Neural Mechanisms of Approximate Number Processing in Math-Anxious Individuals: An EEG Study

Authors: Liu Jie, Li Jinqi, Shen Chaoran, Hu Xiaohui, Zhao Tinghao, Guan Qing, Luo Yuejia, Luo Yuejia

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Abstract

Approximate number processing refers to the estimation of large quantities of objects without relying on explicit counting. Behavioral research suggests that individuals with high mathematics anxiety exhibit decreased approximate number processing ability, though the neural mechanisms remain unclear. The present study examined the neural mechanisms underlying approximate number processing in high mathematics anxiety individuals, comparing differences in electroencephalographic activity between high and low mathematics anxiety groups: (1) no significant between-group differences in behavioral performance; (2) increased amplitude of the P2p component in the high mathematics anxiety group; (3) no significant numerical ratio effect for delta-band event-related synchronization (ERS) and beta-band event-related desynchronization (ERD), whereas the low mathematics anxiety group demonstrated significant numerical ratio effects on these indices. This study provides electrophysiological evidence for the decreased approximate number processing ability in high mathematics anxiety populations.

Full Text

The Neural Mechanisms of Approximate Number Processing in Individuals with Mathematical Anxiety: An EEG Study

LIU Jie[1,2,3], **LI Jinqi**[1,2], **SHEN Chaoran** , **HU Xiaohui**[1,2], **ZHAO Tinghao** , **GUAN Qing**[1,2], **LUO Yuejia**[1,2,3*]

[1]Center for Brain Disorders and Cognitive Neuroscience, Shenzhen University, Shenzhen 518060, China

[2]School of Psychology and Sociology, Shenzhen University, Shenzhen 518060, China
[3]Shenzhen Institute of Neuroscience, Shenzhen 518060, China
School of Education, Changzhi University, Changzhi 046000, China
Department of Cognitive Science, Case Western Reserve University, Cleveland, Ohio, USA

Abstract

Approximate number processing refers to the estimation of large quantities without relying on explicit counting. Behavioral research suggests that individuals with high mathematical anxiety exhibit impaired approximate number processing abilities, yet the underlying neural mechanisms remain unclear. This study investigated the neural mechanisms of approximate number processing in high mathematical anxiety individuals by comparing EEG activity between high and low mathematical anxiety groups. We hypothesized that: (1) there would be no significant behavioral differences between groups; (2) the high mathematical anxiety group would show increased P2p component amplitudes; and (3) while the low mathematical anxiety group would demonstrate significant numerical ratio effects in -band event-related synchronization (ERS) and -band event-related desynchronization (ERD), the high mathematical anxiety group would not. These findings provide electrophysiological evidence for impaired approximate number processing abilities in individuals with high mathematical anxiety.

Keywords: mathematical anxiety; approximate number system; EEG; time-frequency analysis

Mathematical anxiety refers to negative emotional responses toward mathematical processing (Ashcraft, 2002). It is highly prevalent and widely impactful: according to the OECD' s PISA 2012 results, 33% of 15-year-old adolescents across 65 participating countries and regions reported feeling helpless when facing mathematical problems (OECD, 2013).

Individuals with high mathematical anxiety perform normally on general cognitive tasks but show significantly impaired mathematical abilities, including complex mathematical operations such as calculation and problem-solving (e.g., Ashcraft & Krause, 2007) as well as basic numerical processing (Lindskog, Winman, & Poom, 2017; Maloney, Risko, Ansari, & Fugelsang, 2010; Maloney, Ansari, & Fugelsang, 2011). For instance, research has found that high mathematical anxiety individuals process symbolic numerical magnitude differently than low anxiety individuals (e.g., Dietrich, Huber, Moeller, & Klein, 2015; Maloney et al., 2010, 2011; Núñez-Peña & Suárez-Pellicioni, 2014). In a numerical magnitude comparison task (e.g., determining which of two numbers is larger), Dietrich et al. (2015) found that high mathematical anxiety individuals exhibited stronger numerical distance effects, with a significant interaction between difficulty and group: performance differences between groups were smaller for large numerical distances (e.g., 1 vs. 4) but larger for small distances (e.g., 3 vs. 4). Using a similar task, Núñez-Peña et al. (2014) found that high mathematical anxiety individuals showed greater numerical distance and size effects in both behavioral measures and EEG amplitudes (200–250 ms at midline electrodes Fz, Cz, Pz). The numerical size effect refers to the increased difficulty when comparing larger numbers (e.g., 9 vs. 10) compared to smaller numbers (e.g., 1 vs. 2), with an interaction between difficulty and group such that group differences were smaller for comparisons involving smaller numbers. These enhanced distance and size effects indicate impaired numerical magnitude processing in high mathematical anxiety individuals.

Two primary theories explain why mathematical anxiety impairs mathematical performance. The *disruption account* posits that high mathematical anxiety temporarily consumes cognitive resources (primarily working memory), thereby reducing mathematical ability (Ashcraft & Kirk, 2001). High mathematical anxiety individuals must simultaneously process negative emotions associated with anxiety while performing mathematical tasks that typically rely on working memory resources, with this emotional burden impairing working memory and task efficiency. In contrast, the *reduced competency account* suggests that high mathematical anxiety directly results from low mathematical ability (Carey, Hill, Devine, & Szücs, 2016; Maloney et al., 2010, 2011).

