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MEASUREMENT OF COGNITIVE LOAD WITH THE EEG

Measuring cognitive load through event related potentials and event related desynchronization/synchronization

Bachelor's Thesis
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Züberwangen, 01.06.2021

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Abstract

Numerous studies have demonstrated that cognitive load levels vary throughout different task demands. Various techniques to measure cognitive load have been discussed in recent years. However, the electroencephalogram (EEG) has been declared as the most accurate one. In this paper, two specific EEG analyzing techniques, event related potentials and event related alpha and theta desynchronization/synchronization, have been examined in their characteristics of reflecting cognitive load in diverse experimental settings. Ten research papers have been analyzed. The results of this analysis show that the amplitude of the frequently used event related potential P300 is inversely proportional to cognitive load. Moreover, when cognitive load is high, alpha oscillations desynchronize while simultaneously theta oscillations synchronize. While event related potentials are associated with time periods, alpha and theta oscillations are sensitive to frequencies. However, both potentials successfully reflect cognitive load levels.

Keywords: Cognitive load, EEG, event related potentials, event related desynchronization/synchronization

1. Introduction

Human cognition contributes to the formation and accumulation of new information and keeps it available for possible use in the future (Sweller, 2010). The relationship between long term memory, where information is being stored, and working memory, where information is being processed, influences the interaction with the external world. Cognitive load theory (CLT) comprises the working memory and the long-term memory (Antonenko et al., 2010). Cognitive resources which are necessary for completing a task are referred to as "mental effort" (Cabañero et al., 2020). Hence, cognitive load describes mental effort while processing information (Antonenko & Keil, as cited in Zheng, 2018, p., 95). It becomes progressively important to know more about the cognitive load as it can easily be influenced by given instructions on tasks and even has an effect on information processing (Sweller, 2010). Thus, depending on the way information is presented during a task, the load on the working memory (cognitive load) changes (Anderson et al., 2011). Furthermore, if cognitive load outranges working memory capacity, learning will be impaired (Mills et al., 2017).

Several techniques to measure cognitive load are utilized in research. Subjective measurements such as rating scales, have been identified as being ineligible to reflect fluctuations in cognitive load (Antonenko et al., 2010). Moreover, taking into consideration that an individual's cognitive capacity depends on factors such as fatigue and motivation (Hunter, 2020), subjective ratings tend to be biased (Antonenko & Keil, as cited in Zheng, 2018, p., 95). In contrast, objective measurements that target brain activity, have been labeled as highly advantageous, because they correlate with workload (Hogervorst et al., 2014). Amongst these neurophysiological measurements, the electroencephalogram (EEG) has been found to be the most promising technique to reflect cognitive load. The EEG measures cognitive load directly (Swerdloff & Hargrove, 2020) and with high temporal precision (Hunter, 2020). It has several analyzing methods, which can be interpreted differently regarding human cognition (Birkas, 2020). Event related potentials (ERP) as well as event related desynchronization (ERD) and synchronization (ERS) have been associated with cognitive demands (Hunter, 2020).

In sum, we see that there are various measurement techniques regarding cognitive load. However, it is necessary to compare the techniques among themselves to ensure that the right decision is made when it comes to choose between them. With the improvement of measuring cognitive load, further implications to optimize learning conditions can be proposed. The aim of this thesis is to examine the properties of the frequently used EEG analyzing methods, ERPs and ERD/ERS, in measuring cognitive load. However, taking into consideration that the cognitive load is not measured in the same experimental paradigms throughout the chosen research papers, this thesis merely focuses on the measurement of cognitive load itself and how the different analyzing techniques respond to an alteration of experimental conditions.

According to the objective of this thesis, the following structure is proposed: In a first step, a theoretical background is provided. The concept of the cognitive load theory, as well as the functioning of the EEG will be explained in further detail. In a next step, the current state of research considering the measurement of cognitive load will be briefly discussed, followed by a presentation of the EEG components this thesis focuses on. After shortly mentioning the methodical procedure of the literature research, the results follow: The changes in ERP as well as in ERD/ERS depending on various experimental tasks will be illustrated. In the following discussion, the results will be critically reflected. Furthermore, limitations of the current thesis will be highlighted and implications for further research will be proposed. At the end of this thesis, a conclusion of the results will be drawn.

2. Theoretical background

The following chapters will provide a theoretical background about the objective of this thesis. In the first section the cognitive load theory will be presented. A detailed explanation of the EEG function and its measurement techniques will follow afterwards.

