Maths Anxiety and cognitive state monitoring for neuroadaptive learning systems using electroencephalography

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***Abstract*—Mathematical competence is important to acquire for everyday and professional purposes, but often represents a considerable hurdle for students, who may associate it with unpleasant experiences. Our goal is to use neuroscience and neural engineering to support students to improve their mathematical understanding. More specifically, we are interested in the development of a non-invasive electroencephalogram (EEG)-based neuroadaptive Brain-Computer Interface (BCI) learning environment that optimizes learning outcomes by adapting the learning content provided according to the cognitive load of the learner. In this paper, we investigate what cognitive states occur when students with and without Math Anxiety learn to solve a math problem presented in the form of a novel computer puzzle. Results of an offline analysis of data recorded from 10 study participants suggest that different cognitive states occur, each with specific features that a BCI could potentially detect.**

***Index Terms*—Math Anxiety, neuroadaptive technologies, Brain Computer Interfaces (BCI), electroencephalogram (EEG)**

I. Introduction

Math Anxiety is defined as a “feeling of tension and anxiety that interferes with the manipulation of numbers and the solving of mathematical problems in ordinary life and academic situations” [1]. This has consequences on the career, occupation, and personal growth of a person as the desire to avoid math shapes the choices of an individual. Approaches to reduce Math Anxiety, especially in a classroom setting, usually focus on expressive writing [2] to help students control anxious feelings or on changing the mindset and motivation of the students thanks to the use of Mindset theories and Mathematical mindset approaches, respectively [3]. In the context of education, it has been shown that learning outcomes are best if the training program and learning content are tailored to the learner’s specific needs [4]. According to the Cognitive Load Theory, in fact, the type and amount of cognitive load learners experience while studying instructional materials is one of the crucial factors for successful learning [5]. Optimal learning conditions are characterized by providing challenges for learners without inducing cognitive overload.

The capability to assess a moment-to-moment level of working memory load to make immediate online adaptation of the instructional material provided seems a good educational approach and may help students with Math Anxiety to overcome their difficulties. A technological solution to achieve this goal would be constructing an adapting learning environment that focuses on continuously detecting different cognitive states of the learner and then adapts the type of learning content provided according to the learner’s current cognitive state to facilitate learning. Such a technological tool can be designed in the form of a Brain-Computer Interface (BCI), a technology which directly links a human brain and a technical system in which a pattern recognition system is implemented to recognize specific patterns in brain signals that are elicited by a particular cognitive state [6]. The detection of the cognitive state of interest subsequently triggers the

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adaptation of the system [7].

Different types of BCIs have been designed and they can be categorized as active, when the user utilizes the BCI to actively control a device, and passive when the BCI monitors the neural activity of the end user and passively adapts the environment according to the needs of the person. Regarding the recording method, a BCI can be either invasive with microelectrode arrays implanted inside the skull through a surgical operation or non-invasive if brain signals are acquired thanks to sensors placed on the scalp [8]. Finally, BCIs can either be synchronous or asynchronous in the way they operate. In a synchronous BCI the interaction between the user and the system has to happen within a certain period of time defined by the system. In an asynchronous BCI, the user can interact with the application at any time by generating a specific cognitive state.

BCI technology was originally intended to provide a communication system for people unable to use functional neuromuscular channels (e.g., locked-in or paralyzed patients). However, in recent years BCIs have extended their original field of use to healthy people and the classical definition has changed to include technological systems able to replace, restore, enhance, supplement, or improve the communication outputs of the end users [9]. Applications of BCIs in healthy users are various and range from the initial control of devices as a means to communicate to other applications such as user state monitoring, training and education, gaming and entertainment, cognitive improvement, and safety and security. Such new uses usually explore the possibility to quantify, in real-time (a so called 'online BCI'), the actual cognitive state of the user thanks to spontaneously generated brain signals (passive BCIs, pBCI). This technology could be able to detect specific brain states even before the user becomes consciously aware of them and before they trigger behavioural (re)actions.

