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Dr. Emri Zsuzsanna, Dr. Antal Károly, Csordás Georgina, Dr. Prantner Csilla, Dr. Kis-Tóth Lajos: Advantages of EEG monitoring in education

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Abstract: Affordable, portable, and easy-to-use devices, as well as computer programs that allow the quantitative analysis of EEG signals, provide the opportunity for wide-ranging educational applications of EEG. However, the use of EEG data is complicated by the presence of significant individual differences in resting activity; therefore, this technology is not suitable for analyzing educational processes on its own. However, when used together with other methods, it could provide valuable data on learning-related brain activity.

In our study, we used the Emotiv EPOC EEG headset and monitored brain activity during closed- and open-eye relaxation, reading, and arithmetic calculation. We used the Fourier Transform (FFT) to analyze the spectral content of the EEG signal, determined the power of the theta, alpha, and beta EEG bands, and then calculated the attention, engagement, and cognitive load values for each task. Participants also solved a test related to the tasks, evaluated their performance, and filled out a questionnaire about their impressions of the measurement. We made our conclusions by combining the data from the EEG, the test, and the questionnaire results. We found an increase in the alpha power related to tiredness, increased attention during reading, and high cognitive load during calculation, especially when the result was correct. Participants diagnosed with dyslexia showed lower alpha peak frequency during open-eye relaxation and increased theta activity during reading. Although they needed more time to complete the reading task, their test results were similar to the results of the control group.

Our results suggest several possible usage of EEG in education. It enables the continuous monitoring of alertness, can detect fatigue, and helps keep task difficulty at an optimal level. However, the beta theta ratio used in this study to determine attention level does not seem suitable for monitoring sustained attention. EEG can also give us useful insight into the performance of students with special needs, helping teachers provide adequate tasks and guidance.

Keywords: attention, cognitive load, dyslexia, educational evaluation, EEG

1. Introduction

For the development of effective teaching practices, validated methods and tools are needed to reliably detect the presence and quality of teaching practices and monitor students' academic progress. Thus, we not only need to gather and analyze effective teaching methods, but we also have to associate their impact on student learning in online environments and everyday classrooms (Hannafin et al., 2010).

1.1. Evaluation of classroom activities

Tests, questionnaires, interviews, and classroom observations are usually used for the evaluation of teaching techniques. The general problem with tests is that retaking them does not produce the same result; the test-retest reliability is usually very low. Any method based on self-report has low credibility; several studies have reported that students can not analyze and report their learning process accurately (Rawson et al. 2017). Moreover, questionnaires and interviews conducted after the classroom activity are biased by the final part of the activity; by that time, first impressions are often forgotten (Cohen and Manion, 1994). Classroom observations can be made directly or by video recording. The latter allows continuous monitoring without the interruption of regular classroom activities. It provides more accurate feedback about the teacher's activity than the students, but it needs a well -documented framework and educated raters, and still, its trustworthiness is affected by inter-rater reliability (Hannafin et al. 2010). To monitor students' activity during classes, the continuous measurement of their somatic or autonomic nervous system responses was suggested. The use of EEG recordings appeared promising, especially since EEG signals are closely related to behavior and cognition (Nunes and Srinivasan, 2006).

1.2. Features of EEG activity and their relation to cognition

Resting EEG activity shows considerable individual variability. One source of the differences among individuals is their genomic variation, the characteristics of the alpha activity determined mainly by the genetic background (Beijsterveldt and Baal, 2002). Some variances could be connected to psychiatric disorders (Newson and Thiagarajan, 2019) or learning disabilities (Roca-Stappung et al., 2017). Their effect is manifested by changes in the powers of specific EEG bands. These changes are not unique; there is a substantial overlap across disorders. Usually, EEG power increases across lower frequency bands (delta and theta) and decreases across higher frequencies (alpha, beta and gamma) (Newson and Thiagarajan, 2019). For instance, studies reported an increase in theta activity in developmental dyslexia, especially in frontal and occipital regions, and a decrease in occipital beta and alpha as well as frontal alpha activities (Cainelli et al., 2023).

Resting state EEG also reflects vigilance, anxiety, and it changes with cognition. With drowsiness alpha activity tends to increase, while with stress and anxiety it decreases (Rajendran et al., 2022). Frontal theta and beta ratio is associated with attention and cognitive control (Angelidis et al., 2018). Cognitive load is calculated as the ratio of frontal theta and posterior alpha powers, while the ratio of frontal beta and the sum of theta and alpha powers reflects engagement (Bootz et al., 2018).