2.1 Cognitive load theory

Sweller (2010) distinguishes two types of knowledge: Biologically primary and biologically secondary knowledge. Whereas the biologically primary knowledge is acquired unconsciously, the biologically secondary knowledge is built consciously through mental effort. The cognitive load theory refers to the biologically secondary knowledge. Precisely, the focus of this theory lies on the relation between working memory capacity and the cognitive effort required for a task (Anderson et al., 2011). Processing new information claims more working memory capacity. This is associated with higher cognitive load (Antonenko et al., 2010), since cognitive load measures the occupied space of working memory (Mills et al., 2017). Available working memory capacity and cognitive load are inversely related to each other (Anderson et al., 2011).

Cognitive load is divided into three categories: Intrinsic cognitive load, extraneous cognitive load and germane cognitive load (Sweller, 2010). Intrinsic cognitive load reflects the mental effort that arises with the difficulty of an underlying task (Anderson et al., 2011). Germane and extraneous load are both associated with the instruction of a task. While extraneous load arises through the specific instruction (design) of a task and is believed to be an unnecessary mental burden (Antonenko et al., 2010), germane load is associated with the formation of new cognitive patterns (Anderson et al., 2011).

The different cognitive loads come together in memory (Mills et al., 2017). Hence, overall load is measured in research settings as it is believed to reflect an individual's mental effort (Antonenko et al., 2010). Mental effort describes cognitive resources during a task and is therefore synonymous to cognitive load (Cabañero et al., 2020).

2.2 Electroencephalogram

The electroencephalogram, commonly named EEG, is a neurophysiological measurement technique that allows to have insight into brain activity (Birkas, 2020). EEG signals can be either recorded extracranially where electrodes are placed on the scalp or directly from the cortical surface. The electrode placement follows an international standard 10-20 electrode system. To ensure the conductivity with the skull, an electrode recording gel is applied. However, current research shows that dry electrodes can also be applied to measure brain activity (Swerdloff & Hargrove, 2020).

Processes in the brain are usually an activation or inhibition of several neuronal networks (Schultheis & Jameson, 2004). These processes are mainly electric and generate different electrical fields. The electric signals emerge by neural activity dependent movement of ions through the neurons (Cabañero et al., 2020). These signals are detected by the change in amplitude per electrode compared to a reference electrode and are then split into sine waves through the Fast Fourier transformation (Anderson & Wisneski, 2008). Considering that electrical changes only last milliseconds, the EEG has a very high temporal resolution (Birkas, 2020). Numerous advantages of the EEG are its noninvasiveness and the relative low cost when compared to other neuroimaging methods. However, there are some disadvantages worth mentioning: The EEG has a poor spatial resolution since the signals are measured through several tissue layers. Also, the EEG is known to be susceptible to muscular activities, eye movement, and cardiac activity (Lakshmi et al., 2014). Nonetheless, the EEG detects different levels of cognitive load with a validity value between .75 and .91 (Mills et al., 2017). The recorded EEG signals can be divided in five wave patterns that reflect different behavioral states and differ in their frequencies: Alpha, beta, theta, gamma, and delta waves (Birkas, 2020). In this thesis, special attention is paid on alpha and theta waves since they are associated with cognitive load (Antonenko et al., 2010). Whereas the EEG has several different analyzing techniques, this thesis focuses on two specific techniques that differ from one another: event related potentials (ERP) and event related desynchronization/ synchronization (ERD/ERS). Both, ERPs and ERD/ERS are sensitive to cognitive demands. While ERPs are analyzing methods in the time domain, ERD/ERS are measures in the frequency domain (Hunter, 2020).

3. Measurement of cognitive load

There are several different techniques to measure cognitive load. The currently most utilized measurement techniques are subjective rating scales where participants are asked to assess cognitive load (Antonenko et al., 2010). An example for such a questionnaire is the "National Aeronautics and Space Administration Task Load Index" (NASA-TLX) (Devos et al., 2020). After completing an experiment, participants fill out this specific survey. The questionnaire contains six items which determine mental demand, physical demand, temporal demand, effort, performance, and frustration. It features a visual analogue scale ranging from 0 to 100. Also, it was shown that the NASA – TLX is highly reliable when measuring cognitive load. However, it is still unclear whether subjective measures can provide a continuous measurement of cognitive load (Antonenko et al., 2010).