II. CONTRIBUTION

One of the open issues in the context of developing BCIs as an adaptive learning environment is the fact that learning is a complex phenomenon which cannot be explained only by taking into consideration one cognitive or affective state at a time. A BCI trained to recognize only one cognitive state can interpret the actual state of the learner in an inappropriate way. For example, by increasing the difficulty level of some learning content when the Mental Workload (MWL) is classified as 'low' to avoid boredom for the student, where the 'low' workload may be caused by frustration [10]. If additional states are monitored, for example fatigue, motivation or attention, a more complete picture of the learner's condition is obtained, and the overall performance of the system can be improved.

Motivation and learner engagement are vital to learn new content effectively. The Cognitive-Affective Theory of Learning with Media [11] has shown that affective features of a lesson can increase learner engagement. In other words, cognitive processing and learning can be influenced by situational interest, positive emotions, frustration and confusion and while learning occurs, these emotions can arise, disappear or change [11]. A student can express interest at the beginning of an exercise due to the novelty of the learning content but soon this initial interest can turn into motivation to continue studying or frustration if a sense of confusion arises due to discrepancies in knowledge acquired and information provided.

Developing an affective adaptive tutoring system, which combines information about both the emotional (collected via facial expression, shifts in posture, galvanic skin response, etc.) and cognitive state of the user (collected via electroencephalography, EEG) would allow the system to respond appropriately to the needs of the user. This can be done if the adaptation of the learning content difficulty takes into consideration the complex state of the learner.

Verkijika for example developed a BCI able to detect math anxiety arising in children playing a mathematics educational game and providing them visual feedback on how to control it [12]. In their research, children reported lower anxiety levels during the second experimental session compared to the first one, indicating that the feedback given by the BCI was effective in helping the children reduce their anxiety levels [12]. Their study represents a good example of a BCI that does not focus on modifying learning content according to the learner's state, but it focuses on making the user aware of their emotions in order to autonomously reduce their anxiety levels, substituting to a certain degree the emotional support obtained in a social context.

In a social context, or by simply having a teacher looking at the whole class, facial expressions, body movements and other behavioural signals of discomfort would be picked up and addressed. If this social context is taken away, the student alone may not know how to properly cope with anxiety or distress. The possibility to properly address the problems of a student has been highlighted especially in recent years, due to the pandemic, with many students and teachers using online classes as the only way to continue their activities [13].

For the above reasons, it is of utmost relevance to adopt a holistic approach and monitor different cognitive states. To get a holistic overview, we conducted an experiment to investigate which cognitive states, known from the literature and reflected in the patterns of the EEG, occur during the solving of a mathematical problem. Cognitive states of interest include:

1) **MWL**, which is defined as the load in Working Memory (number of items to store there), number of tasks to perform simultaneously or as a measure of amount of cognitive resources engaged in a task. Working Memory provides transient holding of information necessary for a complex task and has a limited capacity: as soon as the items to remember drain its resources and fill its capacity, MWL increases as well. Most Working Memory tasks recruit a network that spreads from the prefrontal cortex (PFC) to the parietal areas [14], [15]; specifically, it has been shown that the PFC is used for controlling attention, selecting strategies, to solve a task and manipulating information stored in Working Memory [14].

2) **Math Anxiety**, which is investigated by taking into consideration beta β (14-28 Hz) and gamma γ (30-59 Hz) oscillations in frontal and parietal areas: participants with high levels of Math Anxiety (HMA) exhibit a greater β-band power than participants with Low Math Anxiety (LMA) while anticipating the arithmetic problems and exhibit greater γ-band power activity while solving the arithmetic problems compared to participants with Low Math Anxiety [16].
3) **Fatigue**, which increases according to the time spent solving a task and can be described as the unwillingness to continue performing a specific cognitive task and it is associated with increased power in frontal and parietal Theta θ (5-7 Hz) activity [17].
4) **Motivation** or avoidance towards a task, which can be monitored in the changes in hemispheric frontal asymmetry: motivating events and tasks produce greater magnitudes of EEG Alpha α and Beta β band power in the Left Prefrontal cortex in response to affective and motivational stimuli and during changes in motivation related to a task [18].

We expect that monitoring multiple states and training a classifier to recognize their simultaneous presence during a learning experience will help to improve the adaptation and correctness of the learning environment. So far, only one work has been published on the topic, but it is not related to Math Anxiety specifically [19]. We want to close this knowledge gap.

