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Mathematical Cognition and its Neural Correlates During Development: A Scoping Review with Systematic Search

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Abstract

Mathematics learning begins in schooling and plays a role in children's cognitive development, predicting academic achievement and professional success. Its development is influenced by linguistic, metacognitive, emotional, and cognitive factors. Cross-sectional neuroimaging studies have highlighted the involvement of the intraparietal sulcus and prefrontal cortex in mathematical tasks. However, longitudinal studies capituring the neural correlates of mathematical development in school-aged children remain scarce and heterogeneous. To provide an overview of current evidence on longitudinal studies of mathematical cognition with neural correlates, we conducted a review with a systematic search strategy. Nineteen studies were identified, revealing mathematics as a dynamic, multi-component system that evolves from a structural foundation into a functionally specialized network. Findings emphasize the central role of parietal and frontal regions, with contributions from temporal, occipital, and subcortical areas, while also underscoring the lack of naturalistic studies and diverse sociocultural samples.

Keywords: Mathematical cognition; longitudinal studies; children; neural correlates

Introduction

Mathematics learning, formally initiated during the early years of primary education in many countries, is expected to encompass the development of counting, reading, writing, and number comparison skills, as well as the understanding of the number line and the practice of basic arithmetic operations (BRASIL, 2018).

Mathematical and numerical cognition plays a fundamental role in children's cognitive development, serving as a predictor of academic achievement and professional success (Reyna et al., 2009; Parsons & Bynner, 2005). Even educational guidelines emphasize that mathematical knowledge is essential for all students in basic education, both for its application in everyday life in contemporary society and for the formation of critical citizens (BRASIL, 2018).

Understanding how these skills develop is crucial for designing effective educational interventions. Among the factors that influence the development of mathematical abilities are linguistic, metacognitive, emotional, and cognitive components, such as number sense and working memory (Bellon, Fias, & Smedt, 2019; Souza & Matias, 2020; Ven, Prast, & Weijer-Bergsma, 2023).

Neural correlates associated with mathematical tasks have been investigated over the past two decades in many cross-sectional studies. Since the earliest neuroimaging research with mental arithmetic tasks, a significant activation has been reported in parietal and prefrontal regions across both hemispheres (Dehaene et al., 1996).

Both symbolic arithmetic and numerical magnitude comparison consistently engage the bilateral intraparietal sulcus (IPS), along with prefrontal and occipital regions. The IPS has emerged as a hub for numerical magnitude representation across different task contexts, while prefrontal regions support executive control and working memory demands inherent to mathematical processing. This neural architecture appears to underlie core numerical abilities across the lifespan, from symbolic processing to arithmetic fact retrieval (Nieder & Dehaene, 2009).

However, some cross-sectional studies suggest that critical developmental changes occur in the organization of these neural networks during the lifespan. While younger children show greater prefrontal activation during numerical tasks, older children and adults demonstrate increased parietal specialization, suggesting a developmental shift toward more efficient neural processing with mathematical learning and age (Rosenberg-Lee et al., 2011). Furthermore, resting-state functional connectivity studies have revealed that intrinsic network properties, independent of task-specific demands, also relate to mathematical abilities in children (Skagerlund et al., 2018; Zhao et al., 2019; Lynn et al., 2022).

Despite this growing knowledge, longitudinal neuroimaging studies tracking the development of mathematical cognition in children remain scarce and methodologically heterogeneous. Most research consists of cross-sectional designs. Additionally, longitudinal studies employing neuroimaging in combination with mathematical and numerical tasks in children are crucial for achieving a causal understanding of the trajectories of neural and behavioral change underlying children's acquisition of mathematical competence and also for enabling the identification of possible early neural markers that might predict individual differences in mathematical learning. A systematic synthesis of longitudinal neuroimaging evidence is essential to clarify these developmental pathways.

The aim of this study was, through a scoping review with a systematic search, to synthesize the findings of longitudinal studies that used neuroimaging to investigate mathematical and numerical cognition in school-aged children, highlighting the main results, the methodologies applied, and the gaps in

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the literature.

