# Exploratory EEG Analysis of Brain Activity in Children during Addition and Timed Addition Tasks

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**Abstract:** Mathematics learning is affected by both cognitive and affective factors being mathematics anxiety one of the main barriers to both performance and engagement in mathematics. Understanding mathematics anxiety requires understanding its causes and manifestations, and studies that address its psychophysiological dimension, mainly through biometric markers, are of great help in this regard. In this sense, time pressure (endogenous or exogenous) usually interacts with mathematics anxiety being its influence on the performance of arithmetic tasks especially significant. Specifically, this study compares EEG activity between a scenario where 15 schoolchildren (8-9 years old) perform sums and another where they perform similar sums but under time pressure. This comparison was chosen as an initial exploratory comparison being the initial phase of a broader study aimed at developing a neurofeedback tool that, using electroencephalographic (EEG) signals, detects states of mathematics anxiety during the performance of mathematical tasks in naturalistic or semi-naturalistic school contexts. The results exhibit significantly higher activity during timed sums in frontal and parietal areas in the theta frequency bands (3-7Hz, related to workload and working memory) and high beta (20-30Hz, associated with arousal and anxiety). These results represent an initial step towards comprehending the cortical processes involved in mathematical tasks within semi-naturalistic contexts and provides some initial insights for further exploration.

**Keywords:** EEG, Mathematics anxiety, Addition, Brain Frequency bands, Timed task.

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## 1 Introduction

We live in a dynamic, ever-changing society in which the ability to manage information, solve problems, model real situations and adapt to new environments and demands are decisive; under these conditions, those who understand and can use mathematics flexibly, creatively and competently will have better opportunities and options for defining their own future. We can affirm, without any doubt, that in contemporary society it is essential to have adequate mathematical competencies and that deficiencies in this area limit the possibilities of personal development and constitute an important socioeconomic cost for nations.


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Studies such as those carried out by the International Association for the Evaluation of Educational Achievement -I.E.A.- (e.g. TIMMS) or by the OECD (PISA - Programme for Indicators of Student Achievement) provide a diagnosis of the educational system robustness in terms of mathematical competence by country or economy, having paid increasing attention to affective aspects in their latest editions. In particular, the results from PISA 2022 (OECD, 2023) show how mathematics anxiety correlates negatively with the level of mathematical proficiency in all the educational systems that participated in the study, regardless of the characteristics of their students or their schools. Moreover, the report shows how one more point on the mathematics anxiety index is associated with an average decrease of 18 points, once the appropriate corrections for students' socioeconomic level have been made (OECD, 2023)

Mathematics anxiety has often been considered as a unidimensional construct. However, there are already numerous studies that provide evidence of a multidimensional structure showing different clearly distinguishable factors (Lukowski, et al., 2019). A review of the contributions that have been made to research in this regard allows us to identify a series of factors that, in fact, correspond to different situations in which mathematics anxiety can occur manifesting particularities specific to the situation, so that it can, in turn, manifest itself in isolation in such contexts or in several of them. Among the dimensions or situations most commonly associated with mathematics anxiety are numerical manipulations (including arithmetic operations), mathematical problem solving, evaluative situations involving mathematics (excluding tests), examinations or similar tests, mathematical learning situations in the classroom, school mathematical situations outside the classroom (homework, for example), mathematics in everyday situations, and situations affected by a feeling of collective responsibility or self-demand.

Together with the need to address the multidimensionality of mathematics anxiety and its contextual or situational dependence, understanding mathematics anxiety also requires knowledge of its manifestations, i.e., what type of responses in some of the situations mentioned are caused, or may be caused, by mathematics anxiety states. In this sense, responses are usually classified and studied in four very specific typologies. A first category of responses is called affective, and accounts for manifestations of fear, worry, stress, nervousness or rejection of mathematics, among others. This category appears in other studies under the label of cognitive category. A second category corresponds to responses of a physiological nature, responses that are usually measured through biomarkers by observing heart rate, sweating, galvanization of the skin, feelings of dizziness, panic, etc., but also by focusing on brain activity through devices such as EEGs. A third category is associated with working memory activity, that is, the ability to keep active and accessible the information needed for a specific task demand, sometimes referred to as working memory. Finally, a fourth category focuses on behavioral responses, paying attention to effort before a mathematical task, efficiency in the organization of work, selection of optimal strategies, procrastination or avoidance of mathematical tasks, among others.