Objective measures that usually include a secondary task do not measure cognitive load continuously, because the cognitive load that emerges from the primary task is measured by the performance in the second task (Antonenko et al., 2010). An example for a secondary task could be to continuously tap with the foot while solving a N – back test as primary task (Cabañero et al., 2020). This second task has its own load. Psychophysiological measurements are believed to measure cognitive load at a high rate and with high sensitivity, since they are able to measure continuous body data (Schultheis & Jameson, 2004).

Among the psychophysiological measurements, such as heart rate variability, eye blink frequency and chemical measures, the EEG seems to be the most promising technique as it is believed to reflect workload (cognitive load) most sensitively (Hogervorst et al., 2014). However, seeing that the spatial resolution is very low, it is not possible to draw out activated brain areas precisely (Antonenko et al., 2010). Nevertheless, the EEG measures the cognitive activity within milliseconds and therefore provides a highly sensitive measurement of the continuous changes in participant's cognitive load.

3.1 Event related potentials

When the EEG recording changes due to a stimulus being presented, the generated signal is called an event related potential (ERP) (Birkas, 2020). An ERP is the averaged amplitude change over many trials when a certain event occurs (Antonenko et al., 2010). By averaging the continuous EEG signal, oscillatory background activity that could impair the signal, is dispersed. Thus, ERPs display an electrocortical response to a particular event (presentation of a stimuli) (Antonenko & Keil, as cited in Zheng, 2018, p., 100).

Recent research of cognitive load focuses on one particular component of the ERP: The P300 (Schultheis & Jameson, 2004). The P300 is a positive peak of the ERP that occurs around 300 milliseconds after the stimulus was presented (Hogervorst et al., 2014). The P300 is associated with stimuli which are relevant for the current task participants are engaging in, but which appear at a low probability (Schultheis & Jameson, 2004). Also, it has been shown that the P300 mirrors cognitive level processing (Hunter, 2020) and its amplitude is inversely proportional to cognitive load (Swerdloff & Hargrove, 2020). Hence, the lower the cognitive load during a task, the larger is the P300 amplitude. Schultheis & Jameson (2004) addressed the complexity when measuring cognitive load with the P300: The P300 often requires the help of a secondary task (e.g., push a button whenever a certain light pattern appears while reading a text as the main task) which is usually an addition to the experimental assignment. Secondary tasks, however, tend to falsify the measurement of the cognitive load as they may interfere with the individual’s main activity. To avoid these possible consequences, Schultheis & Jameson (2004) use an alternative and apply the “Novelty – P300” in their study. The Novelty – P300 is associated with highly unexpected, new stimuli. Although the Novelty P300 shows the same properties as the P300, it can be measured without having a secondary task.

3.2 Event related (de-)synchronization

ERD/ERS is a percentage change in frequency band power during a task compared to a baseline interval (Antonenko et al., 2010). It is associated with a decrease (ERD), respectively an increase (ERS) of band power which reflects the synchronism of the underlying neurons (Pfurtscheller & Lopes Da Silva, 1999). An ERD/ERS index can be calculated by subtracting the measured power during a task from the baseline power and dividing the difference through the baseline power again (Antonenko et al., 2010). While a positive index predicts a decrease in band power (desynchronization), a negative value is associated with a power increase (synchronization).

While alpha oscillations of the EEG are known for their ability to mirror cognitive resource availability (Hunter, 2020), theta oscillations are related to workload (Hogervorst et al., 2014). Both oscillations are believed to relate to cognitive load during tasks that differ in their complexity (Antonenko et al., 2010). When a stimulus is presented to a participant during a task, we not only see ERPs in the EEG but also specific changes in the frequency domain. Simultaneously to an ERP, ERD/ERS of frequency bands take place as they both are a result of a stimulus being presented (Antonenko. as cited in Zheng, 2018, p., 101). While ERPs are time locked, ERD/ERS are phase locked and therefore require a frequency analysis to be detected properly (Pfurtscheller & Lopes Da Silva, 1999). Desynchronization is a relative to a baseline subsiding power within a frequency band whereas a synchronization is an ascent of power (Antonenko, as cited in Zheng, 2018, p., 101). Alpha desynchronization forms local functioning networks which are relevant for the task at hand while synchronization reflects an inhibition of processes that are task irrelevant (Hunter, 2020).

