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NEURAL CORRELATES OF NUMERICAL COGNITION IN GIFTED AND NON-GIFTED ADOLESCENTS: A MAGNETOENCEPHALOGRAPHY STUDY WITH IMPLICATIONS FOR NEUROPEDAGOGY

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Abstract:
The present study employs magnetoencephalography (MEG) to examine event-related potential (ERP) differences between gifted and non-gifted adolescents during mathematical tasks involving numerical enumeration and simple addition. Drawing on the framework of neuropedagogy — an emerging interdisciplinary field that bridges brain science, cognitive science, and educational practice — the research investigates which cortical regions are differentially activated when children engage with counting, enumeration, and digit identification. Forty-three participants aged 12 to 15 years were allocated to four groups defined by giftedness classification and sex. MEG data were preprocessed using Fieldtrip (MATLAB) and subjected to independent component analysis (ICA) for artifact removal; features extracted from region-of-interest (ROI)-averaged waveforms included peak amplitude, root mean square (RMS), mean absolute amplitude, peak latency, and spectral power across the alpha, beta, gamma, delta, and theta frequency bands. Group-level analyses using t-tests with false discovery rate (FDR) correction revealed that gifted children exhibited reliably higher occipital amplitude measures when all trials were pooled, a pattern that intensified specifically during addition (SUM) trials. Across both groups, digit identification consistently elicited greater oscillatory amplitude than addition — particularly in beta and gamma bands over parietal, frontal, and temporal ROIs — consistent with the lower computational demands of perceptual relative to arithmetic processing. By-digit analyses, treated as exploratory, suggested that larger digits (7 and 8) elicited greater neural effort than smaller ones, and that gifted children showed distinct occipital latency profiles for specific digits. These findings contribute to growing evidence that numerical cognition recruits differentially organized cortical networks in gifted learners and carry direct implications for evidence-based instructional design.

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1. Introduction

For decades, the sciences of the brain and the science of education maintained largely parallel trajectories, each accumulating knowledge without systematic mechanisms for cross-fertilisation. The past two decades have witnessed sustained effort to close this gap, and the field of neuropedagogy has emerged as one of the most ambitious attempts to do so: it aspires to translate findings from neuroscience and cognitive science directly into classroom practice, equipping teachers with scientifically grounded tools for understanding how their students learn, process, and retain information (Ansari *et al.*, 2011; Thomas *et al.*, 2019). Despite the intellectual appeal of this project, its empirical foundations in mathematics education remain underdeveloped. Relatively few studies have examined the neural substrates of mathematical thinking in school-aged children using neuroimaging; fewer still have done so with the specific aim of characterizing differences between children who have been identified as mathematically gifted and those who have not. The question of what distinguishes the gifted mathematical mind is not merely of theoretical interest. Mathematics teachers routinely make instructional decisions — about pacing, scaffolding, the balance between procedural and conceptual emphasis — that rest implicitly on assumptions about how different learners process numerical information. If those assumptions are uninformed by empirical evidence about brain function, they risk perpetuating mismatches between instructional design and cognitive architecture. The present study was motivated by precisely this concern. Using magnetoencephalography (MEG), a non-invasive neuroimaging technique that offers millisecond-resolution tracking of cortical magnetic fields (Papanicolaou & Tarkka, 1996), we examined how gifted and non-gifted adolescents differ in their neural responses to tasks involving digit identification and simple addition, with particular attention to the spatial and spectral signatures of those differences.

MEG offers several properties that make it well-suited to this line of inquiry. Unlike functional MRI, which measures hemodynamic responses that lag several seconds behind neural events, MEG captures the direct magnetic correlates of synaptic currents, yielding temporal resolution that approaches the millisecond range (Rowley & Roberts, 1995). This fidelity is especially valuable in the study of arithmetic processing, where the sequence of cognitive operations — perceptual encoding, magnitude representation, retrieval, response selection — unfolds rapidly and may differ systematically between learners. Recent advances in optically pumped magnetometer (OPM) technology have further expanded the practical accessibility of MEG, reducing the constraints that cryogenic systems impose on participant movement and enabling more naturalistic testing conditions.

The theoretical framework that organizes the present investigation draws on three converging bodies of literature. First, the neuropedagogy literature provides the educational motivation: it documents both the growing interest among teachers in brain-based knowledge (Hook & Farah, 2013) and the continuing gap between what neuroscience has established and what reaches pedagogical practice (Ansari *et al.*, 2011). Second, the developmental cognitive neuroscience of numerical cognition offers a detailed account of the cortical networks recruited during enumeration, counting, and arithmetic — networks centered on the intraparietal sulcus (IPS) but extending to occipital, temporal, and frontal regions depending on task demands (Naccache & Dehaene, 2001; Temple & Posner, 1998). Third, a small but growing body of research on giftedness and brain function suggests that high-achieving individuals may deploy these networks differently, raising the possibility of identifiable neural markers of mathematical talent. The present study contributes to this third strand while speaking directly to the first.

The paper is organized as follows. Section 2 reviews the relevant theoretical background, covering the neuropedagogical framework, the MEG technology, and the developmental literature on numerical cognition and its neural correlates. Section 3 describes the participants, apparatus, stimuli, and analytical procedures. Section 4 presents the results of group comparisons across multiple ROIs, frequency bands, task conditions, and individual digits. Section 5 situates the findings within the broader literature, addresses the educational implications, and acknowledges the study's limitations. Section 6 offers conclusions and directions for future research.

2. Theoretical Background

2.1 Neuropedagogy: Bridging Brain Science and Educational Practice

Neuropedagogy is best understood not as a discipline in its own right but as an applied integrative enterprise that draws simultaneously on cognitive neuroscience, developmental psychology, and pedagogy (Ansari *et al.*, 2011). Its defining ambition is to render findings from brain research actionable in educational contexts — to move, in other words, from descriptive accounts of how the brain learns to prescriptive guidance for how teachers might facilitate that learning more effectively. The accelerated development of neuroimaging technologies over the past two decades, including EEG, fMRI, PET, and MEG, has dramatically expanded the empirical base from which such guidance might be drawn, enabling researchers to observe brain function in real time during cognitive tasks that simulate, or in some cases replicate, school learning activities (Ansari *et al.*, 2011).

