3. ERD/ERS of the theta (left) and the alpha (right) frequency bands

## 4.2 TRP

The average theta TRP was lower in the LC than the HC task when considering all the participants cumulatively, as shown in Figure 4 on the left. On the contrary, the average alpha TRP was higher in the LC than in the HC task. The results were the opposite when considering the first task of each group only. Namely, the average theta TRP was higher and alpha lower in the LC than in the HC task.

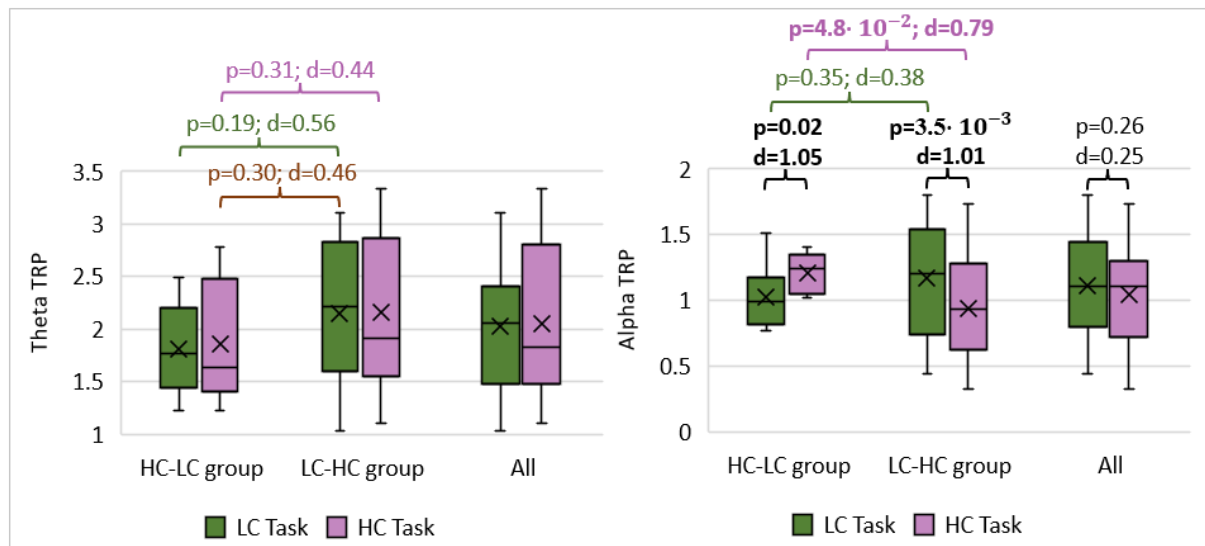


Figure 4. TRP of the theta (left) and the alpha (right) frequency bands

Furthermore, the average theta TRP and the average alpha TRP (significant differences) of the participants in the HC-LC group were lower in the LC than in the HC task. Similarly, the average theta TRP of the LC-HC group was lower in the LC than in the HC task. Conversely to the HC-LC group, the average alpha TRP of the LC-HC group was significantly higher in the LC than in the HC task. The average theta TRP in the HC task was higher when performed as the second than the first in order, while alpha TRP was significantly lower in the same task and case. On the contrary, both theta and alpha TRP were higher when the LC task was conducted as the first than the second in order.

## 4.3 CLI

The average CLI was higher in the LC than the HC task when considering all the participants cumulatively, as shown in Figure 5. Similarly, the CLI was higher (significantly in this case) in the LC than in the HC task when considering the first tasks only.

Furthermore, the average CLI of both groups was higher in the LC than in the HC task.