Approximate number processing represents a core component of basic number sense and forms the foundation for complex mathematical operations such as calculation and reasoning, significantly predicting mathematical achievement (e.g., Halberda, Mazzocco, & Feigenson, 2008). As a non-symbolic numerical representation, approximate number processing develops prior to language and symbolic numbers from a cognitive developmental perspective. Both animals and human infants possess the ability to estimate and compare approximate quantities (Brannon, Jordan, & Jones, 2010; Izard, Sann, Spelke, & Streri, 2009; Xu, Spelke, & Goddard, 2005). Consequently, approximate number processing is characterized by minimal influence from working memory and reduced interference from educational or cultural factors (Sullivan, Frank, & Barner, 2016). Investigating basic mathematical processing in mathematical anxiety individuals can thus help illuminate the origins of deficits in higher-level mathematical operations.

Do individuals with mathematical anxiety show impaired approximate number processing? Current behavioral research suggests they may. Lindskog et al. (2017) found that approximate number processing ability is influenced by mathematical anxiety levels: in a sample of 79 healthy university students, both correlation and partial correlation analyses (controlling for visual scanning speed and general intelligence) revealed significant negative correlations between mathematical anxiety levels and approximate number processing ability. However, no previous research has examined the neural mechanisms underlying approximate number processing in mathematical anxiety individuals. The present study aims to provide EEG evidence for this phenomenon.

The P2p component is considered a crucial index of approximate number processing (Fornaciai, Brannon, Woldorff, & Park, 2017; Hyde & Spelke, 2009, 2012; Libertus, Woldorff, & Brannon, 2007; Park, DeWind, Woldorff, & Brannon, 2015), representing a positive deflection occurring approximately 200 ms post-stimulus. Libertus et al. (2007) first demonstrated that P2p amplitude could be modulated by non-symbolic numerical distance. Participants compared dot arrays (ranging from 1–4 and 6–9) to the reference number 5, and arrays with greater distance from 5 elicited larger P2p amplitudes. Hyde et al. (2009) employed an adaptation paradigm (passive viewing task) in which four identical dot arrays were presented sequentially, followed by a fifth array that was either the same or different in quantity while controlling the ratio between the new and familiar arrays. This study found that P2p amplitude at occipital electrodes was modulated by numerical ratio. Hyde et al. (2012) replicated this finding and localized the P2p component to the right intraparietal sulcus using source localization methods. Park et al. (2015) more systematically controlled for visual properties of the dot arrays (such as individual dot area and sparsity) using the same adaptation paradigm as Hyde et al. (2009). Through regression analysis, they found that P2p amplitude at parieto-occipital electrodes was modulated by numerical changes but not by other visual attributes. These findings suggest that P2p amplitude is associated with the precision of approximate number processing, with higher precision corresponding to larger P2p amplitudes. If high mathematical anxiety individuals have impaired approximate number representations, we would expect them to show significantly different P2p amplitudes compared to low anxiety individuals.

Beyond phase-locked event-related potentials (ERPs), neural oscillations provide an effective metric for controlling neuronal firing timing (Engel & Fries, 2010). Methodologically, time-frequency analysis can assess event-related neural oscillatory information, revealing stimulus-locked changes in EEG rhythmic power to infer underlying neuronal rhythmic adjustments (excitation or inhibition). Time-frequency analysis is a common method for investigating event-related neural oscillations. Two studies have examined neural oscillations during approximate number processing. Libertus and Brannon (2009) found that in 7-month-old infants viewing dot arrays, -band (8–12 Hz) and -band (4–6 Hz) oscillatory strength changed between novel and familiar arrays, with -band strength modulated by the ratio between novel and familiar quantities. Park (2018) employed steady-state visual evoked potentials (SSVEP), presenting dot arrays at 8 Hz while changing dot quantity, size, and sparsity at 1 Hz. The results showed that neural oscillatory strength at 1 Hz (-band, 1–3 Hz) was modulated by quantity changes in both child and adult participants, but not by changes in other visual properties (dot area, sparsity). This suggests that -band neural oscillations can be modulated by numerical ratio during approximate number processing, independent of other visual attributes, while the significant -band effects in Libertus et al. (2009) may have resulted from visual rather than numerical properties. We hypothesized that if EEG oscillatory power in specific frequency bands can be modulated by quantity, and if high mathematical anxiety individuals have impaired approximate number processing, then group differences in oscillatory power should be observable in these frequency bands.

In summary, EEG research indicates that the P2p component is closely related to approximate number processing, and low-frequency neural oscillatory strength can also be modulated by approximate number processing (Fornaciai et al., 2017; Hyde et al., 2009, 2012; Libertus et al., 2007, 2009; Park et al., 2015; Park, 2018). The present study employed cognitive behavioral testing to match high and low mathematical anxiety groups on basic visual processing speed, visual attention ability, intelligence, and general anxiety levels. We recorded EEG signals while participants completed approximate number processing tasks and conducted both time-domain and frequency-domain analyses. We hypothesized that if high mathematical anxiety individuals have impaired approximate number processing abilities, significant group differences would be observed in P2p amplitudes and in low-frequency neural oscillations between high and low mathematical anxiety individuals.