The reception of neuropedagogy within the teaching profession has been, on the whole, enthusiastic. Studies examining teacher attitudes toward brain-based knowledge have consistently found that practitioners welcome the prospect of grounding their instructional decisions in scientific evidence, even when they acknowledge that the translational relevance of specific findings remains uncertain (Hook & Farah, 2013; Serpati & Loughan, 2012; Friedman *et al.*, 2019). Exposure to neuropedagogical content through professional development programs has been shown to strengthen teachers' sense of professional efficacy and to open new thinking directions regarding student diversity and learning difficulty (Dubinsky *et al.*, 2019; Luzzatto & Rusu, 2019). The Achva project, which introduced neuropedagogical content into a master's-level teacher education programe, and the Brain U initiative represent the most fully documented examples of this kind of field implementation to date (Dubinsky *et al.*, 2019).

Alongside these optimistic reports, the literature has been careful to identify structural obstacles to the uptake of brain science by educators. A persistent concern is the proliferation of neuromyths — factually incorrect or grossly oversimplified beliefs about brain function that have become embedded in educational discourse. Howard-Jones (2014) catalogued several such myths, including the claim that humans use only ten percent of their brain and the belief that students can be reliably classified as left-brained or right-brained learners. These misconceptions are not merely harmless folklore; they shape instructional decisions in ways that may actively disadvantage certain students. A more structural challenge is the epistemological distance between the level of analysis at which neuroscience operates and the level at which pedagogy is practiced. Bruer (1997) characterized the attempt to apply brain research directly to education as a "bridge too far," arguing that our knowledge of synaptic development, critical periods, and neuroplasticity remained too coarse-grained for reliable pedagogical application. Although more recent scholarship has been less skeptical — Thomas (2019) argued that the accumulation of findings about general principles of brain function now warrants bolder translational effort — the challenge of moving from neural mechanism to classroom practice without distortion remains real.

The present study engages with this challenge directly. Rather than drawing on general principles of neuroplasticity or attention, it uses MEG data to generate specific, empirically grounded observations about how gifted and non-gifted adolescents process numerical information at the neural level. These observations have the potential to inform instructional decisions about how mathematics is presented, sequenced, and scaffolded for different learner profiles.

2.2 The MEG Device: Technical Principles and Advantages

Magnetoencephalography records the tiny magnetic fields produced by the synchronized electrical activity of neuronal populations in the cortex. The physical basis of MEG lies in the relationship between electrical current and magnetic field: when neurons fire, ionic currents flow through their dendrites and generate perpendicular magnetic fields that, while extraordinarily weak — several orders of magnitude smaller than the earth's ambient magnetic field — can be detected by superconducting quantum interference devices (SQUIDs) housed within a magnetically shielded room (Papanicolaou & Tarkka, 1996; Papanicolaou, 1998). Modern whole-head MEG systems are equipped with between 150 and 300 such sensors, providing the spatial coverage necessary for source localisation while maintaining the temporal resolution — extending to the sub-millisecond range — that distinguishes MEG from haemodynamic imaging methods (Johnsrude & Hauk, 2005).

The primary advantage of MEG over fMRI for the study of rapid cognitive processes is precisely this temporal fidelity. Whereas fMRI measures the blood-oxygen-level-dependent (BOLD) response, which peaks several seconds after the neural event it reflects, MEG captures the direct magnetic correlate of intracellular currents, yielding a signal that is time-locked to neural activity with millisecond precision (Chen *et al.*, 2019). This property is critical for studying arithmetic cognition, where the temporal sequence of processing stages carries theoretical significance. A second advantage is that magnetic fields pass through the tissues of the skull without the conductivity distortions that attenuate and smear the electric fields measured by EEG, conferring on MEG a spatial resolution advantage — although MEG spatial resolution remains lower than that of fMRI, particularly for deep subcortical structures (Johnsrude & Hauk, 2005).

The imaging in the present study was conducted using an OPM-based MEG system. OPM technology replaces cryogenic SQUIDs with optically pumped atomic magnetometers, which operate through the interaction of laser-pumped atomic vapor with ambient magnetic fields. Because OPMs can be positioned directly on the scalp surface — within a few millimeters, compared to the 2 cm or more required by cryogenic systems — they capture a stronger signal with improved spatial resolution, particularly in superficial cortical areas. The smaller sensor-to-scalp distance also means that the measured field patterns are more spatially concentrated, enabling better source separation. For the imaging of children, who are disproportionately likely to move during MEG recording, OPM systems offer a further practical advantage: unlike fixed cryogenic arrays, they can in principle accommodate small head movements without the signal degradation that conventionally limits pediatric MEG (Rowley & Roberts, 1995). In the present study, participants wore a 128-sensor helmet, and real-time monitoring was maintained throughout acquisition via intercom and video camera.

2.3 On Numerical Cognition Development: Enumeration, Counting

A foundational distinction in the developmental literature separates two related but conceptually distinct numerical processes: counting and enumeration. Counting, in the strict sense, denotes the sequential recitation of number names in their conventional order — a procedural competence that children begin acquiring around age two. Enumeration, by contrast, requires the child to map number names onto discrete objects in a set, verify that each object is counted exactly once, and interpret the final number name as representing the cardinality of the entire set — a considerably more demanding achievement that is typically not consolidated until around age six (Butterworth, 2005). The distinction is not merely definitional: the two skills recruit partially dissociable cognitive processes, and mastery of rote counting does not automatically transfer to principled enumeration (Butterworth, 2005).

The developmental trajectory of enumeration has been the subject of sustained empirical investigation. Gelman and Gallistel (1978) identified five counting principles — the one-to-one principle, the stable-order principle, the cardinal principle, the abstraction principle, and the order-irrelevance principle — which they argued constitute a pre-verbal conceptual framework that children bring to the task of learning to count. This nativist account has been extensively debated; Gast and subsequent researchers found that very young children's enumeration is initially constrained by the perceptual organization of the objects to be counted, with homogeneous arrays yielding more reliable performance than heterogeneous ones (as reviewed in Ginsburg, 1997). However, Ginsburg and Seo (2004) found evidence of surprising abstraction capacity even in young children, suggesting that the nativist and constructivist accounts are not as incompatible as they might appear. By age four, children appear to have access to both protoquantitative knowledge — allowing them to reason about more and less without recourse to exact numerical representations — and genuinely numerical knowledge about cardinality (Gelman & Gallistel, 1978; Starkey *et al.*, 1990).