Based on the above, we consider that an approach to the complexity of mathematics anxiety is only possible from the acceptance of its multidimensionality and responsive variability. In this study we will consider only responses that fall into the category that we have called physiological and that is because although in the last decade relevant works have been generated that have contributed to better understanding mathematics anxiety (Dowker et al., 2016; Ramirez et al., 2018; Sammallahti et al., 2023; Hannula et al., 2024) its physiological foundations still require more attention, as do those related to motivation, emotions and commitment to learning (Pekrun, 2023). This need has led to an increasing number of studies that attempt to investigate the brain processes involved in situations of mathematics anxiety (Klados et al., 2017; Liu et al., 2019).

In turn, thanks to scientific advances, more and more studies can be found that analyze bio-signals associated with mathematics learning processes, and particularly those associated with anxiety, both in children and in university students (Geršak et al., 2020; Klados et al., 2017; Poole et al., 2021). However, these studies have been conducted under laboratory conditions, which are far from semi-naturalistic or naturalistic contexts. Questions such as "What is the brain activity like when faced with learning mathematics?" or "What kind of brain activity occur when faced with different types of mathematical tasks under certain conditions such as time pressure?" are important and open up a wide field of research within what has come to be called "real word neuroscience" (Matusz et al., 2019).

In this paper we are particularly interested in the second of the questions mentioned above. In this sense, it must be said that there are multiple proposals for establishing typologies of mathematical tasks, differentiated, among other things, by the guiding criteria of their genesis, such as, for example, their purpose (recalling previous knowledge, discovering patterns or regularities, motivating or engaging, (self-) evaluating, ...), their level of difficulty or their cognitive demand (memorization, procedures without connections, procedures with connections, doing mathematics) as established by Smith and Stein (Smith & Stein, 1998), its connection with reality (academic, semi-real, real), the concreteness of objectives and solutions (open or closed), organizational criteria in the classroom (individual, collective, mixed), ... In our case mathematical tasks will be associated with early arithmetic and algorithmic thinking for two reasons. The first has to do with the predictive power of the acquisition of mathematical competence at early ages on later academic performance (Claessens & Engel, 2013) and, second, the fact that the first manifestations of mathematics anxiety appear already in school associated in some cases with the perceived difficulty of mathematical tasks, in many cases coinciding with the beginning of work with algorithms, the need for development of pre-algebraic thinking or the transition to processes of abstraction and symbolism (Namkung et al., 2019).

Moreover, considering the combination of multidimensionality and responsive variability previously mentioned, we will focus our attention on the cell of the associated matrix in which physiological responses in terms of brain activity and arithmetic manipulations related to basic operations intersect. In this contextual framework, different works have pointed out the presence of a temporal restriction or time limit to execute such operations as a potential cause of mathematics anxiety that can affect the correct execution of these operations for both children and adults (Boaler, 2014; Hunt & Sandhu, 2017), highlighting the importance of taking this aspect into account in the design and planning of mathematical activity in the classroom in relation to arithmetic. We consider that understanding how the presence of time pressure, either endogenous or exogenous or both, conditions the performance of basic numerical manipulations and how its influence manifests itself in terms of brain activity is an important step towards understanding how these types of decisions and under what assumptions they can lead to or provoke mathematics anxiety. It is with this purpose in mind that this study is proposed, being aware that its results should be taken with great caution, as befits an exploratory approach. Thus, we only attempt to obtain some reference regarding the differentiated cortical states produced by the 'time' variable. Determining the characteristics of EEG signals specific to mathematics anxiety would require new experiments.