Alpha bands synchronize over a broad spectrum of the cortex whenever task demands are low (Hunter, 2020). The bigger the task demand, the greater the desynchronization of alpha. Thus, the alpha ERD is broader when cognitive load is increased. Interestingly, theta oscillations behave inversely: with increased task demand, and therefore greater cognitive load, theta bands synchronize (Antonenko et al., 2010). In consequence, theta desynchronization occurs when cognitive load decreases.

4. Method

For this thesis, a literature search was carried out. The research for this thesis addressed the topic of cognitive load measurement using the EEG. The following search engines were used during the time span of February 2021 until early May 2021: PubMed, Google Scholar and PSYNDEX. Furthermore, the research column of the central library of Zurich was used.

Utilized key words included: EEG, cognitive load theory, measurement of cognitive load, event related potential, event related desynchronization/synchronization and fMRI. The literature search was done entirely in English.

To ensure actuality, the research had several inclusion and exclusion criteria. Literature published after the year of 2000 was favorized and included into this thesis. Therefore, an exclusion criterion was the date of publication: Papers published before the year of 2000 were excluded. An exception was made for the research papers of Klimesch (1999) and Pfurtscheller & Lopes Da Silva (1999), as they provide information of great relevance for this thesis. In sum, ten papers were selected to help the purpose of comparing ERP and ERD/ERS properties during cognitive load measurement.

5. Results

In the following section, selected research papers that broach the issue of measuring cognitive load will be summarized. The research papers are listed depending on the EEG analyzing technique with which the cognitive load was measured.

Addressing the issue of cognitive load during learning, Mills et al. (2017) examined how to model cognitive load as reliable as possible. Through a proper measurement of cognitive load an intelligent tutoring system (ITS) can be created. It provides tailored instructions for participants so that the cognitive load is advantageous for learning. The authors used an EEG based detector and analyzed its sensitivity to measure cognitive load when participants engaged with an ITS named “Guru”. Twelve high school students (from ninth grade) participated in this study. They were asked to perform cognitive inducing tasks such as N-back, forward digit span, column addition and Tetris. The participants also completed a tutoring session with Guru. The instructions delivered by Guru varied in their difficulty and therefore caused different levels of cognitive load. Therefore, the experimental conditions could be divided in “easy” and “difficult” conditions. The main finding of this study was that the EEG spectral features (frequency band power) showed validity rates between .75 - .79 when the cognitive load (easy vs. difficult) were manipulated through the difficulty of the cognitive tests (forward digit span, N – back, Tetris and column addition). However, the validity rate was even higher (.87) when participants were asked to fix their gazes on a target cross on the screen during the “easy” condition and only received instructions from Guru during the “difficult” condition, without solving any cognitive tasks. The highest validity rate (.91) was shown when participants were asked to fix their gazes on a target cross during the easy condition, and solved cognitive load inducing tasks under the difficult condition.

Hogervorst et al. (2014) went further and examined several different variables. Among other things, they determined the value of combining different features to measure cognitive load. Thus, they combined analyses of different sensor groups to measure cognitive load. 14 participants, their age ranging between 23 and 40 years, were asked to perform a N-back task. Between stimulus blocks, they assessed their cognitive load on a scale (RSME). EEG data as well as skin conductance and ECG (electrocardiogram) were recorded throughout the experiment.

EEG data showed a cognitive load measurement accuracy of .86. Eye measures showed an accuracy of .75, while skin conductance was .63 and ECG .61. They calculated the average ERP over all trials. The spectral alpha and theta power were also calculated for each block. The averaged ERP and spectral power of alpha and theta waves showed an accuracy of over 0.85. However, when only theta power was measured, the accuracy decreased. Also, combining EEG data with other features such as physiological variables did not significantly improve accuracy.

A detailed presentation of alpha and theta oscillations is given in the review article of Klimesch (1999). He not only discusses the basic theory of alpha and theta oscillations, but also tonic and phasic changes in them. Tonic changes are under no volitional control and occur at a slow rate (e.g., age related changes). It is shown that alpha power increases from childhood to adulthood before decreasing for the remaining life span. However, phasic changes (event related changes) show that the band power of alpha and theta depends on task demands. During a task that demands cognitive effort, theta activity is increased while alpha is decreased. Klimesch, (1999) distinguishes upper alpha bands (10 – 12 Hz) from lower alpha bands (6 – 10 Hz). The study assumes that upper alpha ERD is the result of increased attention during a semantic task. Moreover, theta ERS might be associated with episodic memory performance.