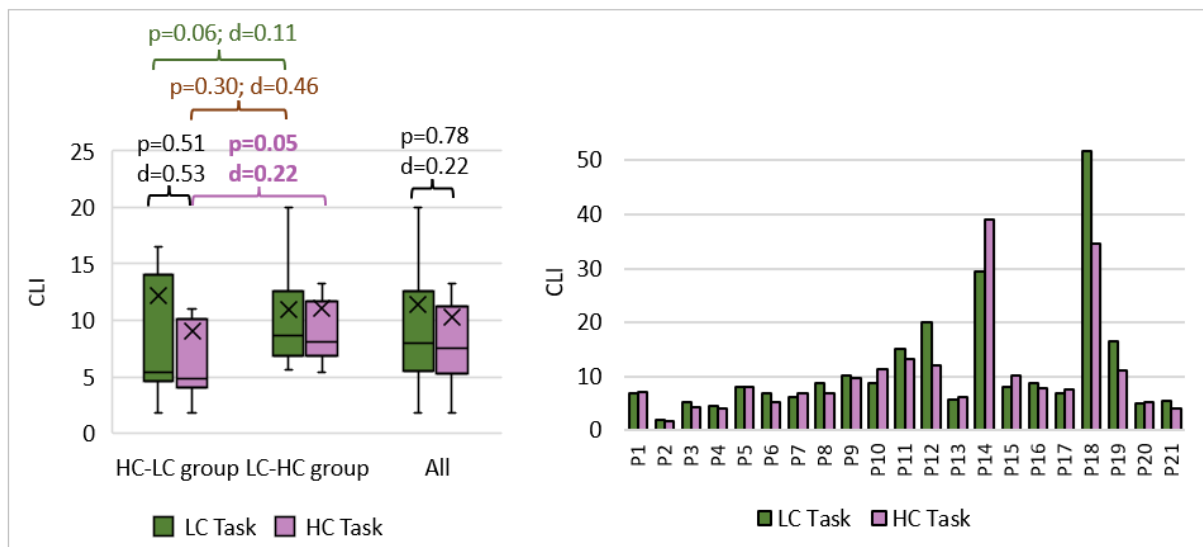


Figure 5. The CLI across the participants (left) and per the participants (right)

The average CLI was significantly higher in the HC task when performed as the second task (LC-HC group) than the first in order. On the contrary, the average CLI was higher in the LC task when conducted as the first than the second task.

## 5 DISCUSSION

The cognitive load in two CAD modelling tasks of different complexity levels was measured and analysed using three EEG-based indicators (ERD/ERS, TRP, and CLI) suggested by the available literature. The usage of three indicators was motivated by the need for more clarity on the insights they might provide on cognitive load in the CAD context since the literature does not offer such knowledge.

The analysis revealed inconsistent cognitive load results when using these indicators. In particular, the calculated ERD/ERS and TRP imply higher cognitive load in the HC than the LC task, while CLI showed the opposite result. Higher cognitive load in the HC task was indicated by the higher theta ERD/ERS and TRP as well as the lower alpha ERD/ERS and TRP. Although not statistically significant, such results align with the previous studies that used ERD/ERS (e.g. Zhu et al., 2021) and TRP (e.g. Jia et al., 2021) for measuring and comparing cognitive load in design activities. On the contrary, the CLI was significantly higher for the LC than the HC task, thus implying the higher cognitive load imposed by the lower-complexity CAD modelling task. In addition to the ERD/ERS and TRP results gained within the herein-presented study, such result contradicts the previously reported findings (see Dan and Reiner, 2017). The possible explanations of the CLI not reflecting the effects of CAD modelling task complexity on cognitive load may be related to the CAD tasks having the characteristic topological distribution of theta and alpha activity. Similar explanations have been offered for the other types of tasks (Antonenko et al., 2010).

Hence, the results imply that the chosen EEG-based indicator matters when measuring and analysing cognitive load in CAD modelling tasks. In addition, it might be that the available indicators should be adjusted for CAD context due to the characteristics of CAD tasks. Although it is suggested to measure and analyse cognitive load considering both the theta and alpha frequency bands, the results suggest that they may reflect different effects. Namely, the average theta ERS and TRP were higher in the HC task and they seem to have a more prominent role in distinguishing cognitive load between the HC and the LC tasks performed as the first in order (according to the effect sizes). These results suggest that theta may be more indicative of differences in cognitive load imposed by the varying CAD modelling task complexity. The suggestion is in line with previous studies that reported on the theta band being related to encoding new information - the cognitive operation highly represented when generating CAD models from technical drawings (Klimesch et al., 2005). On the contrary, the average alpha ERS and TRP were lower in the second task of both groups, regardless of their complexity. Since different tasks were performed as the second in order, such behaviour may not be elicited by the CAD modelling task complexity (and the associated cognitive load accumulated during only one task). Instead, the alpha frequency band may be more sensitive to the task sequence and indicative of the overall cognitive load