This study can be located as the first research contribution in a more ambitious project that seeks, ultimately, to develop, based on the classification of physiological signals (electroencephalography -EEG-, electrocardiography -ECG-, and skin conductance -GSR-), tools that allow the detection of anxiety produced by different types of mathematical tasks to provide better knowledge about the effects of each task on students. In simpler terms, our final goal is to create tools that can detect signs of anxiety in students' physiological responses while they are solving math problems, allowing teachers to identify when students may be experiencing anxiety in real time. This would provide teachers with evidence (not based on subjective measures such as scales) to deal with mathematics anxiety when designing their own didactic proposals. From such research, it would be possible to generate an automatic system based on EEG signals for the detection of anxiety states in front of different mathematical tasks and their treatment through neuro-feedback procedures (Sitaram, et al., 2017). Specifically, in this paper we aim to characterize the differences in electroencephalographic activity between two similar tasks which have been assigned different execution time. Given that execution time implies a stressor element (Caviola et al., 2017; Hunt & Sandhu, 2017), we consider that it can be a good starting point to identify features in the EEG signal that help us to understand brain processes and to guide future signal classifiers.

## 2 Materials and methods

Considering that this study, as it has already mentioned, is part of the early stages of a wider one whose focus is on characterizing the continuous signals recorded in naturalistic or semi-naturalistic contexts, we have elected to undertake an exploratory analysis of frequency spectrum characteristics, like approaches used in fields such as video games or marketing. For a better understanding of these methods, see the work by García-Monge and colleagues (García-Monge, Rodríguez-Navarro, & Marbán, 2023).

### 2.1. Context and participants

The study was conducted with a group of 15 third-grade primary school students, aged between 8 and 9 years old (9 girls and 6 boys), in a school where the researchers have an established collaboration. According to Rosenberg-Lee and colleagues (Rosenberg-Lee et al., 2011), the second and third grade (7-9 years) is an important period for the acquisition and mastery of basic mathematical skills. They observed that within this narrow interval, significant changes in brain response and connectivity related to arithmetic tasks emerge, being these results like those from Battista (Battista et al., 2018).

The students were familiar with some members of the research team as they engage in weekly activities together. The design of the school tasks, on which the recordings were conducted, was agreed upon with the teachers of the group, considering their concerns, following the ethical principles usually suggested by researchers for the interventions in semi-naturalistic and naturalistic settings (Howard-Jones, et al., 2016; Liu & Zhang, 2021).

## 2.2. Procedure

To minimize the impact on the students when introducing these devices into the classroom and to take advantage of the opportunity for students to better understand neuronal functioning, a workshop was conducted one week before the study commenced. The workshop consisted of several stations where the group was introduced to different aspects of brain activity through various playful neurofeedback devices. Due to the limitation of the number of devices and to avoid disrupting the normal course of classes excessively, a semi-naturalistic intervention was chosen (Matusz et al., 2019). For the study, an adjacent classroom to the group's regular classroom, used for manipulative mathematics tasks, was utilized. Students were summoned to this room in trios or pairs. While the different devices were being placed on them, they were reminded of some details about the collection of brain activity via EEG explained in the workshop.

After the devices were placed and the correct reception of the signals was confirmed, two baseline recordings were taken (2 minutes with eyes closed and 2 minutes with eyes open, looking at a point in the central part of a blank sheet of paper). Based on the baseline state recordings, the students' electroencephalographic activity was recorded while listening to different explanations about applications of mathematics and performing some arithmetic tasks. The tasks compared in this study were the completion of 16 additions of two single-digit numbers, and the completion of additions of two single-digit numbers within one minute. The additions were printed on a sheet of paper and participants wrote their answers below each pair of numbers. To make the students more aware of the passage of time, a one-minute hourglass was placed in front of them. These task were arranged with the teachers. A task that would not pose significant difficulty for the group of children was sought. Following the teachers' recommendations, this type of addition was chosen, as more complex additions, subtractions, or multiplications could have hidden the targeted isolated effects of time pressure on brain activity as the only variable of interest concerning mathematics anxiety under study.