The strategies children deploy in solving arithmetic problems evolve substantially across the early school years. Early problem-solving relies on object-based and finger-based enumeration strategies; with development, these give way to more efficient verbal and mental retrieval procedures (Zur & Gelman, 2004). Crucially for the present study, the choice of strategy at any given point is not random but reflects a child's implicit cost-benefit calculation regarding accuracy and processing time, and the distribution of strategies in use at any moment reveals the current state of their numerical knowledge system (Siegler & Robinson, 1982). The neural correlates of this developmental progression — the question of which brain regions support which strategies at which ages — remain incompletely understood.

2.4 Neural Substrates of Numerical Processing

The neuroimaging literature on numerical cognition has converged on a broadly agreed characterization of the cortical networks involved. The intraparietal sulcus (IPS), particularly its horizontal segment in both hemispheres, has consistently been implicated in the representation and comparison of numerical magnitude across a range of paradigms and imaging modalities (Naccache & Dehaene, 2001). Naccache and Dehaene's (2001) meta-analytic synthesis of parietal activations proposed a three-component architecture within the parietal lobe: the bilateral IPS, associated with quantitative semantic processing; the left angular gyrus, associated with verbal processing of number names; and the posterior superior parietal system, associated with spatial attention and the direction of attention to internal spatial representations. This tripartite model has been influential, though subsequent work has questioned the exclusivity of IPS involvement in magnitude processing.

Evidence from developmental populations is particularly relevant to the present study. Temple and Posner (1998) examined brain regions involved in number comparison among 5 to 9-year-old children and found that the inferior parietal region — responsible for abstract representation of number magnitude — develops and responds before formal mathematical instruction is acquired, and does not undergo gross structural change until maturity. This early establishment of parietal number-sensitive circuitry contrasts with the more protracted development of executive and prefrontal systems, which are recruited for more demanding arithmetic tasks. The finding has implications for how giftedness might manifest neutrally: if gifted children differ in the efficiency or organization of these parietal circuits, this might be detectable through the kinds of amplitude and latency differences that ERP analyses are designed to reveal. Several studies have challenged the unqualified primacy of parietal cortex in numerical processing. Shuman and Kanwisher (2004) conducted a series of experiments designed to tease apart numerical from non-numerical activations in the parietal lobe and found no reliable evidence of IPS selectivity for numerical magnitude relative to matched non-numerical tasks, suggesting that IPS involvement may reflect domain-general rather than number-specific processing. Cohen-Kadosh *et al.* (2005) similarly pointed to the temporal lobes as potentially important contributors to numerical cognition. These findings are consistent with the view that the neural representation of number involves a widely distributed network rather than a dedicated module, and they motivate the present study's examination of multiple ROIs — frontal, parietal, occipital, and temporal — rather than a parietal-only focus.

The role of the occipital cortex in numerical processing, though less frequently theorized, is gaining empirical traction. Visuospatial representations of quantity — including number lines, dot arrays, and digit forms — are known to engage occipital regions, and differences in visual processing efficiency between learners may partially account for differences in mathematical performance (Michels *et al.*, 2018). For gifted children, who may rely more heavily on visual and spatial mental representations when solving mathematical problems, the occipital contribution to arithmetic processing may be disproportionately large. The present results speak directly to this possibility.

3. Methodology

3.1 Participants

Forty-three children between the ages of 12 and 15 years participated in the study. Participants were allocated to four groups defined by the intersection of giftedness classification and sex: gifted boys (n = 11), non-gifted boys (n = 10), gifted girls (n = 11), and non-gifted girls (n = 11), yielding a total of 22 gifted and 21 non-gifted participants. Giftedness classification was determined by school records and standardized assessment criteria used by the Israeli education system. All participants were free of neurological conditions, had no history of epilepsy or head injury, and were not currently taking psychoactive medication. Written informed consent was obtained from parents or guardians, and assent was obtained from the children themselves prior to participation. No metal objects, jewelry, or magnetic materials were permitted in the MEG room; participants were asked to remove all such items before entering the shielded environment.

3.2 MEG Testing Procedure

Each participant was tested individually. On arrival at the MEG facility, the experimental procedure was explained, and the participant was given the opportunity to ask questions. The 128-sensor helmet was positioned on the participant's head, and the screen was centered in the participant's visual field. The testing team monitored comfort and minimized potential sources of movement throughout the session. During recording, the participant communicated with the team via intercom; continuous visual monitoring was maintained via camera. At the conclusion of testing, the sensors were removed, and the participant was debriefed. The procedure was entirely non-invasive and did not involve any physical discomfort.

3.3 The Stimuli

Visual stimuli were presented via a Hitachi CP-SX635 projector equipped with an ultra-long throw lens positioned outside the magnetically shielded room. Images were relayed via a two-mirror system onto a screen (43 cm × 34 cm) positioned approximately 60 cm from the participant's eyes. A photocell-equipped device ensured accurate measurement of stimulus onset timing relative to the stimulus-delivery software. Background luminance was set to the mean overall luminance of the stimuli to minimize abrupt luminance changes at stimulus onset; viewing distance and image dimensions were monitored and held constant across participants to control for their influence on cortical responses. Brain activity was recorded using a 128-sensor MEG system.

Figure 1: The subject brain recording is being taken

Stimuli consisted of numerical problems drawn from two task conditions. In the identification (ID) condition, participants were asked to identify a single digit presented on screen. In the addition (SUM) condition, participants were presented with simple two-operand addition problems involving the digits 1 through 8. Each question was repeated five times across the experimental session. Participants responded by selecting the correct answer from among several options displayed simultaneously, using a button box while remaining connected to the MEG sensors throughout. Only trials on which the participant selected the correct response were retained for analysis; trials with incorrect responses were excluded prior to further processing.

3.4 Preprocessing

Raw MEG data were acquired in FIF format and processed using the Fieldtrip toolbox (MATLAB). Trial definition was based on participant-specific CSV logs exported during acquisition, which contained stimulus onset times and condition labels. Only correct-response trials were retained. Data were band-pass filtered between 1 Hz and 40 Hz; a notch filter at 24 Hz was applied to remove line-noise artefacts arising from building infrastructure, whose mechanical oscillations at approximately 24 Hz were identified as a recurring contamination source. Baseline correction was applied across the entire trial window. Data were down sampled to 1000 Hz to reduce computational load while preserving the temporal resolution required for ERP analyses.