Grissmann et al. (2017) investigated cognitive load with the help of subjective assessments, task performance and EEG measures. The aim of the study was to create as realistic conditions as possible. 24 female university students between the ages of 19 and 32 participated in this study. Among cognitive load, affective valence was a focus of this study as well. Participants were asked to perform 12 blocks of a N-back task (to manipulate cognitive load). Additionally, affect was induced using pictures from the International Affective Picture System (IAPS). Furthermore, participants were asked to assess their cognitive load on a scale (NASA). The rating of cognitive load showed a positive correlation between cognitive load assessment and subjective experience. Moreover, the task performance, measured through reaction time, also showed a positive correlation with cognitive load. The EEG measurement showed increased frontal theta ERS and alpha ERD when cognitive load was high. However, there was no significant interaction between affect and cognitive load.

In the review article of Antonenko et al. (2010), a variety of possibilities to measure cognitive load are discussed. A particular focus lies on the EEG. The review points out the changes in alpha and theta activity: Alpha ERD and theta ERS occur when cognitive load is increased. Furthermore, it was shown that the integration of "leads" could alter the cognitive load during reading tasks. Leads prepared the participants for what information had yet to come in the next passage while they were reading the previous one. Alpha, as well as theta ERD/ERS were measured. It was shown that participants gained a better conceptual knowledge about the hypertexts, when leads were included. Moreover, alpha ERD and theta ERS were both decreased when leads were included. In addition, the "neural efficiency hypothesis" was discussed. The hypothesis states that intelligence is a result of how efficiently the brain works. Cognitive load of "gifted" (above – average intelligence) and "average" students was measured when they participated in tasks featuring different medias. With the help of the EEG, alpha power was measured during the one-minute presentation of a text, picture, and a video. The main findings were that intelligent participants showed reduced cognitive load during all formats. Moreover, cognitive load showed a negative correlation with alpha power.

Berka et al. (2004) went a different way and combined various EEG waves. Through signal analyzing techniques, slow and fast eye blinks were identified. Each second of the EEG recording was then classified into a category: "high vigilance", "low vigilance", "relaxed wakefulness" and "sleepy". A system called "B – Alert" used information about alpha, beta, and theta frequency bands to assign these categories to each second of the EEG. Hence, the B-Alert system is a quantification of the EEG in real-time. In this study the efficacy of an EEG sensor headset and the B-Alert system to reflect mental workload during cognitive tasks were examined. 45 individuals (ages range between 18 and 50) participated in this study and were distributed over different tasks. The Warship Commander Task influences cognitive load by multitasking while the three-level cognitive task consists of different cognitive assignments which differ in their difficulty. Both tasks manipulate cognitive load. The image learning and recognition tasks were applied for the evaluation of the B – Alert indexes. It was shown that increased task difficulty resulted in an increase of the B-Alert system (percentage of high vigilance). Furthermore, the B-Alert system decreased when participants showed a training effect (improved performance in session two compared to session one). Also, the B-Alert percentage was higher during the memory task than in the recognition task.

In a user study of Anderson et al. (2011), cognitive load, that was needed to interpret a visualization, was measured with the help of the EEG. The effects of different visualization techniques on cognitive load were examined. The visualization task contained box plots. 17 participants (whose ages are not mentioned) were recruited for this study and completed 100 single trials that were performed independently. Each trial contained two chosen distributions which were displayed in box plots. In between the trials, a one-minute resting period was inserted to collect EEG baseline data. The participants had to point out the one distribution with the larger interquartile range as fast as possible. They specifically focused on the alpha and theta frequency bands. The results showed that with the help of the alpha and theta frequency bands, different cognitive loads were depicted depending on the type of box plots presented. They also showed a positive correlation between cognitive load and task difficulty. Also, alpha and theta frequencies equally contributed to the measurement of cognitive load.

In another study, Hunter (2020) examined electrophysical measures of cognitive effort. They took the measured cognitive effort as an indicator of cognitive spare capacity. Furthermore, they investigated how the predictability of sentences during speech processing affects the measurement of cognitive spare capacity. ERPs and frequency dependent EEG activity were measured during the tasks. 22 young adults (ages range between 19 and 26) were recruited to participate in the study. The participants completed a sentence-recognition task that served the purpose of examining how memory load and sentence predictability can modulate cognitive load. During high cognitive demand, alpha ERD could be measured. Thus, alpha ERD was greater when sentences were unpredictable. There was no significant interaction between cognitive load and sentence predictability. Furthermore, the P300 amplitude was higher during low cognitive load and when sentences were predictable.