## 2.3. Instruments

Three EEG devices, Epoc Flex (Emotiv, San Francisco), were utilized, each consisting of 32 channels with passive Ag/AgCI sensors (EasyCap, Herrsching) mounted on an EasyCap neoprene cap that allows for customizable positioning. Conductivity was facilitated by a gel. The sampling frequency was set at 128Hz. The Emotiv amplifier, positioned on the cap, wirelessly transmitted the signal to a computer where it was collected through an online application (Emotiv Pro), from which the data could be subsequently downloaded in CSV or EDF formats. Following the pipeline of previous studies (Buján, et al., 2022; García-Monge, Guijarro-Romero et al., 2023). The data underwent pre-processing using EEGLab for Matlab. IIR Butterworth high-pass (0.5Hz) and low-pass (45Hz) filters were applied. Data artifacts were cleaned through initial visual inspection, followed by the application of an Artifact Subspace Reconstruction (ASR) algorithm to discard channels muted for more than 5 seconds or exhibiting high-frequency noise exceeding 4 standard deviations. Subsequently, the data were re-referenced using common average referencing (CAR). Finally, Independent Component Analysis (ICA) was applied, and components dominated by non-neuronal sources (artifacts) were discarded.

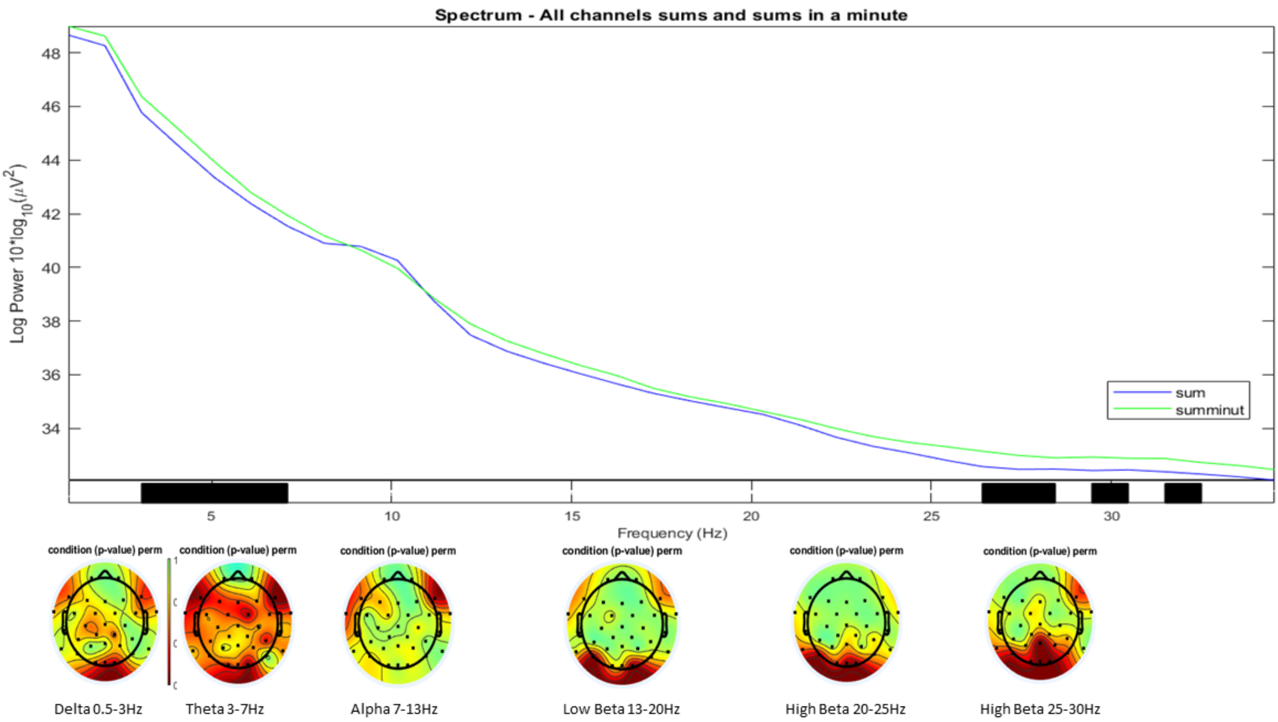
## 2.4. Analysis

The EEG data were segmented into 2-second epochs, and the absolute and relative spectral powers for different frequency bands (delta 1-3Hz, theta 3-7Hz, alpha 7-13Hz, and beta 13-30Hz – low beta 13-20Hz and high beta 20-30Hz) were computed for the various channels using Fast Fourier Transform (FFT). To conduct comparisons between pre-test