To that end, we followed the initial items of the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) checklist, which include the prior definition of the review objectives, eligibility criteria, information sources, search strategy, data items to be extracted from the articles, as well as the selection and data extraction process. We chose not to classify this study as a Systematic Review because not all PRISMA requirements were met. Nevertheless, the definition of the objective using the PICOS method, the establishment of inclusion and exclusion criteria, and the search process were all determined a priori and conducted systematically. Therefore, we chose to highlight in the title only that the search for articles was systematic and standardized.

Methodology

Inclusion and Exclusion Criteria

Articles with participants between 5 and 10 years of age were included in the review, thus covering the end of the preschool stage and the early years of primary school, where formal mathematics instruction begins. Articles that included other populations beyond this age range were retained, provided that this age group was part of their sample.

Additional inclusion criteria were having at least two temporally spaced measurements, data from at least one measure of mathematical abilities, and some type of functional or structural neural correlate.

Cross-sectional studies, reviews or meta-analyses, and book chapters were excluded.

Systematic Search Strategy

The search was conducted on the same date across the following literature databases: PubMed (MEDLINE), Web of Science (Clarivate) and Scopus (Elsevier).

Articles cited by the initially selected studies were also included, provided they met the inclusion and exclusion criteria. Finally, two AI-based bibliographic search tools, Elicit and Consensus, were used to verify whether any additional articles beyond those identified would be suggested through their automated search processes.

No restrictions were placed on the publication dates of the articles, in order to provide an overview of the development of the literature on this topic.

The keywords used in the database searches were divided into four distinct blocks, considering the parameters of interest for the present review. Each of these blocks of keywords, with their respective logical Boolean operators, is described below. The search in each database was performed by connecting the four blocks with the operator AND.

Block 1- Acquisition of Mathematical and Arithmetic Skills: ("mathematical development" OR "arithmetic development" OR "numerical development" OR "calculation skills" OR "arithmetic learning" OR "math skills" OR "mathematical proficiency" OR "number processing").

Block 2- Neural Correlates: ("neuroimaging" OR "fMRI" OR "functional magnetic resonance imaging" OR "fNIRS" OR "functional near-infrared spectroscopy" OR "brain imaging" OR "DTI" OR "diffusion tensor imaging" OR "structural MRI" OR "cortical activity" OR "neural activation" OR "brain activation" OR "brain development" OR “EEG” OR “electroencephalogram”).

Block 3- Longitudinal Studies: ("longitudinal" OR "longitudinally" OR "follow-up" OR "prospective" OR "trajectory" OR "trajectories" OR "longitudinal design" OR "repeated measures" OR "longitudinal study" OR "developmental trajectory").

Block 4- Study Population with School Age Children: ("children" OR "child" OR "childhood" OR "school-age" OR "early school" OR "elementary school" OR "primary school" OR "5-10 years" OR "ages 5-10" OR "6-8 years" OR "preschool" OR "early elementary").

Conducting the Review

Initially, the database search using the additive combination of the four keyword blocks returned 80 studies, with 21 from PubMed, 29 from Web of Science, and 30 from Scopus. Most of these were duplicates. After screening titles and abstracts, 12 articles were selected for full-text reading, all of which were included in the final synthesis.

Following the inclusion of articles identified through citations of the selected studies and those suggested by the AI-based bibliographic tools Consensus and Elicit, the final synthesis comprised 19 studies. The number of excluded studies at each stage of screening can be found in Figure 1.

The analysis was conducted through thematic categorization of the findings, with descriptive assessment of methodological characteristics.

Results

Sample Characteristics

The Table 1 presents a summary of the sample characteristics of the included studies, such as age at the beginning of the study, sample size and whether the study focused on children with typical development or with dyscalculia.

It is evident that the vast majority of studies included older children, with very few following children from the end of preschool and through the beginning of primary education. Regarding sample sizes (n), most studies included at least 30 participants, despite the methodological challenges of conducting neuroimaging assessments such as MRI in children. Studies such as McCaskey et al. (2018, 2020) were categorized as having small sample sizes because their samples were divided into two subgroups—children with dyscalculia and controls—each with a relatively small n. A similar situation occurred in the study by Xie et al. (2024), in which the sample was composed of one group that underwent five years of abacus training and a control group.