1.3. Portable EEG systems

Portable EEG systems typically include fewer electrodes than medical headsets. However, their lower price and less time -consuming setup make them more accessible in real-life settings. Several studies showed that consumer EEG headsets can be used as research tools (Badcock et al., 2013; Kuber and Wright, 2013; Sawangjai et al., 2019). Portable EEG technology is still at an early stage of development; it encounters many challenges: considerable measurement errors, long setup time in large-scale samples, and inconvenience when wearing it for a long time (Xu and Zhong, 2018). These technical limitations are diminishing, and the announcement of new, lighter, and more comfortable headsets using sensors with better signal detection characteristics appears every year (He et al., 2023). Part of the measurement errors result from the differences in contact quality between the sensor and the scalp. These can be mitigated using relative values or the changes between two cognitive states instead of the raw data.

Several aspects of human cognition were measured by EEG in laboratory conditions, but so far, only a few studies have been conducted in more naturalistic settings (Xu and Zhong, 2018). Portable EEG systems have been widely used in reading contexts. Usually, the learner's attention level is calculated during web-based reading, using different types of reading materials (books, picture books, etc.) or when learners use sitting, standing, or walking postures for reading. A few studies focused on other teaching and learning subjects, such as mathematics, programming, or science (Xu and Zhong, 2018). Another well -researched area is edutainment; portable EEG systems are used to measure engagement and motivation levels during game -based learning, aiming to achieve an ideal balance between playful and educational content (Gergulescu and Muntean, 2016) or to track progressive improvement in skills of children with special needs (Gallud et al., 2023). Very few studies verified that the specification of cognitive processes by EEG measurements is reliable in the tested real-life environment and that EEG values either change with the investigated cognitive process or correlate with the learner's achievements (Xu and Zhong, 2018). The validation of these results is important since the settings of laboratory and real -life studies differ fundamentally. Laboratory settings use a reductionist approach (well -defined, clearly separated short inputs) that affords control over the investigated cognitive process, while in naturalistic environments, researchers deal with several inputs at the same time, some of them present for a long period but remain ignored most of the time (Janssen et al. 2021).

1.4. Aims of the study

In this study we explored the usage of EEG data to help educational research and we aim to provide useful insights about student's learning processes. We used a semi-naturalistic learning environment, students worked in a quiet environment without much distraction, followed instructions presented on a laptop, and solved tasks required sustained attention and different skills, similar to classroom tasks.

In this environment, we tested:

- the effect of sustained attention on resting state EEG activity by comparing EEG activity during the two closed-eyed relaxation periods (relaxation before and after tasks);
- if EEG data reflects self-reported stress, or tiredness;
- if the EEG activity has different characteristics in dyslexic students compared to controls;
- how the results of tests, self reports and questionnaires correlate with EEG results.

2. Methods

For this research, we used EEG measurements in combination with tests, questionnaires, and self-assessment of the learning performance. Thirty-one students (15 male) from Eszterházy Károly Catholic University were recruited to participate. The age of the study participants was 24,03±4,54 years, and 5 participants (2 male) were diagnosed with dyslexia during their primary school years. Every participant was briefed about the EEG measurement and the tasks and signed a written consent.

2.1. EEG measurement

The experimental setup was similar to our previous studies (Antal et al., 2017; Emri and Antal, 2022). The Emotiv EPOC wireless EEG headset was used for data acquisition. The headset consists of 14 sensors positioned on the wearer's scalp according to the international 10–20 system. The tasks during EEG measurements were presented on a laptop. All participants performed two types of relaxation, each lasting for 4 minutes: a closed-eye relaxation, where they sat with their eyes closed while listening to relaxing music, and an open-eye relaxation, where they watched a video accompanied by relaxing music. The video consisted of pictures of different landscapes. These periods served as controls. Tasks were either reading a ~2500 -character long part of a novel or arithmetic calculations (Fig. 1.). For the reading and arithmetic tasks, participants could spend as much time with the task as they needed.