and post-test conditions, the EEGLab "Study" tool was employed. This tool facilitated the identification of channels where the most significant differences emerged through permutations. Spectral powers were then examined in these channels. Shapiro-Wilk tests confirmed normal distribution of the data. Analysis of Variance (ANOVA) was applied in RStudio to the frequency measures and channels that exhibited the most significant differences in the permutation tests conducted with the "Study" tool in EEGLab. The magnitude of the effect was quantified using the generalized eta squared ($\eta^2$) measure. According to (Bakeman, 2005) values of 0.02, 0.13, and 0.26 represent small, medium, and large effect sizes, respectively.

## 3 Results

In Figure 1, the comparison of frequency spectra between the "sums" and "sums in one minute" conditions is depicted, along with topographic maps illustrating the most significant differences across different frequency bands.

**Figure 1.** Comparison of spectral powers between the two conditions of the study: Sums and Sums in one minute.

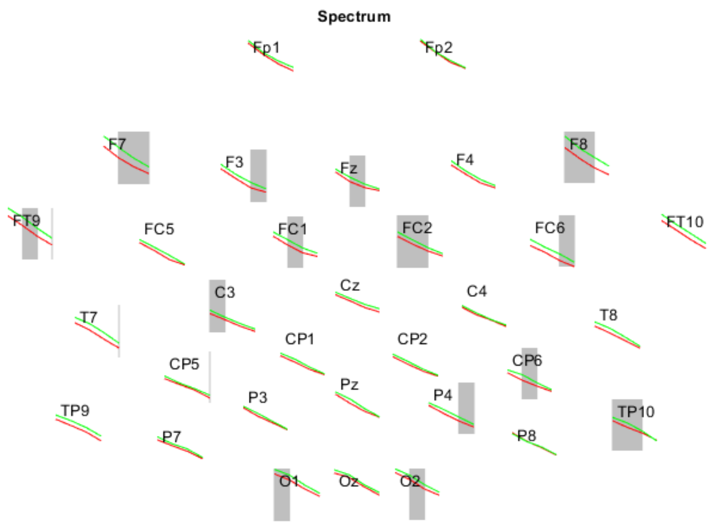



Note. In the frequency spectrum, significant differences are observed in the theta frequency band (3-7Hz) and high beta band (especially between 26 and 30Hz). Beneath the frequency spectrum, topographic maps are displayed, with coloration indicating the significance of differences across various surface areas. Warmer tones would signify greater significance in the difference between the two conditions. In these topographic maps, the greatest differences between the two conditions (dark red colored areas) are found in the theta and high beta frequency bands.