To develop our task, we relied on the definition of 'educational video game' proposed by Malone, which states that games are intrinsically motivating when including clear goals of progressively increasing complexity, when the system provides clear feedback on the performance of users, and when outcomes are uncertain enough to entertain curiosity [20]. This led to the design of a series of puzzles in which a combination of skills such as counting, spatial reasoning and working memory were used to solve them. We presented these puzzles in blocks of increasing difficulty (task condition) and the participants had to solve them while electroencephalographic signals (EEG), electrocardiogram (ECG), galvanic skin response (GSR) and behavioral data such as number of clicks and time taken to solve each puzzle were recorded.

In this paper, we focus on behavioural and EEG data and report preliminary results of EEG patterns of cognitive states that occur during puzzle solving.

III. Materials and Methods

A. Participants and data recordings

Ten individuals, students of the University of Essex (6 females), consented to participate in this study. The study, including the measurement protocol and consent procedure were approved by the local ethics board (Approval-ETH2021-2145). Participants were selected from a pool of 30 students based on their responses to the Math Anxiety Scale [21], which was used to identify five participants with High and five participants with Low Math Anxiety (HMA and LMA respectively) based on the number of questions in which they responded with 'much' and 'very much'.

Participants had normal or corrected to normal vision and were seated approximately 0.7m from the computer screen in an electromagnetically shielded chamber. Participants were asked to use a computer mouse to complete the questionnaires and solve the puzzles which were presented on the screen. To reduce eye strain, the experiment was conducted in a dark environment. EEG was recorded from 62 electrodes placed on the scalp according to the international 10-20 system, band pass filtered between 1 and 60 Hz (Notch at 50 Hz) and digitized at a rate of 2000 Hz. Electrode positions included channels Fp1, AF7, AF3, F1, F3, F5, F7, FT7, FC5, FC3, FC1, C1, C3, C5, T7, TP7, CP5, CP3, P1, P3, P5 P7, P9, PO7, PO3, O1, Iz, Oz, POz, Pz, CPz, Fpz, Fp2, AF8, AF4, AFz, Fz, F2, F4, F6, F8, FT8, FC6, FC4, FC2, FCz, Cz, C2, C4, C6, T8, TP8, CP6, CP4, CP2, P2, P4, P6, P8, P10, PO8, PO4, and O2. EEG impedance was kept below 15 kOhm. Simultaneously horizontal eye movements were recorded from two electrodes that were placed lateral to the eyes, GSR was recorded by placing two passive electrodes on the index and middle finger of the non dominant hand of the participant using the Biosemi GSR sensor; ECG was measured by placing one flat electrode on each wrist. Signals were recorded using a Biosemi active two system (BioSemi B.V., Amsterdam, Netherlands).

B. Experimental Paradigm

The experiment began with three questionnaires: the patient health questionnaire [22], curiosity and exploration inventory, and state anxiety questionnaire [23]. After completing the questionnaires, a 2-minute resting-state EEG was recorded, during which participants were asked to relax and fixate on the screen. Then, the puzzle experiment began: three blocks of 20 puzzles each are presented in an order of increased difficulty. After each block the NASA questionnaire [24] was presented to record the perceived workload of the participant, followed by 15 seconds of rest before the beginning of the next block of puzzles. After the third block, the NASA, State Anxiety, and Math Anxiety Scale were presented again and the experiment ended.

The puzzles themselves consisted of a square grid with a variable lateral size between 4 and 10 rows/columns. Participants were tasked with clicking on the white cells to color them green and bring the total number of green cells in each row and column to the target number (an example puzzle is shown in Fig.1); the difficulty of each puzzle was defined by its lateral size. Puzzle sizes of 4 and 5 (difficulty Easy), 6 and 7 (difficulty Medium), 9 and 10 (difficulty Hard) were used. Triggers linked to specific experimental events like start and end of each puzzle were synchronised with the biosignal recordings via LabStreamingLayer protocol and recorded using Lab Recorder software [25].