In the study of Swerdloff & Hargrove (2020) ten individuals between the ages of 19 and 25 participated. The aim of the study was to prove that ERPs can be applied during three postural tasks: sitting, standing, and walking. While the participants were performing the postural assignments, a cognitive task in form of an oddball paradigm (participants were supposed to pay special attention to tones that appeared infrequently while ignoring the standard ones) was completed simultaneously. The P300 response was analyzed and cognitive load between the tasks was compared. It was shown that the P300 amplitude was lowest during walking while there were no significant differences of cognitive load during sitting or standing.

At last, the study of Schultheis & Jameson (2004) broaches the issue of finding the best assessment method to measure cognitive load online. 13 subjects (ages range between 20 to 21) participated in the study and were assigned to read texts presented on a computer screen. After reading the respective texts which varied in their difficulty, they were asked to answer seven multiple choice questions. While pupil size was measured through the whole experiment, ERPs were only recorded when eliciting tones sounded while the participants were reading the texts. For each trial, four average curves which were evoked through these tones were generated. Summarizing these curves over all participants, the grand average of the P300 results. The P300 displayed an increased cognitive load when participants read the difficult texts. Pupil size however, showed no significant effect of text difficulty.

6. Discussion

The aim of this thesis was to summarize current literature about two EEG analyzing techniques which are utilized for the measurement of cognitive load. To do so, the EEG function as well as the theoretical background of cognitive load, the cognitive load theory, were presented. Moreover, an insight into two EEG analyzing techniques, ERP and ERD/ERS, was given. Subsequently, the most relevant results of selected research papers which addressed cognitive load measurement were listed. Thus, the properties of ERP and ERD/ERS under experimental manipulations of cognitive load were shown.

This section summarizes the previously mentioned results, shows limitations of this thesis, and proposes potential implications for further research. Taking everything into consideration, a conclusion about the objective of this thesis will be drawn in the end.

6.1 Summary

The studies of Mills et al. (2017) and Hogervorst et al. (2014) both showed the accuracy, as well as the validity of EEG data in measuring cognitive load. Compared to other physical measurement techniques such as skin conductance, heart rate and eye measures, the EEG data exceeded in accuracy. This aligns with the theory that the EEG is an accurate measurement technique for cognitive load (Schapkin et al., 2020). Furthermore, Hogervorst et al. (2014) showed that it makes no significant difference in measurement accuracy of cognitive load when the EEG data is combined with physical features. These findings are supported by the results of Schultheis & Jameson (2004). In their study there was no significant effect of text difficulty in pupil size, although the EEG data (P300) showed increased cognitive load when participants read difficult texts. Nevertheless, physical features besides brain oscillations are still broadly utilized to measure cognitive load (Cabañero et al., 2020). Moreover, although the EEG is the most sensitive technique for cognitive load measurement, subjective rating scales are applied the most (Antonenko et al., 2010). A possible explanation could be the higher costs of EEG technologies in comparison to subjective rating scales (Mills et al., 2017) and other physiological measurements.

The theoretical relation between cognitive load and alpha and theta ERD/ERS was first stated by Klimesch (1999) and then supported by the results of Hunter (2020), Grissmann et al. (2017), and Antonenko et al. (2010). With increasing cognitive demand, and therefore higher cognitive load, alpha ERD and simultaneously theta ERS occurs. These findings are in line with the results shown in the study of Anderson et al. (2011). They showed that cognitive load is positively correlated with task difficulty. Moreover, the study of Schultheis & Jameson (2004) found the same relation between cognitive load and task difficulty with the help of the P300. In the review article of Antonenko et al. (2010), it was shown that both, alpha ERD and theta ERS were decreased when participants were prepared for the contents of what they were about to read. This resulted in a better conceptual knowledge about the texts. Seeing that previous knowledge is associated with lower cognitive load (Antonenko et al., 2010), the decrease of alpha ERD and theta ERS is consistent with the earlier mentioned results. The P300 data from the study of Hunter (2020) supports this idea: When participants could predict the sentences that were about to come, cognitive load was low. Also, the negative correlation between alpha power and cognitive load (Antonenko et al., 2010) is consistent with the theory that alpha ERD is associated with low alpha power (Klimesch, 1999).