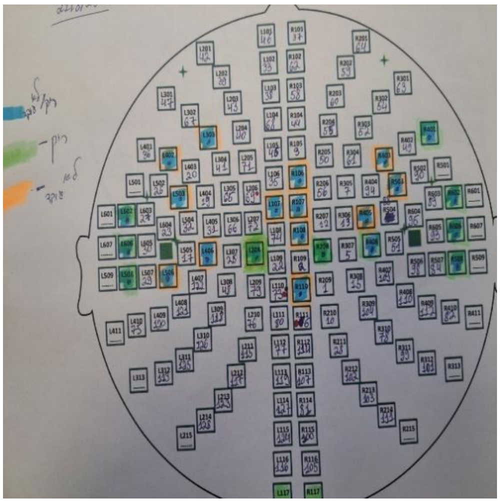


Figure 2: The map consists of 128 sensors

3.5 Artefact Rejection and Independent Component Analysis

Artefact rejection proceeded in two stages. A first round of visual inspection identified trials and channels exhibiting abnormally large variance, non-physiological peak deflections, or clearly artefactual waveform morphologies, which were removed from further analysis. Summary displays — including channel-by-trial heatmaps and per-trial and per-channel scatter plots — were used to flag entries for removal. This initial screening step reduces the influence of extreme data points on subsequent amplitude and power estimates and improves the overall signal-to-noise ratio.

Independent component analysis (ICA) using the Infomax algorithm was then applied to the cleaned data. ICA decomposes the multichannel MEG signal into statistically independent source components, enabling the identification and removal of contributions from non-neural sources — including ocular artefacts (eye blinks and saccades), cardiac artefacts (heartbeat), and respiratory or head-movement artefacts — without requiring the exclusion of entire trials. Components were identified as artefactual based on visual inspection of their scalp topographies and time courses: components with broad, non-focal topographies and slow or irregular time courses (consistent with respiration or movement) or frontal spatial distributions with characteristic blink morphologies (consistent with ocular artefacts) were removed prior to averaging and feature extraction. A second round of visual inspection following ICA confirmed the absence of residual artefactual contamination.

3.5.1 ICA artifact removal

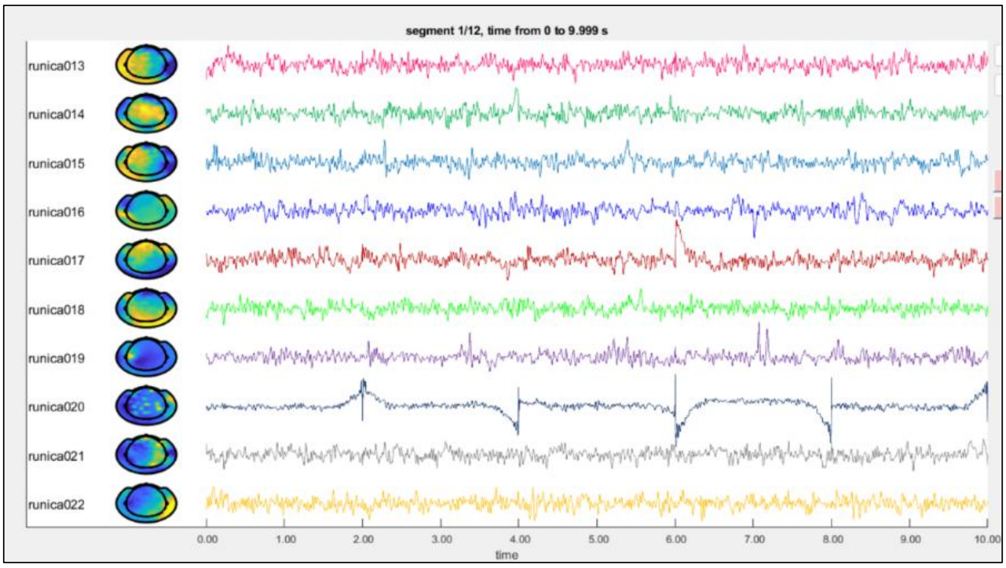


Figure 3: ICA artifact removal

We ran an ICA decomposition and manually screened all components using their time courses and scalp maps. Components showing non-neural artifacts were marked for removal. This preserves neural activity while improving SNR (signal-to-noise ratio) without discarding additional trials. Component 20 is an example of a rejected ICA component reflecting respiration/head-movement artifact. The time course shows slow, recurring transients, and the scalp map is broad and non-focal. The component was removed prior to averaging and feature extraction.

3.6 Feature Extraction and Statistical Analysis

Event-related potentials (ERPs) were computed by averaging the single-trial MEG time series, time-locked to stimulus onset, separately for each participant, condition, ROI, and group. Four cortical ROIs were defined: frontal, parietal, occipital, and temporal. The following features were extracted from ROI-averaged ERP waveforms: peak amplitude, root mean square (RMS), mean absolute amplitude, and peak latency. Spectral power in the alpha (8–13 Hz), beta (13–30 Hz), gamma (>30 Hz), delta (1–4 Hz), and theta (4–8 Hz) frequency bands was also computed for each ROI and condition. To visualize spatial response strength, topographic plots were generated of peak ERP magnitude — defined as the maximum absolute ERP per sensor within the analysis window, averaged across subjects.

Statistical comparisons between groups (gifted vs. non-gifted) and between conditions (SUM vs. ID) were conducted using two-sample Welch's t-tests, which do not assume equal variances across groups and are therefore appropriate given the unequal group sizes. Effect sizes were quantified using Cohen's d. To control the family-wise false discovery rate arising from the large number of simultaneous comparisons across ROIs, frequency bands, and features, the Benjamini-Hochberg FDR correction was applied. Results are reported at both the uncorrected ($p < .05$) and FDR-corrected thresholds to allow readers to distinguish between confirmatory findings and exploratory trends.

4. Results

4.1 Overall Group Differences (Gifted vs. Non-Gifted)

When data were pooled across all trials and task conditions, the occipital ROI was the primary site of reliable between-group differences. Gifted children exhibited significantly higher values than non-gifted controls on three amplitude features — mean absolute amplitude, RMS, and peak amplitude — all at $p \approx .041$. No other ROI yielded significant group differences when all trials were pooled at this threshold. The pattern is consistent with stronger occipital responses in the gifted group, or alternatively with reduced post-stimulus suppression (event-related desynchronization, ERD) in that group relative to controls — a distinction that cannot be resolved on the basis of amplitude measures alone but that may be theoretically informative regarding the nature of visual cortical involvement in numerical processing.

After FDR correction, one finding survived at the corrected threshold in the all-trials analysis: parietal peak latency was reliably later in the gifted group than in the non-gifted group. This is a theoretically significant result, as it suggests that group differences in mathematical cognition may manifest more robustly in the temporal dynamics of parietal processing — the timing of the neural response — than in its raw amplitude. The parietal lobe has consistently been identified as a central node in the numerical magnitude processing network (Naccache & Dehaene, 2001; Temple & Posner, 1998), and latency differences in parietal ERPs may reflect differences in the speed or efficiency of magnitude representation and comparison between gifted and non-gifted children.