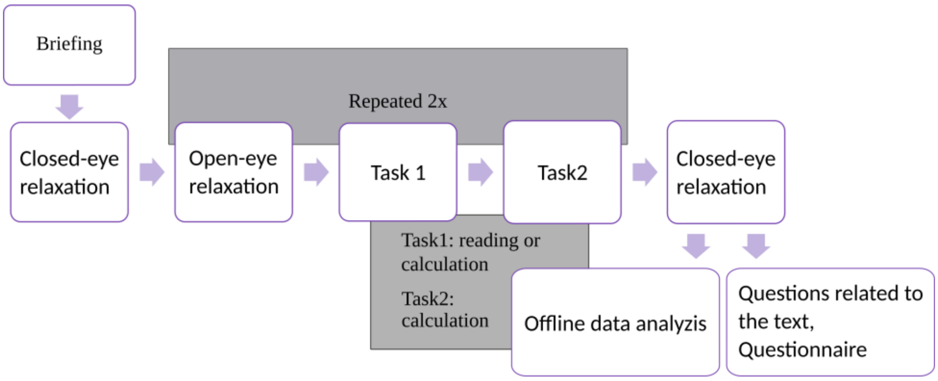

Figure 1 *Experimental design*

2.2. Tests, questionnaires, self-assessment

Following the EEG measurement, participants had to answer questions related to the text, and we also checked the results of the calculations. They also filled out a questionnaire about the tasks: how much they liked the reading material, if they were tired or not, if their performance was bad, average, or good, and how much they slept the previous night. They also rated how nervous they felt during the measurement on a scale from 1 to 9. Finally, participants filled out a learning style questionnaire to specify if they preferred reading, auditory, visual, or kinesthetic ways to accomplish different learning tasks (Fleming and Mills, 1992).

2.3. Data analysis

EEG recordings were offline analyzed, in Python (Python software foundation, 3.8.10), using the 'scipy' (1.8.0) package (Jones et al., 2001). Raw data was band-pass filtered with 0.5 Hz and 30 Hz cutoff frequencies, then standardized to zero mean and unit standard deviation. To limit the effect of high peaks, we clamped the data to the [-6, +6] range. For spectral analysis we used a Tukey window of 2 seconds with a shape parameter of 0.25, 1 second overlap between segments, and segmentwise linear detrending.

Relative EEG power values were calculated by the power of a specific EEG band per the power of the 1-25Hz frequency range. Data are presented as the average ± standard deviation, for comparisons Wilcoxon test (Bauer, 1972) was used, while correlations between the EEG data, tests and questionnaire values were appraised using Spearman's correlation coefficients.

3. Results

3.1. Characteristics of resting state EEG

During closed-eye relaxation alpha activity dominated the EEG activity of all participants, the Fast Fourier transforms showed an alpha peak, which decreased, occasionally disappeared completely (n=4 participants), when the participant opened his or her eyes. We compared the theta, alpha, and beta powers of the two closed-eye relaxation periods (the one before and the one after the tasks). We found a difference only in the alpha activity; frontal alpha power was increased after tasks, from 0.276±0.136 to 0.289±0.130 ($p<0.05$).

The tiredness of participants was rated by their answers to three questions; they scored 1 point each if they said that they were tired, slept less than usual, and had bad performance. Tiredness correlated with beta activity (rho=0.426); those participant who were tired showed larger frontal beta activity (0.114±0.029) than those who were more rested (0.083±0.038; $p<0.05$) during closed-eye relaxation. Self-reported stress did not correlate with any EEG data, which was not surprising since some of the participants showed signs of anxiety during the relaxation (leg shaking, tense neck muscles, or eye movements) yet indicated a low stress level in the questionnaire.

3.2. EEG characteristics in control and dyslexic students

There is no EEG marker for dyslexia, although several studies reported differences between the EEG activity of control and dyslexic persons (Cainelli et al., 2023). We had five participants who had a diagnosis of dyslexia at primary school, but they graduated and took university exams in a similar way to the others; they do not have subject exemptions. During the EEG measurements, they needed more time for the reading task and the arithmetic calculation, but their results were similar to those of the control participants. Controls read 783.509±228.607 characters per minute, while dyslexic participants only 515.642±135.409 characters per minute ($p<0.05$). Control and dyslexic participants required 8.914±4.912 s and 15.158±4.913 s ($p<0.05$), respectively, to complete a single arithmetic operation. EEG activity during closed-eye relaxation did not differ between control and dyslexic participants. In open-eye relaxation, the peak frequency of the alpha peak was lower in dyslexic participants than in controls (control=12.231±1.814Hz, dyslexic=9.750±1.309Hz, $p<0.05$). During reading, dyslexic participants showed larger frontal theta activity (control=0.146±0.011, dyslexic=0.125±0.016, $p<0.05$), and during the calculation task, dyslexic participants showed larger cognitive load (control=1.443±0.310, dyslexic=1.754±0.308, $p<0.05$).