(Antonenko et al., 2010). The statistical significance and large effect sizes of differences in alpha ERD/ERS and TRP between the HC-LC and the LC-HC group align with that assumption. A similar effect of the task sequence on cognitive load levels was previously reported by Dan and Reiner (2017). Furthermore, the complexity levels of the two CAD modelling tasks were intentionally different, while the difference was based on the suggestions provided by Johnson et al. (2018). Based on these complexity levels, the CAD modelling tasks (lower and higher) were associated with cognitive load levels (lower and higher, respectively), as suggested by Cognitive Load Theory (Sweller et al., 2011). However, it is advised to corroborate that association and the obtained cognitive load results with the subjective assessment methods (such as NASA TLX) in further work.

### 5.1 Study limitations

The sample size limits the study. Therefore, it is advised to broaden the study with additional participants to corroborate the recognised differences statistically. In addition, three participants whose data were discarded from the analysis belonged to the same group regarding the task sequence (HC-TC group). It is possible that a difference in the number of participants within the groups affected the lack of statistical significance in some cases (e.g. when the effect size was large).

## 6 CONCLUSIONS AND FURTHER WORK

The study investigated cognitive load in two CAD modelling tasks of different complexity levels using three available EEG-based indicators. The initial analysis revealed different cognitive load results from the employed indicators for the same EEG data. In particular, calculated ERD/ERS and TRP imply higher cognitive load in the HC than the LC task, while CLI showed the opposite result. In addition, the study implies that the cognitive load results obtained through the used indicators are only partially coherent with the CAD modelling task complexity. Hence, the results imply that the chosen EEG-based indicator matters when measuring and analysing cognitive load in CAD modelling tasks. In addition, it might be that the available indicators should be adjusted for CAD context due to the characteristics of CAD tasks. Furthermore, the results suggest the highest cognitive load imposed by the high-complexity CAD modelling task when performed as the second in order. This effect of the task sequence on cognitive load seems to be reflected in changes in the alpha band ERS/ERP and TRP. On the other hand, theta band ERD/ERS seems to be indicative of differences in cognitive load related to the varying CAD modelling task complexity. Further work will measure cognitive load using subjective measurement methods in addition to EEG (such as NASA TLX and interviews). Future analysis will complement EEG data with CAD data to facilitate interpreting the cognitive load results and detail potential explanations of the observed differences and inconsistencies. In addition, the EEG signal's spatial distribution, temporal dynamics, and broader frequency spectra will be analysed in the following steps.

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## REFERENCES

- Antonenko, P., Paas, F., Grabner, R. and van Gog, T. (2010), "Using Electroencephalography to Measure Cognitive Load", *Educational Psychology Review*, Vol. 22 No. 4, pp. 425–438.
- Balters, S., Weinstein, T., Mayseless, N., Medicine, S. and Auernhammer, J. (2022), "Design science and neuroscience: A systematic review of the emergent field of design neurocognition", *Design Studies*, No. November.
- Barrella, E.M., Cowan, C., Girdner, J., Watson, M.K. and Anderson, R. (2019), "Measuring connections: Engineering students' cognitive activities and performance on complex tasks", *Proceedings - Frontiers in Education Conference, FIE*, Vol. 2019-October, IEEE, available at:<https://doi.org/10.1109/FIE43999.2019.9028595>.
- De Clercq, W., Vergult, A., Vanrumste, B., Van Paesschen, W. and Van Huffel, S. (2006), "Canonical Correlation Analysis Applied to Remove Muscle Artifacts From the Electroencephalogram", *IEEE Transactions on Biomedical Engineering*, Vol. 53 No. 12, pp. 2583–2587.
- Dan, A. and Reiner, M. (2017), "EEG-based cognitive load of processing events in 3D virtual worlds is lower than processing events in 2D displays", *International Journal of Psychophysiology*, Elsevier B.V., Vol. 122, pp. 75–84.