2.1 Participants

Using G*Power 3.1 (Faul, Erdfelder, Lang, & Buchner, 2007) to calculate the sample size needed for a repeated-measures ANOVA to detect between-subjects, within-subjects, and interaction effects with a statistical power of 0.7 and medium effect size ($r = 0.25$), we determined that a total of 64 participants (32 per group) were required. We recruited 62 university students for the EEG experiment from 35 different majors. Participants were assigned to high and low mathematical anxiety groups based on their scores on the Chinese version of the Mathematics Anxiety Rating Scale (MARS). From all participants who completed the questionnaire ($N = 341$), those scoring above the 80th percentile were assigned to the high mathematical anxiety group, while those scoring below the 20th percentile were assigned to the low mathematical anxiety group. The two groups were matched on general anxiety levels, visual processing speed, visual attention span, and intelligence test scores, ensuring no significant between-group differences on these measures. This resulted in 31 participants in the high mathematical anxiety group and 31 in the low mathematical anxiety group. One participant failed to complete the experiment, and one was excluded due to excessive EEG noise, leaving 31 high mathematical anxiety participants and 29 low mathematical anxiety participants. Demographic information and cognitive test scores are presented in Table 1 . The groups differed significantly in mathematical anxiety scores ($t(58) = 29.07$, $p < 0.001$, Cohen' s $d = 1.39$) but not in general anxiety scores ($t(58) = 0.20$, $p = 0.84$). All participants provided informed consent before the experiment began.

2.2 Materials, Tasks, and Procedures for Participant Grouping and Screening

The procedure for determining group assignment was as follows: First, 40 high and 40 low mathematical anxiety participants completed three tests on an online psychology experiment platform (www.dweipsy.com/lattice, Zhou, Wei, Zhang, Cui, & Chen, 2015): non-verbal matrix reasoning, rapid visual perception pattern matching, and visual search. The platform recorded both reaction times and accuracy rates, and participants received adequate practice before beginning the formal tests. From these participants, 31 were selected for each group based on the criterion of no significant between-group differences on the three tests (group means are shown in Table 1).

2.2.1 Mathematics Anxiety Scale and General Anxiety Scale

We used the Chinese version of the Mathematics Anxiety Rating Scale (MARS) to assess subjective mathematical anxiety levels. The scale consists of 25 items translated from the abbreviated English version (Alexander & Martray, 1989) by two psychology graduate students who worked independently before reconciling their translations to create a unified Chinese version (see Appendix 1). The scale presents situations that may induce mathematical anxiety (e.g., imagining an upcoming mathematics exam) and asks participants to rate their anxiety on a 5-point Likert scale from 1 (no anxiety) to 5 (high anxiety). Total scores represent mathematical anxiety levels. The MARS showed a split-half reliability of 0.83 and Cronbach' s alpha of 0.79. General anxiety levels were assessed using the Trait Anxiety Inventory (STAI-T; Spielberger, Gorsuch, Lushene, Vagg, & Jacobs, 1983), which contains 20 items with a split-half reliability of 0.88 and Cronbach' s alpha of 0.85.

2.2.2 Non-Verbal Matrix Reasoning

The non-verbal matrix reasoning test, based on Raven' s Standard Progressive Matrices (Raven, Raven, & Court, 1998), was used to assess general intelligence. Participants were required to identify the missing element in a visual pattern based on inherent rules, with 6 to 8 candidate answers presented. Participants used a mouse to select the missing element, and standard 9-point scores were recorded as final performance. The test showed a split-half reliability of 0.81 and Cronbach' s alpha of 0.56.

[Figure 1: see original paper] Schematic diagram of cognitive test tasks

2.2.3 Rapid Visual Perception Pattern Matching

Adapted from the Picture Identification Test in Ekstrom et al.' s cognitive test manual (Ekstrom, French, & Harman, 1976), this test assessed rapid visual processing ability. The untimed test consisted of 120 irregular shapes forming 120 items divided into three sections of 40 items each, with adequate rest periods between sections. Each trial presented a target shape on the left and three choice shapes on the right simultaneously at the center of the screen for 400 ms, followed by a 1000 ms blank screen before the next trial. Participants were instructed to respond as quickly and accurately as possible. The total number of correct responses was recorded as the final score. The test showed a split-half reliability of 0.92 and Cronbach' s alpha of 0.93.

2.2.4 Visual Search

The visual search task D2 was adapted from Bates and Lemay' s (2004) visual attention test. Participants were required to scan each line of characters to find the letter 'd' with two short lines that could be either connected or separated. If such a character was present, participants pressed the 'P' key; otherwise, they pressed the 'Q' key. The test comprised 240 trials, and participants were instructed to respond as quickly and accurately as possible. The total number of correct responses was recorded as the final score. The test showed a split-half reliability of 0.97 and Cronbach' s alpha of 0.89.

Table 1: Mean scores and standard deviations for age, gender, mathematical anxiety, general anxiety, visual processing speed, and visual attention span for high and low mathematical anxiety groups

Group	Age	Gender (M/F)	Math Anxiety	General Anxiety	Visual Processing Speed	Visual Attention Span
High Math Anxious (HMA)	20.68 (1.62)	15/16	94.35 (7.37)	44.70 (5.35)	74.06 (17.24)	5.03 (1.38)
Low Math Anxious (LMA)	20.69 (1.85)	17/12	41.86 (6.56)	44.45 (4.84)	75.86 (16.19)	5.14 (0.88)

Note: Standard deviations are shown in parentheses. Group difference in math anxiety: $t(58) = 29.07$, $p < 0.001$, Cohen' s $d = 1.39$; general anxiety difference: $t(58) = 0.20$, $p = 0.84$.