Furthermore Klimesch (1999) also addressed age dependent changes in alpha power. However, the increase of alpha power from childhood to adulthood and the following decrease for the remaining life span could be related to brain development during adolescence. Moreover, Klimesch (1999) also ascribes specific features to alpha and theta waves: While alpha ERD is related to semantic memory, theta ERS is associated with episodic memory.

Grissmann et al. (2017) included an emotional feature into the measurement of cognitive load to reflect a preferably realistic condition as a lot of cognitive load research is held under strict experimental conditions. The subjective experience of workload, as well as task performance correlate positively with cognitive load. Surprisingly, the affective manipulation did not influence cognitive load, and vice versa. These results contradict with the theory that cognition and emotions are crosslinked (Plass & Kalyuga, 2019). Grissmann et al. (2017) used the frontal alpha asymmetry (FAA) to detect the affective valence in the EEG. It could be possible that this measurement technique was not beneficial for this specific experimental setting. It could have been more advantageous to use the late positive potential which is also broadly utilized when measuring affective valence in the EEG. Seeing that the FAA is easily influenced by features like working memory load, this could also be a possible explanation as to why they could not confirm their hypothesis.

The study of Berka et al. (2004) displayed a decrease of the B – Alert system due to a training effect. This result is consistent with the finding that prior knowledge results in low cognitive load (Antonenko et al., 2010). Therefore, one could conclude that a decrease in the B – Alert system reflects low cognitive load and therefore low vigilance is associated with low levels of cognitive load. This assumption is supported by the positive correlation between the B – Alert system and task difficulty (Berka et al., 2004). Since cognitive load is positively correlated to task difficulty (Anderson et al., 2011), it is reasonable to assume that due to the training effect, task difficulty decreases and therefore results in lower cognitive load. Also, the increase of the B – alert system during the memory task could be explained due to the fact that theta activity is related to episodic memory (Klimesch, 1999).

Considering the ERP feature P300 in this discussion, it was shown that the amplitude of the P300 was higher when cognitive load was low (Hunter, 2020). This finding is in line with the theory that the P300 amplitude is believed to be inversely proportional to cognitive load (Swerdloff & Hargrove, 2020). Also, seeing that the P300 amplitude was greater when sentences were predictable and alpha ERD occurred when they were unpredictable, it could be assumed that predictable sentences are associated with low cognitive load, while unpredictable sentences result in higher cognitive load levels. Interestingly there was no significant interaction between sentence predictability and cognitive load (Hunter, 2020). During the study of Swerdloff & Hargrove (2020) it was shown that the P300 amplitude was lowest during walking. This finding indicates that cognitive load was increased when participants had to walk while completing the oddball paradigm. It can be assumed that while neither sitting nor standing have an additional effect on cognitive load, walking does have an influence. Considering that cognitive load is positively correlated with task difficulty (Anderson et al., 2011), one can suppose that walking makes the task more difficult. However, it could also be possible that rather than walking having a higher cognitive demand, the produced additional noise that results from walking could impair the participants' task performance. Also, seeing that the EEG is susceptible to physical activity (Lakshmi et al., 2014), Swerdloff & Hargrove (2020) had to remove EEG artifacts that resulted from eye blink, sweat, muscle contractions and movement. It could be possible that the walking condition produced more EEG artifacts that needed to be removed, compared to the other conditions, and therefore the P300 data could have been influenced.

6.2 Strengths and Limitations

In this thesis, ten research papers were reviewed. All of them examined the concept of cognitive load in one way or another. Throughout the selected research papers, cognitive load was measured through a variety of tasks. The tasks included visualization of box plots (Anderson et al., 2011), reading of texts (Schultheis & Jameson, 2004), the combination of a cognitive task with either a postural task (Swerdloff & Hargrove, 2020) or including emotional valence and arousal (Grissmann et al., 2017). Hence, the results should be viewed in relation to the experimental assignments as cognitive load effects depend on the way how information is presented (Sweller, 2010).

Furthermore, the variety of the samples was restricted due to some studies featuring students of an higher education (Antonenko et al., 2010; Grissmann et al., 2017). Considering the "neural efficiency hypothesis", participants who have a higher education show different variations of cognitive load during tasks (Antonenko et al., 2010) and therefore cannot be compared to the broad population. Additionally, some of the included studies focused solely on young adults (Hunter, 2020; Swerdloff & Hargrove, 2020; Mills et al., 2017). Moreover, the sample sizes vary from ten (Swerdloff & Hargrove, 2020) to 45 individuals (Berka et al., 2004). Consequently, the discussed results can only be generalized over respective sample related populations.