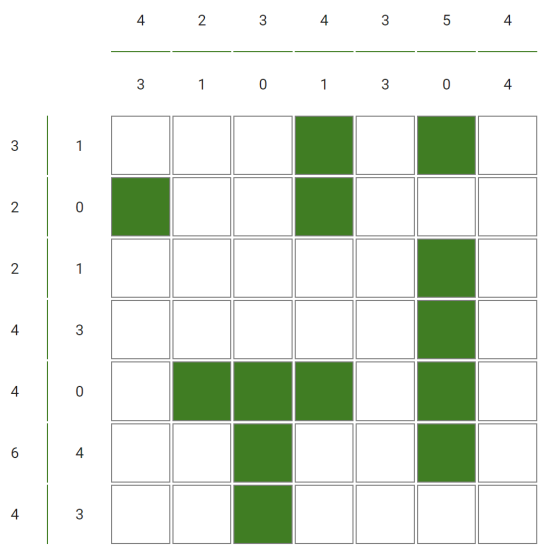

Fig. 1. Example of a 7x7 medium difficulty puzzle. The pairs of numbers on the left side of the puzzle indicate the number of target squares and the number of remaining squares to be filled in each row. The same information is displayed above the puzzle for each column. The goal is to fill the squares in green color in such a way as to bring the number of remaining squares to be filled to zero.

C. Data Analysis

Data analysis was preformed using Matlab. The recordings were down sampled to 256 Hz, band pass filtered from 1 to 60 Hz and line noise was removed with the Cleanline plugin from EEGLAB Matlab toolbox [26]. EEG recordings were visually inspected, noisy and bad segments of the data were removed and the number of electrodes was reduce to 30 (Fp1, AF3, F1, F3, F5, F7, FC3, C3, T7, P3, P7, O1, Oz, POz, Pz, Fpz, Fp2, AF4, Fz, F2, F4, F6, F8, FC4, Cz, C4, T8, P4, P8, and O2). The number of channels was reduced to the minimum number of channels useful to capture the cognitive states of interest, namely Mental Workload (MWL) (Fpz, F3, Fz, F4, AF3, AF4, C4, Cz, C3, P3, Pz, P4, POz, O1, Oz, and O2), Attention (F3, Fz, Cz, C3, C4, Pz), Fatigue (Fz, Pz, F3, F4, F7, F8, Cz) and Math Anxiety (Fpz, Fp1, Fp2, AF4, AF3, Fz, F3, F4, F7, F8, T7, T8, C3, Cz, C4, P7, P3, Pz, P4, P8, O1, and O2).

Artifacts were removed using Independent Component Analysis (ICA) and data sets were re-referenced to the common average reference (CAR) to reduce the effect of localized noise. Participants were then divided in two groups according to their level of Math Anxiety (HMA and LMA).
Each dataset was divided into 7 segments, representing the main moments of the experiment:

1) Initial resting period: 120 seconds of rest collected at the beginning of the experiment.
2) Data coming from the first block of 20 easy puzzles.
3) Post first block resting period (data collected while participants had to solve the NASA questionnaire + 20 seconds of rest staring at a blank screen).
4) Data coming from the second block of 20 medium difficulty puzzles.
5) Post second block resting period (data collected while the participant had to solve the NASA questionnaire + 20 seconds of rest staring at a blank screen).
6) Data coming from the third block of 20 hard puzzles.
7) Post third block resting period (data collected while the participant had to solve the NASA and MAS questionnaires).

Five different band-pass filters (frequency bands δ 2-4 Hz, θ 5-7 Hz, α 8-12 Hz, β 14-28 Hz, γ 30-59 Hz) were designed with the Matlab *designfilt* function to filter the data in specific frequency bands. After filtering the data, the average band-power for each frequency band over the respective segment was calculated by squaring and averaging data coming from all the 30 channels in the different segments independently.

IV. RESULTS

Wilcoxon signed-rank sum tests were performed in Matlab to analyse the data.

1) Behavioural data: The number of mouse clicks performed and time spent on task (TOT) were analysed. Significant differences in the TOT spent to complete medium (p = 0.004) and hard (p = 0.012) puzzles were found, showing participants with High levels of Math Anxiety (HMA) to be faster at solving the puzzles compared to participants with Low levels of Math Anxiety (LMA) (Fig.2).