- Delorme, A. and Makeig, S. (2004), "EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis", *J Neurosci Methods*, Vol. Mar 15 No. 134(1), pp. 9–21.
- Gevins, A. and Smith, M.E. (2003), "Neurophysiological measures of cognitive workload during human-computer interaction", *Theoretical Issues in Ergonomics Science*, Vol. 4 No. 1–2, pp. 113–131.
- Holm, A., Lukander, K., Korpela, J., Sallinen, M. and Müller, K.M.I. (2009), "Estimating brain load from the EEG", *TheScientificWorldJournal*, Vol. 9, pp. 639–651.
- Jia, W., von Wegner, F., Zhao, M. and Zeng, Y. (2021), "Network oscillations imply the highest cognitive workload and lowest cognitive control during idea generation in open-ended creation tasks", *Scientific Reports*, Nature Publishing Group UK, Vol. 11 No. 1, pp. 1–24.
- Johnson, M.D., Valverde, L.M. and Thomison, W.D. (2018), "An investigation and evaluation of computer-aided design model complexity metrics", *Computer-Aided Design and Applications*, Vol. 15 No. 1, pp. 61–75.
- Klimesch, W., Schack, B. and Sauseng, P. (2005), "The functional significance of theta and upper alpha oscillations", *Experimental Psychology*, Vol. 52 No. 2, pp. 99–108.
- Li, S., Becattini, N. and Cascini, G. (2021), "Correlating design performance to EEG activation: Early evidence from experiential data", *Proceedings of the Design Society*, pp. 771–780.
- Maier, A.M., Baltsen, N., Christoffersen, H. and Störrle, H. (2014), "Towards Diagram Understanding: A Pilot-Study Measuring Cognitive Workload Through Eye-Tracking", *Proc. Intl. Conf. Human Behavior in Design*, No. October, pp. 1–6.
- Majdic, B., Cowan, C., Girdner, J., Opoku, W., Pierrakos, O. and Barrella, E. (2017), "Monitoring Brain Waves in an Effort to Investigate Student's Cognitive Load During a Variety of Problem Solving Scenarios", *Systems and Information Engineering Design Symposium (SIEDS)*, IEEE, Charlottesville, VA, USA, pp. 186–191.
- McMahon, C. (2015), "Design Informatics: Supporting Engineering Design Processes with Information Technology", *Journal of the Indian Institute of Science*, Vol. 95 No. 4, pp. 365–377.
- Nguyen, P., Nguyen, T.A. and Zeng, Y. (2018), "Empirical approaches to quantifying effort, fatigue and concentration in the conceptual design process: An EEG study", *Research in Engineering Design*, Springer London, Vol. 29 No. 3, pp. 393–409.
- Nolte, H. and McComb, C. (2021), "The cognitive experience of engineering design: an examination of first-year student stress across principal activities of the engineering design process", *Design Science*, Vol. 7 No. May, available at: <https://doi.org/10.1017/dsj.2020.32>.
- Pfurtscheller, G. and Lopes da Silva, F.H. (1999), "Event-related EEG/MEG synchronization and desynchronization: basic principles", *Clinical Neurophysiology*, Vol. 110 No. 11, pp. 1842–1857.
- Robertson, D., Ulrich, K. and Filerman, M. (1991), *Cognitive Complexity and CAD Systems: Beyond the Drafting Board Metaphor*, No. WP #3244-91-MSA, Cambridge, Massachusetts.
- Shealy, T., Gero, J., Hu, M. and Milovanovic, J. (2020), "Concept generation techniques change patterns of brain activation during engineering design", *Design Science*, pp. 1–27.
- Sivanathan, A., Lim, T., Ritchie, J., Sung, R., Kosmadoudi, Z. and Liu, Y. (2015), "The application of ubiquitous multimodal synchronous data capture in CAD", *CAD Computer Aided Design*, Vol. 59, pp. 176–191.
- Sweller, J., Ayres, P. and Kalyuga, S. (2011), *Cognitive Load Theory*, edited by Spector, J.M. and Lajoie, S.P. Springer Science+Business Media, LLC 2013, Springer, available at: <http://www.springer.com/series/8640>.
- Ullman, D.G. (2002), "Toward the ideal mechanical engineering design support system", *Research in Engineering Design - Theory, Applications, and Concurrent Engineering*, Vol. 13 No. 2, pp. 55–64.
- Zhu, Y., Wang, Q. and Zhang, L. (2021), "Study of EEG characteristics while solving scientific problems with different mental effort", *Scientific Reports*, Nature Publishing Group UK, Vol. 11 No. 1, pp. 1–12.