					Overall Group Comparison significant results					
ROI	Feature	Mean_Gifted	Mean_Control	SD_Gifted	SD_Control	t	pval	cohen_d	qval	signif_q05
occipital	peak	5.75E-13	4.28E-13	2.77E-13	8.71E-14	2.154301	0.040908	0.621322	0.501018	0
occipital	rms	4.62E-13	3.53E-13	1.89E-13	8.48E-14	2.137762	0.041752	0.658555	0.501018	0
occipital	mean_abs	4.47E-13	3.42E-13	1.81E-13	8.23E-14	2.147343	0.040919	0.663495	0.501018	0

Figure 4: A small section of analysis table

4.2 Task-Type Effects: Addition Versus Digit Identification

Within-group comparisons between the SUM and ID conditions yielded robust effects across both the gifted and non-gifted groups. The consistent direction of these effects — ID > SUM across multiple ROI and feature combinations, with many comparisons surviving FDR correction — indicates that digit identification reliably elicited higher oscillatory amplitude and power than addition. This pattern was most pronounced in the beta and gamma frequency bands over parietal, frontal, and temporal ROIs. The interpretation is straightforward: addition is computationally more demanding than digit identification, and greater computational demand is associated with greater neural desynchronization (ERD) — that is, reduced oscillatory power — in the task-relevant frequency bands. The ID > SUM direction of effects reflects weaker ERD, or stronger synchronization, during identification: the brain does less computational work during a simpler perceptual task, yielding higher net oscillatory amplitude.

Between-group comparisons restricted to the SUM condition revealed significant gifted-versus-control differences specifically in the occipital ROI: mean absolute amplitude, RMS, and peak amplitude were all higher in the gifted group ($p < .05$). No analogous effects emerged in the ID condition. The specificity of this pattern to the addition condition is noteworthy. It suggests that the occipital advantage in gifted children is not a general feature of their visual processing, but is tied to computationally demanding arithmetic — a context in which visual processing of the operands may play a more important role for gifted than for non-gifted children. This resonates with theoretical accounts that emphasize the role of visuospatial representations in mathematical thinking (Michels *et al.*, 2018) and with observations that some mathematically gifted individuals report relying heavily on mental imagery in their mathematical reasoning.

				Comparison by Task Type Within-group significant results							
Group	ROI	Feature	Mean_SUM	Mean_ID	SD_SUM	SD_ID	t	pval	cohen_dz	qval	signif_q05
gifted	frontal	band_beta	7.21E-30	1.29E-29	2.37E-30	3.27E-30	-6.76655	0.002489	-3.02609	0.168517	0
gifted	frontal	band_gamma	2.52E-30	4.12E-30	5.89E-31	1.17E-30	-4.21287	0.013555	-1.88405	0.195191	0
gifted	occipital	band_alpha	8.50E-30	2.10E-29	2.75E-30	9.95E-30	-3.22859	0.032018	-1.44387	0.268943	0
gifted	occipital	band_beta	6.27E-30	1.19E-29	2.38E-30	2.12E-30	-4.69226	0.009362	-2.09844	0.168517	0
gifted	occipital	band_gamma	2.10E-30	3.86E-30	6.69E-31	9.94E-31	-5.08059	0.007078	-2.27211	0.168517	0
gifted	parietal	band_beta	1.04E-29	1.70E-29	3.24E-30	4.29E-30	-4.79107	0.008705	-2.14263	0.168517	0
gifted	parietal	band_gamma	3.04E-30	5.69E-30	1.01E-30	2.24E-30	-3.61366	0.022483	-1.61608	0.268943	0
gifted	temporal	band_gamma	6.31E-30	1.17E-29	2.44E-30	4.97E-30	-3.31278	0.029577	-1.48152	0.268943	0
control	frontal	peak	5.03E-13	5.37E-13	2.37E-14	1.49E-14	-4.87864	0.03954	-2.81668	0.268943	0
control	occipital	band_beta	6.42E-30	1.59E-29	3.27E-30	6.55E-30	-4.77997	0.041089	-2.75972	0.268943	0
control	parietal	mean_abs	4.27E-13	4.21E-13	7.53E-14	7.43E-14	4.821502	0.040426	2.783695	0.268943	0

Figure 5: A small section of analysis table

4.2.1 Between-groups (Gifted vs. Control)

Across task type, significance (p<0.05), all in the SUM condition and all in the occipital ROI: mean absolute amplitude, rms, and peak amplitude showed Gifted > Control. This pattern is consistent with a larger or more sustained visual evoked response and/or reduced post-stimulus suppression during addition in the gifted group, i.e., greater reliance on visual processing of the operands.

					Comparison by Task Type Between-groups significant results						
Qtype	ROI	Feature	Mean_Gift	Mean_Con	SD_Gifted	SD_Contro	t	pval	cohen_d	qval	signif_q05
SUM	occipital	peak	5.87E-13	4.30E-13	2.78E-13	9.33E-14	2.264723	0.032147	0.659572	0.757685	0
SUM	occipital	rms	4.61E-13	3.53E-13	1.85E-13	8.52E-14	2.169145	0.039071	0.671973	0.757685	0
SUM	occipital	mean_abs	4.46E-13	3.41E-13	1.77E-13	8.25E-14	2.174991	0.0386	0.675959	0.757685	0