3.3. Attention, engagement and cognitive load during reading or calculation tasks

During reading, the alpha power decreased while theta power increased compared to the closed -eye relaxation. The increase in beta activity was not as marked; only occipital beta activity increased significantly. When we compared the power of these EEG bands to the powers during video watching (open-eye relaxation), frontal theta power increased, and frontal alpha power decreased significantly (Fig. 2). Attention, engagement, and cognitive load showed a significant increase compared to closed-eye relaxation, but only attention changed significantly compared to video watching (Fig. 3A).

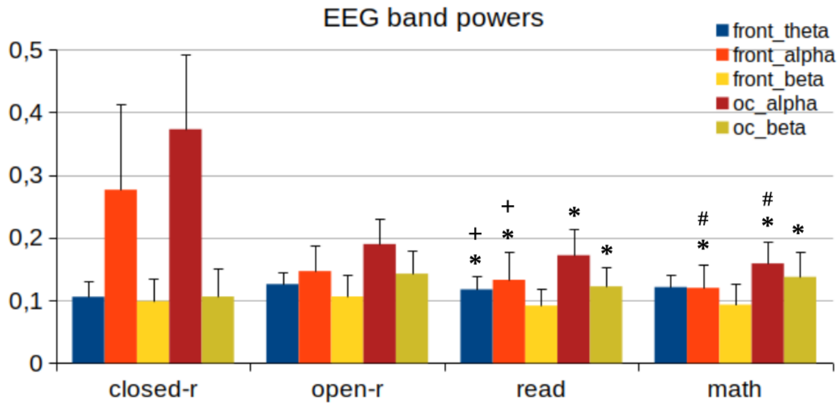

***Figure 2** Comparison of EEG powers during different tasks.*

*Front: frontal; oc: occipital; *+#: p<0.05 compared to closed-r, open-r and read, respectively. Closed-r: closed-eye relaxation, open-r: open-eye relaxation, math: calculation task*

Arithmetic calculation is a more demanding task than reading. Cognitive load increased compared to the reading task (Fig. 3B) while the engagement and attention remained the same. Both alpha and theta power decreased compared to the reading (Fig2).

Participants showed the lowest alpha activity during calculation and the highest theta activity during reading, while the beta activity was similar during the two tasks.

3.4. Relation of self-assessment to EEG data

Next, we calculated Spearman's correlation coefficients to check how the test results and self-assessments correlate with the different EEG waves. We found no correlation between the test results of the reading task and the EEG waves, similarly there were no correlation with the level of tiredness. We argue that both high and low cognitive load values could be related to poor test results (Fig. 3C).

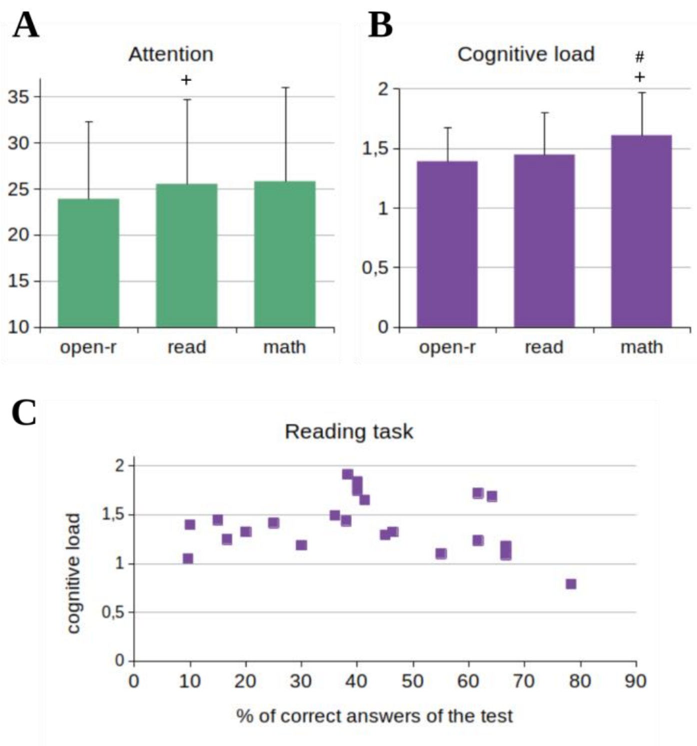

Figure 3 *Comparison of cognitive load and attention values of different tasks.*

A) Attention values during open-eye relaxation (open-r), reading (read), and calculation (math). B) Cognitive load values during open-eye relaxation (open-r), reading (read), and calculation (math). +# p<0.05 compared to open-r and read, respectively. C) High as well as low cognitive load values were associated with poor test results