2.3 EEG Experimental Materials, Tasks, and Procedures

Previous research investigating the neural mechanisms of approximate number processing has typically employed either active numerical processing (e.g., Libertus et al., 2007) or passive numerical processing paradigms (e.g., the adaptation task in Libertus et al., 2009). The present study included both active and passive numerical processing tasks. In the active task, participants judged whether there were more yellow or blue dots in the stimulus image. In the passive task, to maintain alertness, participants judged whether the unique square shape in the stimulus image was yellow or blue (see Figure 2 [Figure 2: see original paper]).

[Figure 2: see original paper] Example stimuli for the two tasks

Participants sat 80 cm from the computer screen and viewed it at eye level. Task presentation was programmed using E-Prime 2.0 (Psychology Software Tools Inc., Sharpsburg, PA, USA). Each trial began with a red fixation cue ("+" or "•") presented at the center of the screen for 800 ms. A red "+" cue indicated an active numerical processing trial, while a red "•" cue indicated a passive trial. After a 1500 ms blank screen, the stimulus image was presented for 300 ms to prevent counting strategies, followed by a 2000 ms blank screen during which participants responded using the 'F' and 'J' keys. Inter-trial intervals varied randomly between 500–2000 ms. All presentation conditions were balanced within participants, and response hands were balanced across participants. The experiment consisted of four blocks with brief rest periods between blocks. Each block contained 96 trials, with every four trials forming a mini-block of the same task type (either all active or all passive numerical processing). Mini-blocks were presented in random order, with different conditions balanced across mini-blocks and blocks. Before the formal experiment, participants completed adequate practice to familiarize themselves with the tasks.

The experimental materials comprised 384 dot array images, with 192 images for each task type. For the active numerical processing task, stimuli consisted of yellow and blue dots randomly distributed on a gray circular background of fixed radius. To minimize interference from irrelevant visual factors, half of the trials matched the total area of yellow and blue dots, while the other half matched the average area of the dots (as in Halberda et al., 2008). According to Weber's law, discrimination between quantities depends on ratio rather than absolute difference (Brannon, 2006; Hauser, Tsao, Garcia, & Spelke, 2003). Therefore, we distinguished between large-ratio (2:1 to 3:1) and small-ratio (1.1:1 to 1.5:1) conditions, with numerical ranges from 1 to 16. Passive viewing task stimuli were designed similarly, with the exception that one random dot was replaced by a square shape. Each image subtended a visual angle of 3°. Difficulty in the passive task was controlled by varying the visual angle range of the random dots.

2.4 EEG Recording and Analysis

EEG signals were recorded using a 64-channel electrode cap based on the international 10–20 system with a Brain Products system. The bandpass filter was set at 0.01–100 Hz, with AC sampling at 1000 Hz per channel. Impedance for all electrodes was maintained below 10 kΩ. FCz served as the reference electrode during recording, and offline analysis employed average reference. Vertical electrooculogram (VEOG) signals were simultaneously recorded to monitor eye movements and blinks.

EEG data were preprocessed using EEGLAB software (Delorme & Makeig, 2004). The data were first filtered in the 1-45 Hz frequency band, then segmented into epochs from 1000 ms before to 600 ms after stimulus onset. A baseline of 1000 ms was selected because low-frequency transformations require longer time periods, with 1 Hz signals needing at least 1000 ms for proper conversion (Cohen, 2014). This baseline length was also consistent with previous time-frequency analysis parameters (e.g., Zhang, Hu, Hung, Mouraux, & Iannetti, 2012). The 600 ms post-stimulus window was selected based on previous P2p research (e.g., Park et al., 2015). The "automatic epoch rejection" function in EEGLAB was used for artifact removal with default parameters, followed by Independent Component Analysis (ICA) to remove ocular and muscular artifacts. Since the passive numerical processing task involves implicit numerical processing that should be homologous to active processing at the neural level, the "task type" variable was included in statistical analyses to examine its influence on EEG indices during numerical processing. The average number of trials removed per condition before averaging was: active large-ratio 9 ± 6, active small-ratio 9 ± 6, passive large-ratio 9 ± 7, and passive small-ratio 10 ± 7. A three-way repeated-measures ANOVA revealed no significant differences in retained trial numbers across within-subject conditions ($ps > 0.05$) or between groups ($F(1, 58) = 2.11$, $p = 0.15$).

2.4.1 Time-Domain Analysis

Based on previous literature, the P2p component is an important index of approximate number processing (Fornaciai et al., 2017; Hyde et al., 2009, 2012; Libertus et al., 2007; Park et al., 2015). This component is primarily distributed over posterior parieto-occipital regions along the dorsal visual processing stream (Park et al., 2015). Accordingly, we selected the P2p component at occipital electrodes for ERP statistical analysis. We calculated the mean amplitude across selected occipital electrodes within the 175-225 ms time window and conducted a 2 (ratio type: large vs. small) $\times$ 2 (task type: active vs. passive) $\times$ 2 (subject type: high vs. low mathematical anxiety) repeated-measures ANOVA.