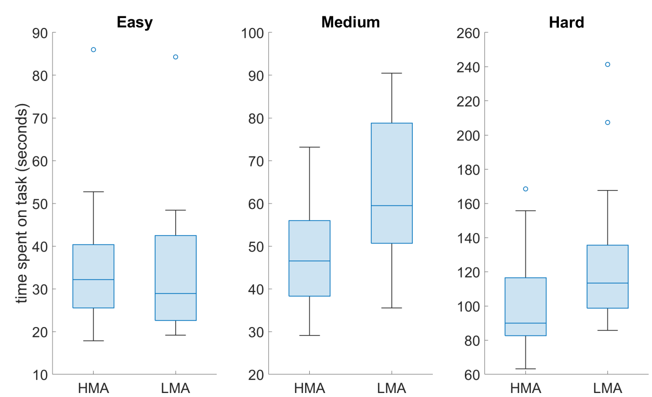

Fig. 2. Boxplot of time spent on the tasks for participants with High Math Anxiety (HMA) vs participants with Low Math Anxiety (LMA) according to puzzle difficulty (from left to right: easy, medium and hard puzzles)

2) EEG Pattern: Workload was indicated by an increase in frontal θ bandpower (Fz) and a decrease in parietal α (Pz) during the task condition compared to the resting condition (p = 0.051). Fatigue is shown as an increase in frontal θ bandpower (Fz) and posterior θ bandpower (Pz) during the task condition (p = 0.057). Attention was indicated by an increase in frontal δ bandpower (Fz) for increased attention during the task blocks (p = 0.051) while drowsiness appears as a decrease in central α bandpower (Cz, C3, C4, Pz) when attention increases (Fig.3). Math anxiety was indicated by an increase in frontal β bandpower (Fz, F3, F4) during the

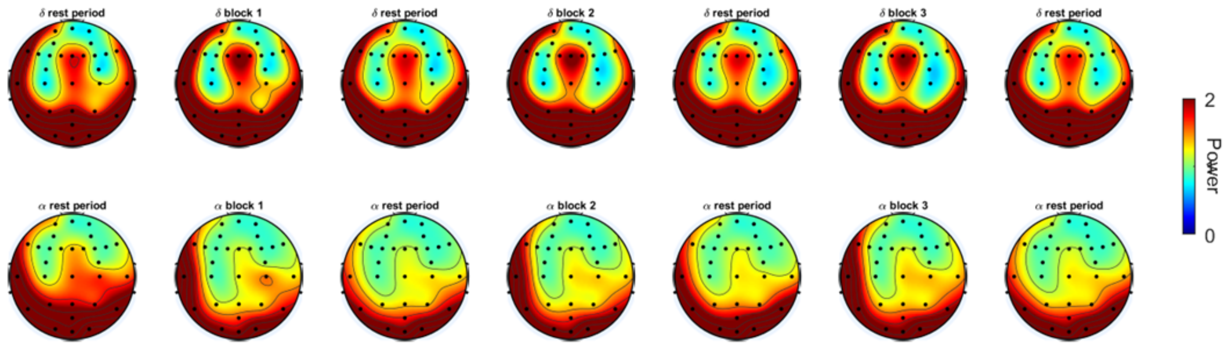

Fig. 3. Average δ (top row) and α (bottom row) bandpower calculated over all participants for each of the seven segments (from left to right: Initial resting period, easy puzzles, rest 1, medium puzzles, rest 2, hard puzzles, rest 3)