The speed of the reading showed a weak correlation (rho=0.448) with the level of attention. Those who liked the text showed larger occipital alpha power (rho=0.456). Participants who preferred reading as a learning style did not achieve better test results nor showed lower cognitive load or higher attention. The results of the calculation task showed a weak positive correlation with the cognitive load (rho=0.376). The average beta activity increased with tiredness (rho=0.359), and the self-rated difficulty of the calculation (rho=0.357). Learning style preferences correlated with some of the test results, the number of aural or reading style preferences positively correlated with the result while the number of visual style preferences correlated with the speed of the calculation, with the difficulty kinesthetic learner style preferences correlated (Fig. 4).

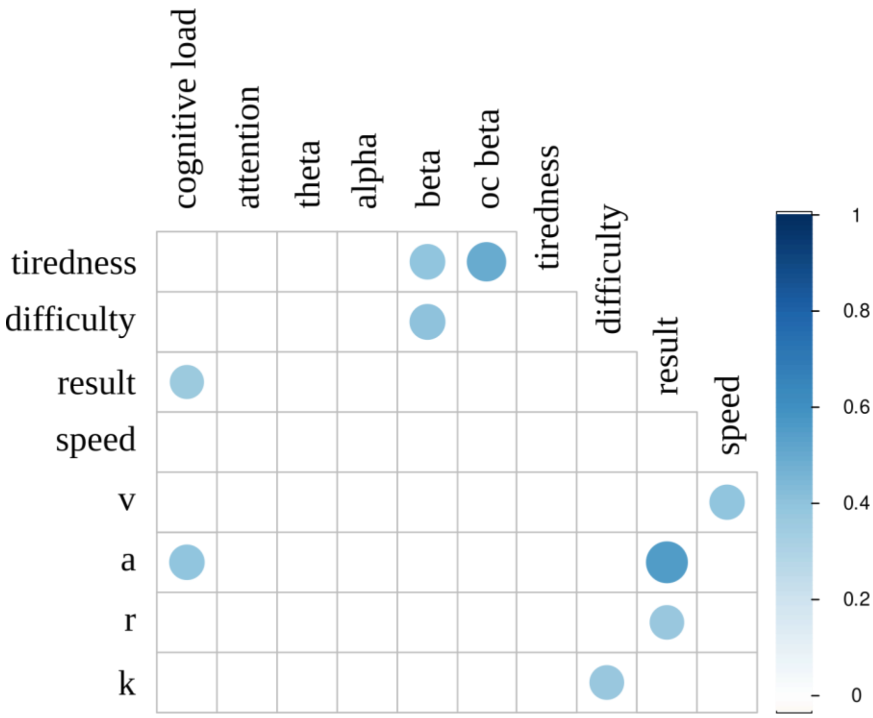

Figure 4. Correlation between EEG bands, test and questionnaire results ($p<0.05$). Learning style preferences: v: visual, a: auditory, r: reading, k: kinesthetic.

4. Discussion

Our results strengthen the possible usage of EEG in education for monitoring mental tiredness (fatigue) and cognitive load during the learning process.

According to previous research, fatigue is reported to result in decreased accuracy, loss of motivation, and poor performance (Gonzales et al., 2011). An increase in alpha reflects the increased efforts to stay awake and maintain sustained attention (Klimesch, 1999). During simulated driving, the increase in alpha power could be detected after 12 minutes (Balasubramanian et al., 2011). In our study, we also detected an increase in alpha power by the end of the EEG measurement, although the test results of the last task were not lower than the first. Thus, our participants have not yet shown other signs of mental fatigue. During tasks, those participants who arrived already tired for the measurement showed higher beta power than those who were rested. Since beta activity is connected to sensory information processing, its increase might represent a compensatory mechanism, helping the maintenance of sustained attention and good performance. To ensure that participants do not become exhausted during the tasks, we did not plan too long measurement sessions. In our experiments, even those participants who were tired could keep up a nearly constant level of concentration during tasks; EEG band powers did not differ between the beginning and the end of the task.