The most notable differences are observed in the theta frequency band in frontal and right parieto-temporo-occipital areas, as well as in parieto-occipital regions within the high beta frequency range, particularly between 25 and 30Hz. (Sauseng et al., 2010)

For the theta frequency band, permutation analysis revealed certain channels with more significant differences (Figure 2). Conducting repeated measures ANOVAs for these channels, some of them exhibited notably significant differences and moderate to high effect sizes. For channel F7, the repeated measures analysis of variance unveiled a highly significant difference in theta EEG activity between sums and sums in one-minute conditions ($F(1, 49) = 44.5473$, $p < .001$), with an observed effect size ($\eta^2$) of 0.21, indicating a substantial difference between conditions. Similarly, the difference was significant in channel F8 ($F(1, 49) = 23.5296$, $p < .001$, $\eta^2 = 0.16$); Additionally, channel FC2 displayed a highly significant difference ($F(1, 49) = 36.8788$, $p < .001$, $\eta^2 = 0.21$); as did channel P4 ($F(1, 49) = 54.1017$, $p < .001$, $\eta^2 = 0.32$).

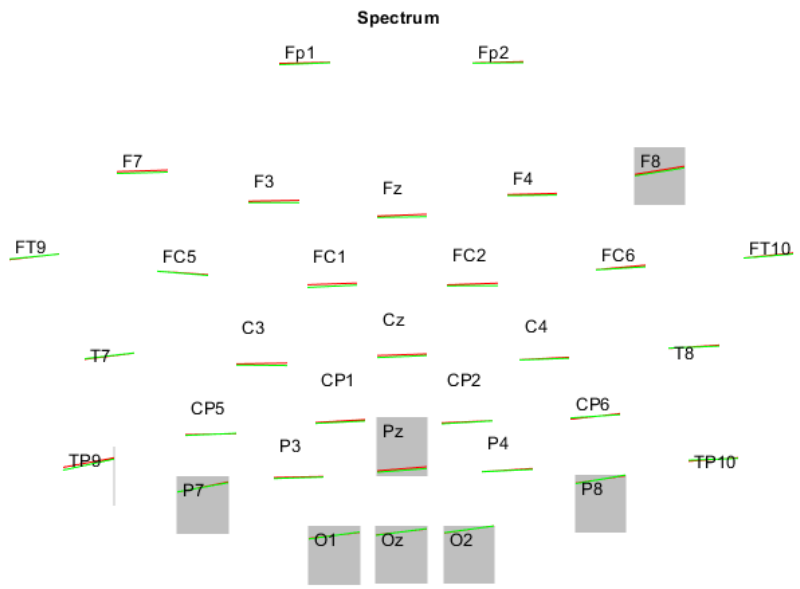
**Figure 2.** Theta spectral power across different EEG channels.




Note. This figure compares theta spectral power (3-7 Hz) between the two conditions (sums vs. timed sums) across multiple channels. Gray shaded areas indicate channels with statistically significant differences between conditions. The graphs were generated using the 'Study' function in EEGLAB with a permutation procedure, and subsequent analyses of variance were conducted on the highlighted channels to assess the significance of these differences.

As depicted in Figure 1, permutation analysis revealed differences in the high beta range (20-30Hz). Further exploration of these differences via repeated measures analysis of variance on channels with the greatest disparities (Figure 3) highlighted recordings from the right prefrontal and parietal zones, showing the most significant results. For channel F8, a highly significant difference in spectral power in the high beta frequency band (20-30Hz) was found between the sums and sums in one-minute conditions ($F(1, 49) = 80.9066$, $p < .001$), with an observed effect size ($\eta^2$) of 0.49, emphasizing a substantial difference between the conditions. Similarly, channel P7 exhibited a highly significant difference in spectral power ($F(1, 49) = 188.2075$, $p < .001$), with a high effect size ($\eta^2 = 0.65$), indicating a notable discrepancy between the conditions. Additionally, channel P8 showed a significant difference in spectral power ($F(1, 49) = 50.8427$, $p < .001$), with an observed effect size of 0.3, further underscoring a marked distinction between the conditions.

**Figure 3.** Beta spectral powers across EEG different channels.




Note. Comparison of spectral powers between the two conditions of the study (Sums-Sums in one minute) across different channels in the high beta frequency band (20-30Hz). The gray strip highlights channels with significant differences. These graphs are provided by the 'Study' function in EEGLAB through a permutation procedure. With the data from the indicated areas, analyses of variance were subsequently performed to determine the significance of the differences.