However, the selected research papers showed that the EEG seems to be a very accurate measurement technique to analyze cognitive load (Hogervorst et al., 2014). Moreover, it became clear that ERPs as well as ERD/ERS can successfully reflect the cognitive load.

6.3 Outlook

Still, there seems to be some uncertainty regarding the role of theta activity in measuring cognitive load. It is stated that alpha oscillations are associated with semantic information processing (Hunter, 2020) while theta oscillations are related to episodic memory (Antonenko et al., 2010). Considering that alpha bands are related to semantic information procession tasks (Hunter, 2020), it could be advantageous to make use of alpha ERD/ERS to measure cognitive load when the experiment features a reading task. Furthermore, the association between theta activity and episodic memory could be beneficial when cognitive load is measured in a context where previous experience plays a role. ERPs like the P300 however, often appear when a highly unexpected event occurs (Schultheis & Jameson, 2004) respectively when special attention is paid to a target stimuli (Swerdloff & Hargrove, 2020). These relations propose the utilization of ERPs in tasks that resemble the oddball paradigm as it features unexpected stimuli and requires special attention. Seeing that ERPs need to be averaged over multiple events under the same conditions so that the oscillatory background activity (EEG noise) disappears makes it difficult to compare analyses from a lab to real life.

Additionally, it is still unclear to what extent alpha and theta oscillations contribute to the measurement of cognitive load. While Anderson et al. (2011) assert that alpha and theta oscillations equally affect the measurement of cognitive load, Hogervorst et al. (2014) showed that the measurement accuracy decreased when only theta bands were considered. This discrepancy arises the need to further investigate the contribution of theta activity in regard of cognitive load measurement.

Furthermore, Cabañero et al. (2020) mentioned the importance of the electrode placement: Depending on the task, the different frequencies cover a greater or lesser brain area. Measured ERPs at Pz were the most accurate ones. While alpha bands also were measured on the same spot, theta was best measured on Fz (Hogervorst et al., 2014). This measurement accuracy squares with the topographical activity differences between theta and alpha oscillations (Antonenko & Keil, as cited in Zheng, 2018, p., 107). While alpha activity is more distinctive over occipital and parietal lobes, theta is most prominent over the frontal lobe. These differences in location dependent measurement accuracy should be respected for further research. A possible combination with another neurophysiological measurement technique could be beneficial. The functional magnetic resonance imaging (fMRI) can depict regional changes in brain activity (Glover, 2011) and should therefore be considered for further research.

Also, since alpha frequency is stated to be an indicator for cognitive performance and changes with age (Klimesch, 1999), further researchers should be careful when trying to compare different age groups. The effect age has on not only human behavior but also on cognition could potentially impair the generalization of experiments featuring mixed age groups. Hence, it is of great relevance to consider such factors which alter throughout the lifespan when recruiting participants.

At last, considering that the cognitive load can be divided into subtypes (Sweller, 2010), it could be beneficial to pay them special attention. By optimizing the distribution of cognitive load over intrinsic, extraneous and germane load, learning processes can be improved (Mills et al., 2017). According to Klepsch et al. (2017), intrinsic cognitive load is reflected through task difficulty, while extraneous load can be manipulated by task instructions. Therefore, it would be beneficial to analyze changes in the mentioned subtypes of cognitive load. Although they are added together in memory, it was shown that depending on which subtype increases in load, learning is improved (Mills et al., 2017)

6.4 Conclusion

While EEG measurements, in general, are known to be sensitive to cognitive demands, ERPs are associated to the time domain while neural oscillations like alpha and theta ERD/ERS are sensitive in the frequency domain (Hunter, 2020).

Both, alpha and theta ERD/ERS occur when cognitive load levels change (Hogervorst et al., 2014). While alpha desynchronizes with increasing cognitive load, theta synchronizes (Klimesch, 1999). Furthermore, the amplitude of the ERP P300 is negatively correlated with cognitive load (Schultheis & Jameson, 2004).

Therefore, the P300 amplitude and alpha ERS are both inversely proportional to cognitive load while theta ERS shows a positive correlation.

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8. Declaration of Originality

I hereby declare that the written work is of my own unaided wording and adheres to scientific integrity principles. (cf. https://www.teaching.uzh.ch/de/infrastruktur/plagiate.html)

Züberwangen, 21.05.2021

Place and Date

Signature