Figure 6: A small section of analysis table

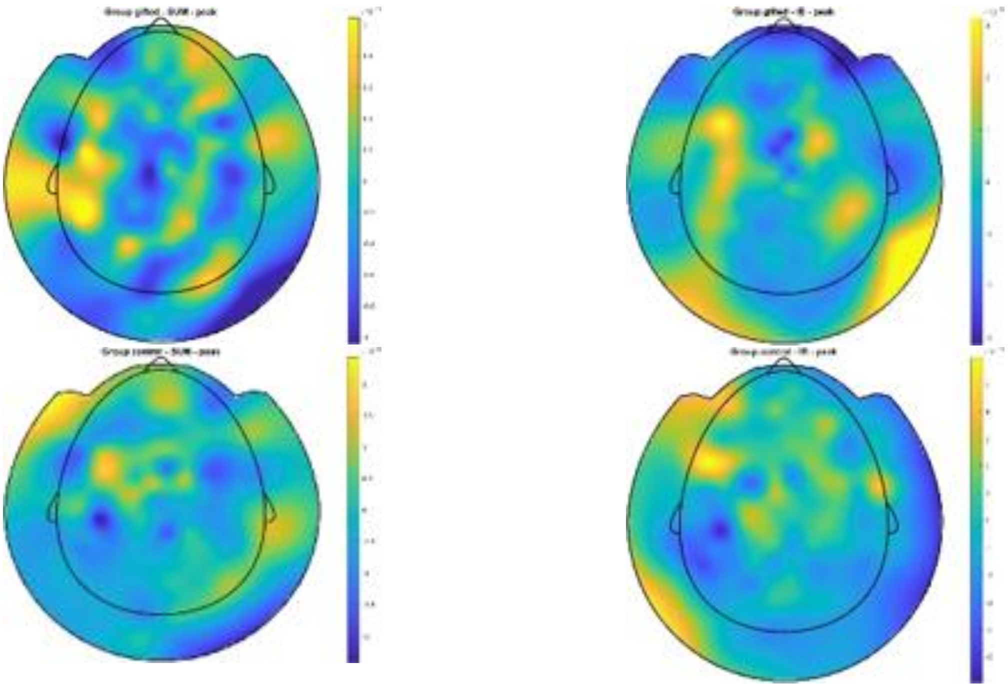


Figure 7: Atopography from the meg showing active areas in the brain

4.3 Comparison by Numerical Answer

Within-group: Pairwise digit comparisons yielded two effects in the Control group: temporal beta showed 6 > 5 (p=0.012, q=0.800) and occipital theta showed 6 > 5 (p=0.028, q=0.800). No other within-group contrasts reached p<0.05. Although these patterns suggest slightly stronger temporal-beta and occipital-theta responses to the digit 6 as compared to 5.

Between-groups (Gifted vs. Control, per digit): effects showed Gifted > Control: for digit 5, theta power (p=0.028), mean absolute amplitude (p=0.033), rms (p=0.034), peak amplitude (p=0.039), and delta power (p=0.049); for digit 3, mean absolute amplitude (p=0.040) and rms (p=0.043). Directionally, this pattern is consistent with a larger or more sustained occipital response or reduced post-stimulus suppression for specific digits in the gifted group.

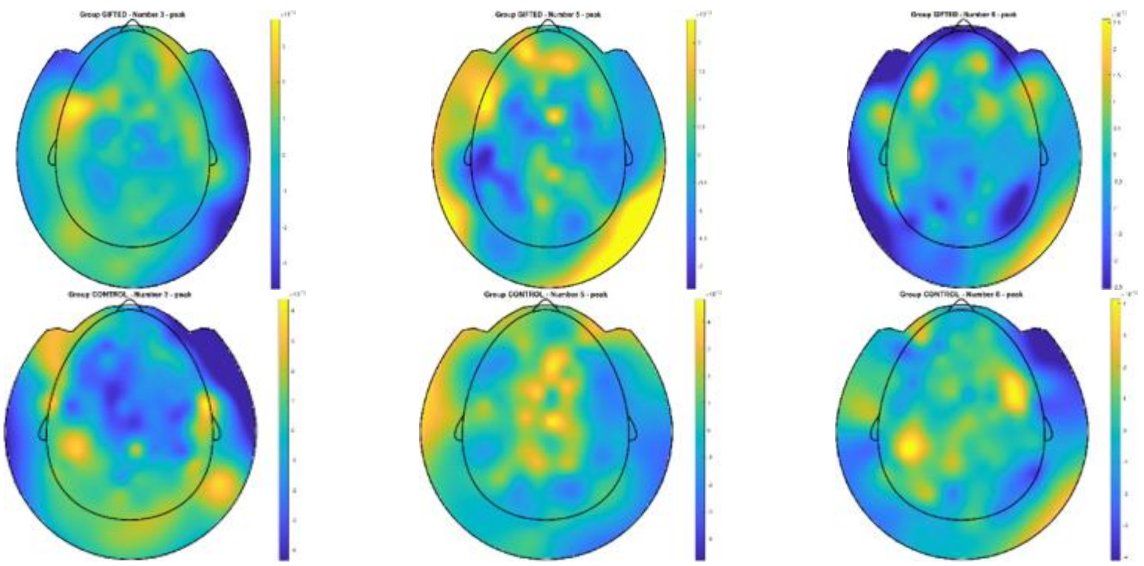
					Comparison by Numerical Answer Between-group significant results						
Number	ROI	Feature	Mean_Gift	Mean_Con	SD_Gifted	SD_Contro	t	pval	cohen_d	qval	signif_q05
3	occipital	rms	4.64E-13	3.55E-13	1.90E-13	8.59E-14	2.124226	0.042968	0.654919	0.598992	0
3	occipital	mean_abs	4.44E-13	3.40E-13	1.79E-13	8.24E-14	2.152665	0.040469	0.667045	0.598992	0
5	occipital	peak	6.16E-13	4.72E-13	2.61E-13	9.14E-14	2.177041	0.038692	0.638219	0.598992	0
5	occipital	rms	4.66E-13	3.56E-13	1.78E-13	8.56E-14	2.231756	0.034204	0.698605	0.598992	0
5	occipital	mean_abs	4.46E-13	3.41E-13	1.69E-13	8.21E-14	2.247083	0.033108	0.705607	0.598992	0
5	occipital	band_delta	2.08E-26	1.15E-26	1.84E-26	5.60E-27	2.067034	0.049192	0.59352	0.598992	0
5	occipital	band_theta	1.32E-28	4.50E-29	1.58E-28	3.61E-29	2.338602	0.028436	0.651525	0.598992	0

Figure 8: A small section of analysis table

Given the multiple comparisons and reduced per-cell trial counts digits 3, 5, 6, 7, and 8 showed scattered uncorrected effects and a recurrent trend of 7/8 > 3/5 in beta/theta power and time-domain amplitude, most prominently over frontal and occipital ROIs. This pattern is consistent with our view that digits 3-6 place broadly similar computational demands, whereas 7-8 elicit greater neural effort.