## 4 Discussion and conclusions

This exploratory study represents an initial endeavor towards characterizing neurobiological markers for identifying mathematics anxiety within naturalistic and semi-naturalistic contexts among school-aged children. To this end, EEG signals were compared across two conditions: performing arithmetic tasks and performing timed arithmetic tasks as a stress-inducing factor, followed by analyzing differences in the frequency spectrum. The theta and high beta frequency bands exhibited the most pronounced disparities.

Various studies have linked theta frequency to working memory demands (Sauseng et al., 2010) and increased cognitive load (Gevins & Smith, 2000). Our findings may align with these investigations. It is plausible to posit that timed arithmetic tasks impose greater demands on working memory processes, thereby elevating cognitive load, particularly given that the regions exhibiting the most significant differences, namely the right prefrontal and parietal areas, have been associated with working memory processes (Ranganath et al., 2003). Similarly, activation in the right frontocentral areas has been linked to calculation (Hirsch et al., 2001), and right parietal areas with working memory in finger movements, a common occurrence in children of these ages during arithmetic tasks. In future research, it would be valuable to broaden the sample size and focus on the cortical effects of using fingers in the calculation process, given their role in counting, knowledge of the number system, number-magnitude processing and overall calculation ability in childhood (Michirev et al., 2021) with implications for how numbers are mentally represented by both children and adults (Suggate et al., 2017).

High beta waves (20-30Hz) have been associated with heightened cognitive activity as well as arousal and anxiety states (Abhang et al., 2016). In the studied case, the positions exhibiting the most significant differences correspond to prefrontal areas associated with anxiety dysregulation (Mujica-Parodi et al., 2009) and negative mood states and arousal (Greene et al., 2014) in the case of parietal areas. Given the limitations of our study and the methodological and population differences from previous studies, these interpretations should be approached with caution, serving as conjectures to guide future investigations. Studies such as those by Liu and colleagues (Liu et al., 2019) indicate the activation of the high beta-band as a correlate of mathematics anxiety during the resolution of arithmetic tasks (particularly in frontal areas). Based on various works, the authors suggest that increased beta band activity enhances sensory information processing and attention control. Individuals with high math anxiety may expend more attentional resources on arithmetic tasks, potentially affecting performance due to limited attentional shifting and inhibitory processes.

Given the limitations of our work and the differences in methods and populations referred to by previous studies, these interpretations should be approached with caution, serving as conjectures to guide future research. In particular, based on these results and in order to determine whether this increase in high beta frequency is due to anxiety or arousal states, we need future tests focused on differences between these emotions (Eijlers et al., 2020) that will be complemented with other sources of information such as galvanic skin response (GSR) or heart rate variability (Sihn & Kim, 2022).

This study represents an initial step towards comprehending the cortical processes involved in mathematical tasks within semi-naturalistic contexts and provides some initial insights for further exploration. For instance, it would be intriguing to compare individual differences in these processes or to compare inter-individual differences between children who acknowledge their mathematics anxiety versus those who do not experience such apprehension.

We appreciate that features such as spectral power in different frequency bands may serve as discriminants for training future machine learning models, although we should test other features for univariate analysis, such as non-linear complexity analysis and multivariate analysis (analysis of functional and effective connectivity). This would allow, on the one hand, to deepen the understanding of the multidimensional nature of mathematics anxiety by establishing construct symmetry between concepts and measures of physiological, mental and behavioral variables associated with such anxiety. In turn, the aforementioned models could provide useful technological knowledge for mathematics education in a field of research still emerging, such as that which accounts for aspects related to the interaction of students, especially at early ages, with different mathematical tasks analyzed through biomarkers, allowing the development of informatics tools that facilitate the identification and management of mathematics anxiety by teachers, being this not an easy task as well as a need and a demand (Eronen et al., 2021)

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