2.4.2 Time-Frequency Analysis

For time-frequency analysis, we transformed EEG signals from all trials into time-frequency representations for each participant using Fourier transforms with a fixed 250 ms Hanning window. Complex time-frequency estimates were computed for each data point in the time-frequency space, with time ranging from -1000 ms to 600 ms (1 sample per ms) and frequency from 1 to 45 Hz (1 sample per Hz). The resulting spectrograms were then baseline-corrected at each frequency using the reference period of -900 to -100 ms according to the following formula: , where represents signal strength at time t and frequency f, and represents the mean frequency during the reference period at frequency

f. Single-trial EEG data were analyzed first, followed by averaging across trials to obtain oscillatory power for each condition.

Given the limited research on time-frequency characteristics of approximate number processing, varying study populations, and inconsistent results (Libertus et al., 2009; Park, 2018), we employed a data-driven approach. Point-by-point repeated-measures ANOVAs were conducted across all frequencies (1–45 Hz), 64 electrodes, and the time window from stimulus onset to 600 ms, combined with nonparametric permutation testing (Maris & Oostenveld, 2007) to identify regions of interest (ROIs). The procedure involved four steps: (1) Conducting 2 (task type: active vs. passive) × 2 (numerical ratio: large vs. small) × 2 (subject type: high vs. low mathematical anxiety) repeated-measures ANOVAs at each point in the EEG time-frequency maps, with task type and ratio as within-subject factors and subject type as a between-subject factor. Since our primary focus was numerical processing, we required significant ratio effects to confirm that identified ROIs were related to numerical processing before examining subject type and task type effects. Time-frequency points meeting the following criteria proceeded to subsequent analysis: significant main effect of ratio; significant main effect of subject type given a significant ratio effect; significant main effect of task type given a significant ratio effect; significant ratio × subject type interaction; significant ratio × task type interaction; and significant three-way interaction. All six ROI types required an initial p-value < 0.01 and inclusion of 30 consecutive time points. The F-value at each time-frequency point represented effect strength. (2) To address multiple comparison correction in point-by-point analysis (Maris et al., 2007), time-frequency points showing significant effects for 30 consecutive ms or more were considered a cluster. We calculated the sum of F-values (sum-F) for each cluster as an index of cluster effect strength. (3) Participant type labels were shuffled, and 1000 permutation tests were performed in the time-frequency distribution. Each test involved the same three-way repeated-measures ANOVA as in step (1), yielding 1000 sum-F values for each cluster under permutation. Based on the distribution of these 1000 sum-F values, two-tailed normal distribution tests examined the distribution of sum-F values obtained in step (2) after shuffling subject type labels. (4) To control false positive rates, clusters passing permutation testing with the largest sum-F values were considered valid regions of interest (ROIs) for subsequent statistical analysis (Maris et al., 2007).

3.1 Behavioral Results

Mean accuracy and reaction time (RT) across conditions are presented in Table 2 . Since the passive numerical processing task required color judgments unrelated to numerical processing, passive task data were not included in behavioral analyses. We conducted separate 2 (numerical ratio) × 2 (subject type) repeated-measures ANOVAs on accuracy (ACC) and RT.

Table 2: Mean accuracy and reaction times across conditions and groups

Condition	High Math Anxiety	Low Math Anxiety
	ACC	RT (ms)
Active-Large Ratio	0.91 (0.04)	620 (112)
Active-Small Ratio	0.75 (0.05)	736 (132)
Passive-Large Ratio	0.80 (0.07)	619 (116)
Passive-Small Ratio	0.78 (0.07)	648 (110)

Note: Standard deviations are shown in parentheses.

For accuracy, (1) main effects: numerical ratio was significant (large ratio > small ratio, $F(1, 58) = 772.50$, $p < 0.001$, $p^2 = 0.93$), while subject type was not ($F(1, 58) = 1.07$, $p = 0.31$). (2) Interaction: the ratio × subject type interaction was not significant ($F(1, 58) = 0.77$, $p = 0.78$). See Figure 3 [Figure 3: see original paper]. Following Lindskog et al. (2017), we correlated accuracy across conditions with mathematical anxiety scores. Results showed negative trends between anxiety scores and accuracy for both active large-ratio ($r = -0.16$, $p > 0.05$) and active small-ratio ($r = -0.15$, $p > 0.05$) conditions.

For RT, after excluding error trials and trials beyond three standard deviations, (1) main effects: numerical ratio was significant (large ratio < small ratio, $F(1, 58) = 364.78$, $p < 0.001$, $p^2 = 0.86$), while subject type was not ($F(1, 58) = 0.09$, $p = 0.77$). (2) Interaction: the ratio × subject type interaction was not significant ($F(1, 58) = 1.38$, $p = 0.25$). See Figure 3.

3.2 Time-Domain Results

Topographic maps revealed that the P2p component (175–225 ms) was distributed over posterior scalp regions (including POz, Oz, O1, O2, PO3, PO4, PO7, PO8). We conducted a 2 (ratio) × 2 (task type) × 2 (subject type) repeated-measures ANOVA on mean amplitudes across these electrodes. Results showed: (1) main effects: ratio was significant (large ratio > small ratio, $F(1, 58) = 5.01$, $p = 0.03$, $p^2 = 0.08$), subject type was significant (high math anxiety > low math anxiety, $F(1, 58) = 6.35$, $p = 0.01$, $p^2 = 0.10$), while task type was not ($F(1, 58) = 0.59$, $p = 0.45$); (2) three-way interaction: the ratio × task type × subject type interaction was not significant ($F(1, 58) = 0.14$, $p = 0.71$); (3) two-way interactions: ratio × subject type ($F(1, 58) = 0.31$, $p = 0.58$), task type × subject type ($F(1, 58) = 1.01$, $p = 0.32$), and ratio × task type ($F(1, 58) = 1.12$, $p = 0.30$) were all non-significant. See Figure 4 [Figure 4: see original paper].