				Comparison by Numerical Answer Between-group significant results							
Number	ROI	Feature	Mean_Gifted	Mean_Control	SD_Gifted	SD_Control	t	pval	cohen_d	qval	signif_q05
3	frontal	band_beta	1.66E-29	2.50E-29	3.18E-30	3.65E-30	-3.29694	0.031923	-2.50668	0.999834	0
5	occipital	lat_peak	1.7618	0.068	0.182616	0.049507575	19.57563	7.77E-06	11.1566	0.001398	1
7	parietal	band_alpha	5.41E-29	9.78E-29	6.14E-30	1.70E-29	-4.27667	0.038754	-3.95653	0.999834	0
8	parietal	lat_peak	1.3484	0.136	0.586174	0.139774819	4.420216	0.007923	2.497914	0.713108	0

Figure 9: A small section of analysis table



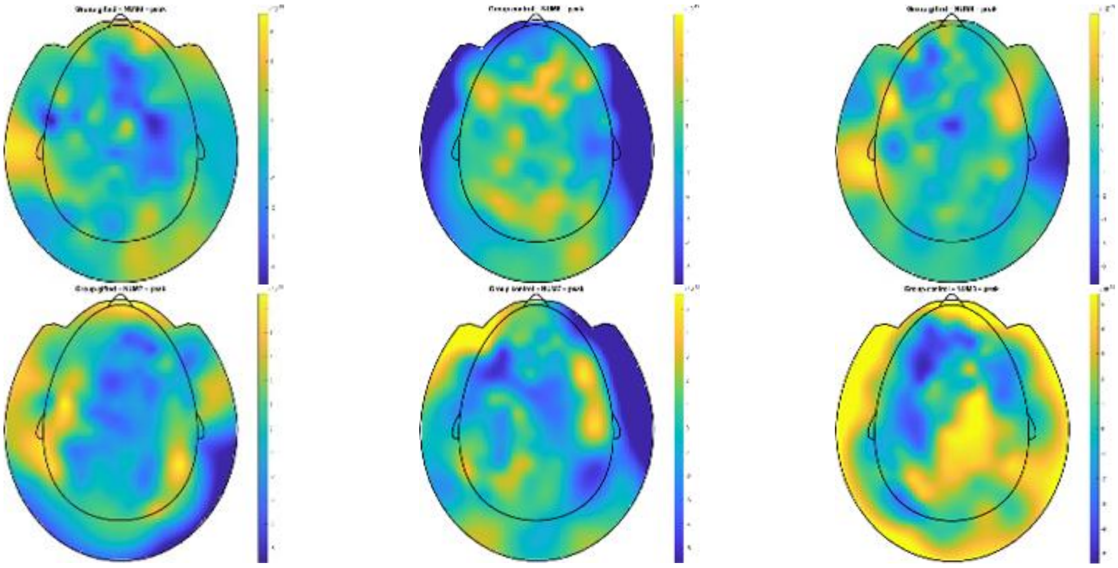


Figure 10: Atopography from the meg showing active areas in the brain

4.3 Digit-Specific Neural Responses

Within-group digit analyses were largely exploratory, and the findings should be interpreted with appropriate caution given the number of simultaneous comparisons and the reduced per-cell trial counts that accompany digit-level analyses. Within the non-gifted group, two effects emerged at the uncorrected threshold: temporal beta power was higher for digit 6 than digit 5 ($p = .012$, $q = .800$), and occipital theta power showed the same direction ($p = .028$, $q = .800$). The failure of both effects to survive FDR correction, combined with the large q-values, indicates that they represent weak trends rather than reliable findings, and they are not interpreted further here.

Between-group digit-level comparisons identified several occipital effects in which gifted children showed higher amplitude measures than non-gifted controls for specific digits. For digit 5, five features reached uncorrected significance: theta power ($p = .028$), mean absolute amplitude ($p = .033$), RMS ($p = .034$), peak amplitude ($p = .039$), and delta power ($p = .049$). For digit 3, mean absolute amplitude ($p = .040$) and RMS ($p = .043$) also showed Gifted > Control at the uncorrected threshold. After FDR correction, one between-group digit-level effect survived: occipital peak latency for digit 5 was reliably later in the gifted group (FDR-significant). Additionally, three uncorrected effects point to potentially interesting patterns: frontal beta power for digit 3 was higher in the control group than in the gifted group; parietal alpha power for digit 7 showed the same direction; and parietal peak latency for digit 8 was later in the gifted group.

Across digits, a recurrent trend emerged — most visibly in the gifted group — whereby larger digits (7 and 8) elicited greater neural activity in beta and theta bands, and higher time-domain amplitude, over frontal and occipital ROIs than smaller digits (3 and 5). Digits 3 through 6 appeared to place broadly similar computational demands on the system, while digits 7 and 8 elicited demonstrably greater neural effort. This pattern is consistent with the well-established numerical distance effect — the finding that the cognitive and neural cost of numerical comparison scales with the size and distance of the numbers involved — and may reflect the greater working memory and magnitude-representation demands associated with processing single-digit numbers that approach or span the boundary typically associated with subitizing limits.

5. Discussion

5.1 Occipital Engagement in Gifted Mathematical Cognition

The most consistently replicated finding in the present dataset is the elevated occipital amplitude in gifted children, which emerges both when all trials are pooled and when the analysis is restricted to the addition condition. This pattern was not anticipated on the basis of prior theoretical accounts, which have largely emphasized parietal and prefrontal regions as the primary sites of group differences in mathematical ability (Naccache & Dehaene, 2001; Shuman & Kanwisher, 2004). Its emergence here invites several interpretations. One possibility is that gifted children engage visual cortical resources more extensively during arithmetic, reflecting a greater reliance on visuospatial mental representations — for example, mental number lines or spatial magnitude representations — when processing the operands of addition problems. This interpretation aligns with theoretical arguments that visuospatial representations of quantity are particularly important for the development of sophisticated numerical knowledge (Michels *et al.*, 2018) and with the observation that mathematically gifted individuals often report a preference for visual and geometric modes of mathematical thinking.

A second interpretation is that the occipital amplitude difference reflects reduced post-stimulus suppression — that is, weaker ERD in the visual cortex — in gifted children. Under this account, gifted children's occipital cortex remains more active following stimulus onset, perhaps because they continue to process the visual properties of the digits more elaborately or for longer. This would be consistent with evidence from other cognitive domains that high-ability individuals sometimes show more sustained engagement with stimulus features that lower-ability individuals process more superficially (Cohen-Kadosh *et al.*, 2005). Distinguishing between these two accounts would require time-frequency analyses that track the temporal evolution of occipital amplitude across the response window — a direction for future work.