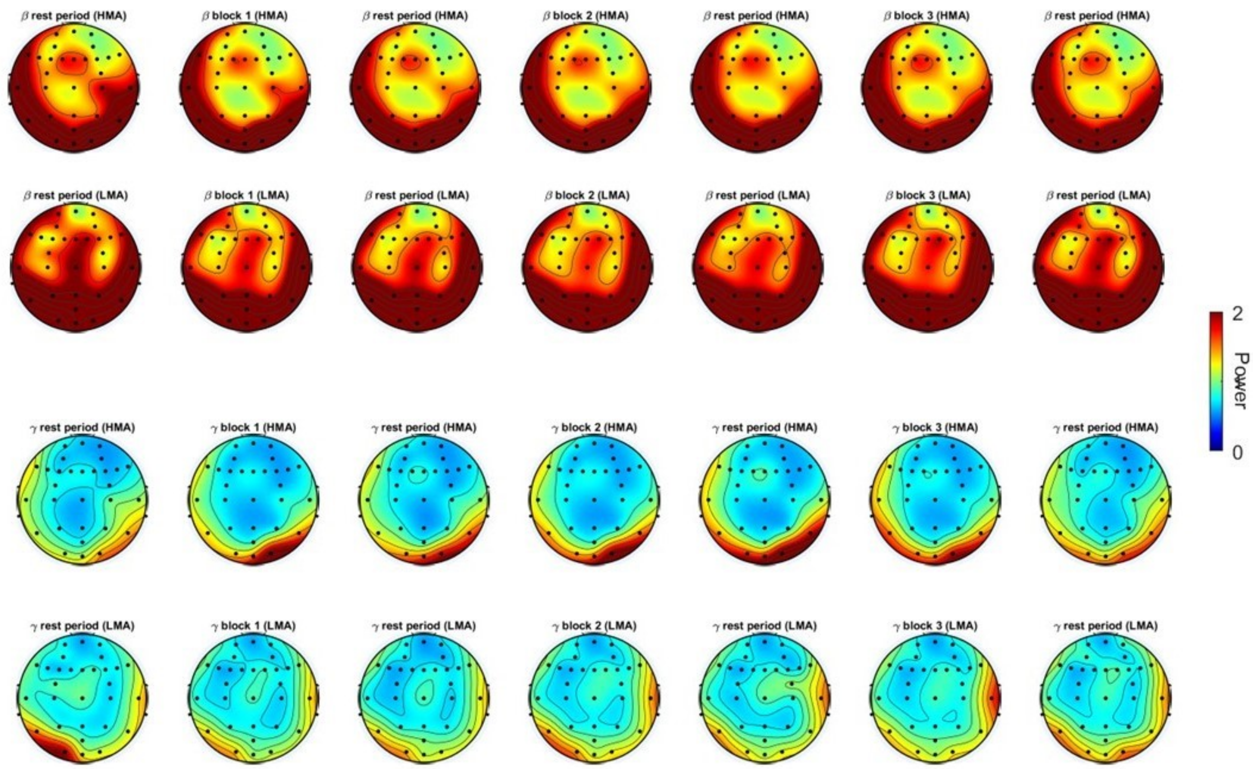

Fig. 4. Average β (top rows) and γ (bottom rows) bandpower in participants with HMA vs LMA for each of the seven segments (from left to right: Initial resting period, easy puzzles, rest 1, medium puzzles, rest 2, hard puzzles, rest 3)

anticipation period (right before the puzzles are presented) for participants with high levels of Math Anxiety and by a bandpower increase in occipital γ (Oz, O1, O2) while solving the task (p = 0.047), possibly related to threat perception, as shown in Fig.4.

Frontal asymmetry was reflected in stronger activity in α bandpower in the Right (AF4) vs Left (AF3) Prefrontal Cortex for participants with high levels of Math Anxiety compared to participants with low levels of Math Anxiety and this reflects avoidance towards the task due to Math Anxiety, however the differences found were not significant (p = 0.4).

V. CONCLUSIONS

We investigated what cognitive states occur when students with and without Math Anxiety learn to solve a math problem presented in the form of a novel computer puzzle. We presented these puzzles in blocks of increasing difficulty and asked the participants to solve them while electrophysiological and behavioral data were recorded.

Our behavioural results are in line with the expectations expressed in the literature. We found that people with Math Anxiety are faster than less anxious people at solving mathematical problems. This is explained as an attempt to rush and finish the math-related task as soon as possible to avoid discon-fort, however, this does not necessarily causes a performance decrease, especially if participants are not distracted or if their Working Memory is not overloaded [27], [28]. The fact that the performance does not change can also help explain why we did not find significant differences in the number of clicks performed between the two groups.

The EEG patterns we found are consistent with those described in the literature, even when a novel task like ours is used, which supports the validity of our experimental design. As expected during a learning experience, different cognitive states can be observed through the use of EEG, which is a safe, portable and relatively cheap system, demonstrating the possibility to use it in real life scenarios. Our results suggest that the combination of workload, attention, fatigue and changes in γ bandpower can be useful to identify both meaningful cognitive states and identify participants with Math Anxiety. This is crucial, because the system can be adapted according to a specific type of learner, which can be recognised by specific EEG characteristics.

These are only preliminary but already promising results and further experiments need to be carried out to confirm the validity of the results.

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