3.3 Time-Frequency Results

Through point-by-point nonparametric permutation testing, we identified: one ROI showing a significant main effect of ratio; no ROI showing a significant main effect of subject type given a significant ratio effect; no ROI showing a significant main effect of task type given a significant ratio effect; one ROI showing a significant ratio × subject type interaction; one ROI showing a significant ratio × task type interaction; and one ROI showing a significant three-way interaction.

[Figure 5: see original paper] shows the average time-frequency distribution, topographic map, and statistical results for the ROI marked at electrodes P5, PO7, O1, and Oz (1-5 Hz, 83-217 ms).

The ROI showing a significant main effect of ratio included electrodes AF3, AF7, AF8, F1, F3, F6, Fz, F7, C1, C2, C3, C4, C6, Cz, CP1, CP2, CP3, CP4, CPz, P1, P2, Pz, and P4 (1-6 Hz, 296-598 ms). Neural oscillations in this ROI manifested as event-related synchronization (ERS). A 2 (ratio) × 2 (task type) × 2 (subject type) repeated-measures ANOVA on mean oscillatory power in this ROI revealed: (1) main effects: task type was significant (active < passive, $F(1, 58) = 7.20$, $p = 0.009$, $p^2 = 0.11$), ratio was significant (large ratio > small ratio, $F(1, 58) = 23.40$, $p < 0.001$, $p^2 = 0.29$), while subject type was not ($F(1, 58) = 0.24$, $p = 0.62$); (2) three-way interaction: the three-way interaction was not significant ($F(1, 58) = 0.36$, $p = 0.85$); (3) two-way interactions: ratio × subject type ($F(1, 58) = 0.28$, $p = 0.60$), ratio × task type ($F(1, 58) = 0.09$, $p = 0.76$), and task type × subject type ($F(1, 58) = 0.77$, $p = 0.38$) were all non-significant. However, this effect was highly correlated with power changes at ocular electrodes, and after controlling for ocular power changes in this time-frequency region, both ratio and task type effects became non-significant.

The ROI showing a significant ratio × subject type interaction included electrodes P5, PO7, O1, and Oz (1-5 Hz, 83-217 ms), with neural oscillations manifesting as event-related synchronization (ERS) (see Figure 5). A 2 (ratio) × 2 (task type) × 2 (subject type) repeated-measures ANOVA on mean oscillatory power in this ROI revealed: (1) main effects: task type was not significant ($F(1, 58) = 0.18$, $p = 0.67$), ratio was marginally significant (large ratio > small ratio, $F(1, 58) = 3.47$, $p = 0.07$, $p^2 = 0.06$), while subject type was not ($F(1, 58) = 0$, $p = 0.98$); (2) three-way interaction: the three-way interaction was not significant ($F(1, 58) = 0.14$, $p = 0.70$); (3) two-way interactions: the ratio × subject type interaction was significant ($F(1, 58) = 12.17$, $p = 0.001$, $p^2 = 0.17$). Simple effects tests revealed that for the high math anxiety group, the difference between large and small ratio power was not significant, while for the low math anxiety group, large ratio power was significantly greater than small ratio power ($t(28) = 3.20$, $p = 0.003$, Cohen' s $d = 0.59$). The ratio × task type interaction was not significant ($F(1, 58) = 1.15$, $p = 0.70$), and the task type × subject type interaction was marginally significant ($F(1, 58) = 2.02$, $p = 0.16$).

The ROI showing a significant ratio × task type interaction included electrodes AF3, F1, F2, F4, and Fz (29-37 Hz, 48-171 ms), with neural oscillations manifesting as event-related desynchronization (ERD). A 2 (ratio) × 2 (task type) × 2 (subject type) repeated-measures ANOVA on mean oscillatory power in this ROI revealed: (1) main effects: task type was not significant ($F(1, 58) = 0.01$, $p = 0.91$), ratio was not significant ($F(1, 58) = 0.27$, $p = 0.60$), and subject type was not significant ($F(1, 58) = 0.11$, $p = 0.74$); (2) three-way interaction: the three-way interaction was not significant ($F(1, 58) = 0.01$, $p = 0.91$); (3) two-way interactions: ratio × subject type was not significant ($F(1, 58) = 0.75$, $p = 0.39$), task type × subject type was not significant ($F(1, 58) = 0.23$, $p = 0.63$), while ratio × task type was significant ($F(1, 58) = 21.37$, $p < 0.001$, $p^2 = 0.28$). Simple effects revealed that for large ratios, active task power was significantly greater than passive task power ($t(59) = 2.69$, $p = 0.009$, Cohen' s $d = 0.35$), while for small ratios, active task power was significantly less than passive task power ($t(59) = 3.13$, $p = 0.003$, Cohen' s $d = 0.41$).