5.2 Parietal Latency as a Marker of Group Differences

The FDR-corrected finding of later parietal peak latency in gifted children, across all trials, initially appears counterintuitive: if gifted children process numerical information more efficiently, one might expect shorter, not longer, response latencies. However, the interpretation of latency differences in ERP data is not straightforwardly equated with processing speed. Longer latency in gifted children may reflect a qualitatively different mode of parietal engagement — for example, deeper or more thorough processing of numerical magnitude before a response is selected, or the sequential engagement of multiple parietal subregions. It is also possible that gifted children are less reliant on automatic, fast-pathway processing and more reliant on controlled, slower analytical pathways when solving mathematical problems, which would manifest as longer latencies despite superior ultimate accuracy. The digit-5-specific occipital latency effect, which also showed later responses in gifted children, adds to this picture.

5.3 Implications for Neuropedagogy and Mathematics Education

The findings carry several implications for educational practice, though these must be stated with appropriate caution given the exploratory character of several analyses and the relatively modest sample size. Most directly, the results support the neuropedagogical argument that gifted and non-gifted children do not simply differ in the speed or accuracy of numerical processing, but in the neural resources they recruit for that processing — a difference that becomes especially pronounced during computationally demanding tasks. This suggests that instructional approaches calibrated to non-gifted learners may not be optimal for gifted ones, not merely because gifted children need more challenging content, but because they may be engaging different cortical systems when solving even superficially similar problems.

The specific involvement of occipital cortex in gifted children's arithmetic processing speaks to the importance of visual and spatial instructional tools. A growing body of research in mathematics education has documented the benefits of visuospatial referents — number lines, area models, spatial diagrams — for mathematical learning across ability levels (Michels *et al.*, 2018). The present results suggest that for gifted learners in particular, such representations may align especially well with the cortical architecture they naturally deploy. This is consistent with the broader argument, supported by multiple neuroimaging studies, that the dorsal visual pathway is reliably engaged when both children and adults work on mathematical tasks involving spatial representations of quantity (as reviewed in the discussion section of the parent document), and that enriching the visual and spatial texture of mathematics instruction may have benefits that extend beyond accessibility to deeper conceptual engagement.

At the same time, the present findings underscore the importance of the neuropedagogical mission articulated by Ansari *et al.* (2011), Hook and Farah (2013), and Friedman *et al*. (2019): teachers need better tools for understanding how different students' brains engage with mathematical content. The between-group differences identified here would not be detectable through behavioural observation alone. Only by imaging brain activity during mathematical task performance can one observe that gifted and non-gifted adolescents are recruiting different cortical systems — differences that may be invisible at the level of response accuracy but that carry implications for how these children should ideally be taught.

5.4 The Digit-Size Effect and Its Educational Relevance

The exploratory finding that larger digits (7 and 8) elicited greater neural effort than smaller ones — particularly over frontal and occipital ROIs in gifted children — connects with a well-established theme in numerical cognition research. The subitizing limit, typically estimated at around four to five items for exact enumeration without counting, is widely regarded as a fundamental constraint on magnitude processing, and the greater neural engagement elicited by digits in the range of 7 and 8 may reflect the operation of exactly this constraint in a symbolic format. From an educational perspective, this suggests that the difficulty of arithmetic problems is not determined solely by the operations they require (addition versus subtraction, etc.) but also by the specific magnitudes involved — a factor that should arguably be considered more explicitly in the design of mathematical learning tasks, particularly for young learners whose magnitude representation systems are still consolidating.

5.5 Limitations

Several limitations constrain the interpretation of the present findings. The sample size of 43 participants, while sufficient for initial hypothesis-testing, limits statistical power and increases the risk that observed effects reflect sample-specific variation. The digit-level analyses, in particular, involve a large number of simultaneous comparisons relative to the per-cell trial counts available, and the preponderance of effects that did not survive FDR correction should be taken as a caution against strong inferential conclusions from those analyses. Future work should aim for larger samples and, where possible, pre-register digit-level hypotheses in advance to reduce the multiple comparison burden. A second limitation is the use of giftedness classification as defined by school records and national criteria, which inevitably introduces heterogeneity within the gifted group and may not capture all dimensions of mathematical giftedness relevant to the neural question being asked. Finally, the cross-sectional design of the present study precludes causal inference: the neural differences observed between gifted and non-gifted children may reflect pre-existing individual differences, the effects of differential educational experience, or some combination of both.

6. Conclusions

The present study set out to examine whether MEG-based neuroimaging could identify reliable neural differences between mathematically gifted and non-gifted adolescents during tasks of digit identification and simple addition, and whether those differences could be situated within the neuropedagogical framework that motivates the integration of brain science into educational practice. The results are affirmative on both counts, if cautiously so. Gifted children showed reliably higher occipital amplitude during arithmetic, particularly during addition, and reliably later parietal peak latency — findings that survived multiple-comparison correction and that are interpretable within existing theoretical accounts of visuospatial involvement in numerical cognition. The exploratory digit-level analyses additionally pointed to a recurrent pattern of greater neural engagement for digits 7 and 8 than for smaller ones, consistent with the role of magnitude-representation demands in shaping cortical responses to numerical stimuli.

These findings contribute to an emerging empirical foundation for evidence-based mathematics teaching. They demonstrate that the giftedness distinction is not merely behavioural but has identifiable neural correlates that manifest in the spatial and spectral properties of cortical responses to mathematical stimuli. They suggest that gifted learners deploy occipital visual resources in ways that non-gifted learners do not, at least during arithmetic processing, and they point to parietal response timing rather than amplitude as the most robust neural marker of group differences after controlling for multiple comparisons. For neuropedagogy, these results carry a concrete message: teachers who understand that their gifted students are recruiting different brain systems during mathematics lessons — not simply processing the same information faster — are better positioned to design instructional environments that genuinely serve those students' learning needs.

Future research should extend this work in several directions. Larger samples would improve statistical power and enable the kind of individual-differences analyses needed to link neural markers to specific aspects of mathematical competence. Longitudinal designs would allow researchers to track whether the neural signatures of giftedness are stable across development or whether they shift with exposure to progressively more demanding mathematical content. Extension to more complex arithmetical operations — multi-digit multiplication, fractions, algebra — would test whether the occipital advantage for gifted children generalizes across the mathematical curriculum or is specific to basic numerical operations. Finally, intervention studies that incorporate neurofeedback or visually enriched instructional materials and assess their impact on both neural response profiles and mathematical learning outcomes would close the loop between neuroimaging science and classroom practice that neuropedagogy has long aspired to close.

Conflict of Interest Statement

The authors declare no conflicts of interest.

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