EEG activity also reflected participants' cognitive load during the different tasks. Watching a video consisting of different landscape images induced the lowest, while arithmetic calculation had the largest cognitive load. Reading induced a similar cognitive load as the video -watching task; the cognitive load was not higher during reading than video -watching, even in the case of participants with dyslexia . However, calculation is a highly demanding cognitive task, and also unlike reading, the task was unusual for the participants too. To get the result of the calculation, participants needed to form the sum of the first two numbers, store it in their working memory, then make the next addition, update the working memory with the new sum, and repeat these operations till the end of the equation. To perform the calculating task, participants needed to constantly use their working memory.

Continuous update of the working memory is accompanied by higher frontal theta activity, while mental effort causes a decrease in posterior alpha activity, resulting in higher cognitive load values (Booth et al., 2018). There is an optimal level of cognitive load, which ensures sufficient mental resources without the overload of the working memory. In our experiment, higher cognitive load values were associated with better calculation task results, meaning that the cognitive load values remained within the optimal range, and whoever could mobilize the necessary mental resources achieved better test results.

Alone, the cognitive load value did not warrant good results. In both tasks, high and low cognitive load values could accompany poor test results. When the test result was poor, although the cognitive load was high, we could conclude that participants either needed more time to complete the task or the teaching method used was inadequate. When poor test results were achieved with low cognitive load, the reason could be the lack of motivation or the misinterpretation of the instruction. With the help of EEG data, we can distinguish between the two scenarios and introduce the appropriate intervention.

In our study, attention values were less conclusive, increasing during reading, but their values did not differ between the video -watching and calculating tasks. Attention showed a correlation only with the speed of the reading. When the EEG correlate of attention was established, laboratory measurements captured the instantaneous response to a sorted input and concluded that the beta theta ratio reflects well attention level; high beta activity helps the sensory-motor coupling while low theta ensures the reception of external stimuli (Angelidis et al., 2018). Our tasks demanded sustained attention and the reception of external inputs and their processing, requiring the continuous update of the working memory. Therefore, especially during the calculation task, theta activity could not stay at a low level all the time; it increased with the memory demand of the task, resulting in lower attention values than during the reading task. We could conclude that the beta theta ratio does not reflect sustained attention satisfactorily.

We also measured the participant's engagement level since learning outcomes highly depend on the continuous maintenance of a high level of engagement (Booth et al., 2018). In our study, we did not find any change in engagement level, which result could be easily explained by the fact that probably only those students who volunteered for the EEG measurement were already motivated and tried to perform well.

Another highly promising area is the use of EEG in special needs education. Although its diagnostic and predictive capability is limited, it could be used to identify which parts of the brain are implicated during a cognitive task and allows us to compare typical with atypical patterns of neural activity (Müller, 2011). EEG technology could yield significant data in the case of dyslexia; since not all struggling readers are suffering from the same problem, brain imaging techniques can help us to differentiate among etiologies that exhibit similar outcomes (Katzir and Pare-Blagoev, 2006). In our study, dyslexic participants showed lower alpha peak values at rest than the controls. Lower alpha peak frequency was associated with slower phonological encoding, one of the main reasons causing impairment in reading ability (Babiloni et al., 2012). Another common characteristic of dyslexia is the increase in theta activity, especially in children (Cainelli et al., 2023). Developmental delay and reduced cognitive processing capacity result in high theta activity at rest (Klimesch, 1999). In our experiment, we found higher theta activity in dyslexic participants during reading but not at rest or during calculation, suggesting that by adulthood, cognitive processing capacity is normal, but reading is still a demanding task, inducing a higher working memory load in dyslexic than in normal persons.

5. Conclusion

EEG is a promising tool to supplement traditional evaluation methods in educational research. Using EEG measurements together with tests, observations, and questionnaires helps teachers to find the appropriate way of intervention when the outcome of a teaching technique is not satisfactory. EEG enables continuous monitoring without the reorganization of the teaching material or the course of the lesson. With EEG, we can monitor alertness and detect the first signs of fatigue, and it can help keep task difficulty at an optimal level to avoid boredom and exhaustion as well. It can also give us useful insight into the performance of students with special needs, helping teachers to provide them with adequate tasks and guidance in inclusive classrooms.

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