The ROI showing a significant three-way interaction included electrodes P5 and PO7 (29–34 Hz, 206–285 ms), with neural oscillations manifesting as event-related desynchronization (ERD). A 2 (ratio) × 2 (task type) × 2 (subject type) repeated-measures ANOVA on mean oscillatory power in this ROI revealed: (1) main effects: task type was significant (active > passive, $F(1, 58) = 8.63$, $p = 0.005$, $p^2 = 0.13$), ratio was not significant ($F(1, 58) = 0.76$, $p = 0.39$), and subject type was not significant ($F(1, 58) = 1.16$, $p = 0.29$); (2) three-way interaction: the three-way interaction was significant ($F(1, 58) = 12.35$, $p = 0.001$, $p^2 = 0.18$). Simple-simple effects revealed that for the high math anxiety group, ratio effects were not significant in either task type ($ps > 0.05$). For the low math anxiety group, ratio effects were significant in the active numerical processing task (large ratio < small ratio, $t(28) = 3.39$, $p = 0.002$, Cohen' s $d = 0.63$) but not in the passive task (see Figure 6 [Figure 6: see original paper]); (3) two-way interactions: ratio × subject type was not significant ($F(1, 58) = 0.11$, $p = 0.73$, $p^2 = 0.17$), ratio × task type was not significant ($F(1, 58) = 0.39$, $p = 0.54$), while task type × subject type was significant ($F(1, 58) = 5.15$, $p = 0.03$, $p^2 = 0.08$). Simple effects tests revealed that the high math anxiety group showed significantly lower power in active than passive tasks ($t(30) = 3.65$, $p = 0.001$, Cohen' s $d = 0.67$), while the low math anxiety group showed no significant difference between task types ($p > 0.05$).

[Figure 6: see original paper] Average time-frequency distribution, topographic map, and statistical results for electrodes P5 and PO7 (29–34 Hz, 206–285 ms)

This study examined the electrophysiological characteristics of mathematical anxiety individuals during approximate number processing tasks. We found no significant behavioral differences between high and low mathematical anxiety groups, but the high anxiety group showed larger mean P2p amplitudes at occipital electrodes. Additionally, while low mathematical anxiety individuals demonstrated significant ratio effects in -band (1–5 Hz) ERS and -band (29–34 Hz) ERD, high mathematical anxiety individuals showed no such ratio effects. These results provide EEG evidence for impaired approximate number processing abilities in high mathematical anxiety individuals and support the reduced competency account.

Although we found no significant behavioral differences in approximate number processing between groups, the direction of correlations was consistent with Lindskog et al. (2017), showing negative associations. The active numerical processing condition in our study was identical to Lindskog et al. (2017), but our failure to find significant negative correlations may be attributed to two factors: first, fewer trials (192 vs. 300 in Lindskog et al., 2017) may have resulted in less stable effects; second, lower task difficulty—half of our active condition trials used large ratios (1:2 and 1:3) compared to the small ratios (3:4, 5:6, 7:8, 9:10) used by Lindskog et al. (2017)—may have created ceiling effects in accuracy. This interpretation is supported by two additional studies: Dietrich et al. (2015) tested 61 high and low mathematical anxiety individuals with 400 trials using ratios from 1:2 to 9:10 (lower difficulty than Lindskog et al., 2017) and found no significant behavioral differences; Colomé (2019) tested 56 healthy university students with only 96 trials using ratios from 1:1.1 to 1:2 and similarly found no group differences. Considering these studies, differences in trial number and task difficulty likely explain why we did not find significant behavioral group differences in the active condition. However, because the theoretical significance of our EEG findings required ratio comparisons to confirm their relationship to approximate number processing, and because excessive trial numbers would cause fatigue and affect performance, we prioritized EEG over behavioral measures. This speculation requires verification in future research.

Previous research indicates that high mathematical anxiety individuals activate brain regions and ERP components unrelated to numerical processing when completing mathematical tasks, such as the amygdala and insula involved in emotion and pain processing (e.g., Lyons & Beilock, 2011; Young, Wu, & Menon, 2012), or show group differences in attention-related P2/P3 components (e.g., Núñez-Peña & Suárez-Pellicioni, 2015; Liu, Li, Peng, Feng, & Luo, 2019). Can we be certain that our P2p component reflects approximate number processing rather than attentional differences? First, our P2p component was localized to occipital regions, whereas group differences in P2 components in Núñez-Peña et al. (2015) were broadly distributed across frontal and parietal regions. Second, our occipital P2p amplitudes were modulated by numerical ratio, with significantly larger amplitudes for large than small ratios, consistent with findings from Libertus et al. (2007) and Hyde et al. (2012) using similar paradigms. These results suggest that our group differences in P2p amplitude genuinely reflect approximate number processing rather than attentional differences. Park et al. (2015) used a passive viewing task requiring no response and found that P2p amplitude increased with numerosity. Together, these findings indicate that P2p amplitude is associated with approximate number processing precision, with higher precision corresponding to larger amplitudes. The significantly enhanced P2p amplitude in high mathematical anxiety individuals, without significant interactions between subject type and ratio or between subject type and task type, can be interpreted as reflecting an overall reduction in approximate number processing precision in this population.

The significant subject type × ratio interaction in -band ERS (1–5 Hz) at occipital electrodes P5, PO7, O1, and Oz (83–217 ms) aligns with Park’ s (2018) findings of 1 Hz effects at occipital electrodes (Oz and PO8). Park (2018) suggested that low-frequency oscillatory power modulated by numerosity at PO8 originated from the P2p component, while effects at Oz reflected earlier visual processing in the C1 component. The C1 component, the first visually evoked potential with a latency of 60–100 ms (Di Russo, Martínez, Sereno, Pitzalis, & Hillyard, 2002), originates in primary visual cortex (Fornaciai et al., 2017). Fornaciai et al. (2017) found that during approximate number processing, a component similar to C1 (50–125 ms) showed polarity changes when stimuli were presented in different visual fields and whose amplitude was significantly modulated by numerical ratio, suggesting that early visual components from primary visual cortex may process numerical information. Our -band oscillations overlap temporally with this component and are modulated by ratio in low mathematical anxiety individuals, leading us to speculate that -band oscillations may originate from this early visual component identified by Fornaciai et al. (2017). However, the relationship between the C1 component and low-frequency oscillations has not been empirically established, and our data cannot support this inference; future studies with rigorous experimental designs are needed to determine whether -band oscillations are related to the C1 component. Our finding that low mathematical anxiety individuals showed significantly greater power for large than small ratios while high anxiety individuals showed no ratio effect indicates that high mathematical anxiety individuals are insensitive to numerical ratios during early processing stages and do not adequately process numerical information. In the three-way interaction simple-simple effects analysis, we also found that in the -band ERD (29–34 Hz, 206–285 ms) at occipital electrodes P5 and PO7, high mathematical anxiety individuals showed no ratio effect in the active numerical processing task, while low anxiety individuals showed significantly lower power for large than small ratios. Since -band activity is associated with top-down cognitive processing (see review by Engel, Fries, & Singer, 2001), ratio effects in the -band may reflect top-down numerical processing, suggesting that high mathematical anxiety individuals may have deficits in top-down cognitive control during approximate number processing. This is the first identification of ratio effects in high-frequency EEG indices of approximate number processing.

Regarding task type, both active and passive tasks activated the P2p component, with no amplitude differences between them. Previous studies have used either active (Libertus et al., 2007) or passive viewing tasks (e.g., Hyde et al., 2009, 2011, 2012; Park et al., 2015; Fornaciai et al., 2017), both of which activate P2p, but no study has compared P2p amplitudes across task types. Our study employed both tasks and found no significant P2p amplitude differences or interactions with numerical ratio, indicating that P2p is automatically activated during approximate number processing independent of task demands. Since passive paradigms are commonly used in infant and animal studies but lack behavioral response indices, our findings provide empirical support for the validity of passive numerical processing paradigms. Significant task type effects in time-frequency indices were observed in two ROIs: first, in the three-way interaction ROI where active task power was significantly greater than passive task power, which we discussed as potentially reflecting stronger top-down processing in active tasks; second, in the frontal ROI (29–37 Hz, 48–171 ms) showing a ratio × task type interaction, where active task power was greater than passive for large ratios but the pattern reversed for small ratios, indicating that EEG indices supporting different task types differ. This difference in frontal -band activity may also reflect top-down numerical processing differences.

Our findings suggest that abnormal EEG indices exist in high mathematical anxiety individuals even during approximate number processing tasks that do not require working memory support, indicating that the disruption account is inadequate. Previous evidence supporting the reduced competency account has come from two sources: first, research on the development of mathematical anxiety (Sorvo et al., 2019; Wang et al., 2014), with a recent longitudinal study using cross-lagged analysis demonstrating that low mathematical ability precedes high mathematical anxiety (Sorvo et al., 2019); second, research on basic numerical processing abilities in high mathematical anxiety individuals (Lindskog et al., 2017; Maloney et al., 2010). The underlying logic is that deficits in foundational mathematical processing (e.g., basic numerical/spatial processing) lead to high mathematical anxiety. Previous studies have found that high mathematical anxiety individuals show lower symbolic numerical processing abilities than low anxiety individuals (e.g., Dietrich et al., 2015; Maloney et al., 2010, 2011; Núñez-Peña & Suárez-Pellicioni, 2014). The approximate number system, an important component of later-acquired numerical processing systems, is characterized by minimal influence from general cognitive processing and educational/cultural factors (Sullivan et al., 2016). Compared to symbolic numerical processing, imprecise representations in the approximate number system better reflect innate characteristics. Lindskog et al. (2017) found significant negative correlations between mathematical anxiety levels and non-symbolic numerical processing ability (i.e., approximate number processing ability). Building on Lindskog et al. (2017), our study provides neurophysiological evidence: significant group differences in P2p amplitude and interactions in low-frequency (1–5 Hz) and high-frequency (29–34 Hz) bands during active numerical processing indicate that high mathematical anxiety individuals have deficits in approximate number processing. The poor performance of high mathematical anxiety individuals in advanced mathematical processing may result from impaired approximate number processing abilities that lead to reduced learning time and motivation after formal mathematics education, further affecting mathematical performance.

A limitation of our study is the lack of significant behavioral group differences. However, this result further demonstrates that even without behavioral differences, high and low mathematical anxiety individuals show abnormalities in neural indices related to numerical processing. In conclusion, our study provides EEG evidence for impaired approximate number processing in mathematical anxiety individuals and supports the reduced competency account of the relationship between mathematical anxiety and mathematical ability. Future research should increase task difficulty and combine behavioral results to verify our findings, and employ longitudinal designs to examine causal relationships among mathematical anxiety, approximate number processing, and mathematical performance.

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Note: Figure translations are in progress. See original paper for figures.