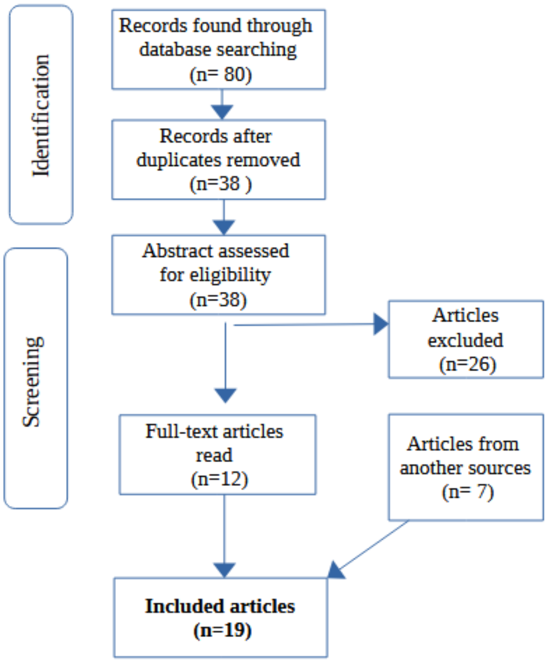

Figure 1: PRISMA diagram. PRISMA = Preferred Reporting Items for Systematic Reviews and Meta-Analyses.

Additionally, the literature is heavily concentrated in WEIRD populations (Western, Educated, Industrialized, Rich, and Democratic), specifically with studies in countries such as the USA, Germany, France, Switzerland and Sweden, with only a few studies conducted with Chinese children, who present clear cultural and educational differences compared to other countries. No study found in this review has included children from Global South nations, which may limit the generalization of the findings to more diverse cultural and socioeconomic contexts.

Experimental Design

The Table 2 presents the general characteristics of the experimental design of the studies included in the review. Only two studies analyzed the longitudinal effects of structured interventions, whereas the others tracked children over time considering only the impact of regular schooling on mathematical learning outcomes. The vast majority of studies conducted two temporally spaced assessments of cognitive tasks, but neuroimaging was often collected only once.

Cognitive Measures: In addition to numerical and mathematical tasks, several studies used other cognitive measures. For example, all the included articles employed some measure of IQ. The use of these tasks is standard practice in the field to control for the influence of general cognitive ability on mathematical outcomes. According to the articles, IQ was used as an inclusion criterion, as control covariate, and also for group matching within a sample.

Most articles used the Wechsler scales, either in full or abbreviated versions. The Raven's Progressive Matrices test, mainly used to measure abstract reasoning and non-verbal intelligence, was employed in the studies by Xie et al. (2024) and Dumontheil and Klingberg (2011). Some studies used specific intelligence test batteries adapted to the language or country of origin, such as the NEMI-2 (Nouvelle Échelle Métrique de l'Intelligence) and the RIAS (Reynolds Intellectual Assessment Scales).

Other cognitive-behavioral measures were also incorporated. Working memory was assessed through visuospatial tasks, such as Spatial Recall, Dot Matrix (both from the AWMA battery), and the Block-Suppression Test, as well as verbal tasks, including Digit Span (forward and backward) and Listening Recall (AWMA battery). One study (Evans et al., 2015) employed the Working Memory Test Battery for Children (WMTB-C). Reading and language skills were evaluated using measures of reading fluency and decoding, most frequently the SLRT-II (words and pseudowords). Attention and inhibition were examined with the computerized TAP battery (Alertness and Go/No-go tests). Socioeconomic status (SES) was evaluated with the Hollingshead Index. In addition, one study assessed mathematical attitudes through measures of interest and engagement using the TOMA-3 subtest.

Main Findings

The studies included in the review highlight several key points in their results and conclusions.

The reviewed studies converge on the conclusion that mathematical learning is supported by a distributed neural system, with the intraparietal sulcus (IPS) emerging as a central hub, present in the results of most structural and functional longitudinal neuroimaging studies. Distinct functional specializations were also observed: the left IPS was specifically linked to improvements in subtraction performance, while the middle temporal gyrus (MTG) was associated with retrieval-based operations such as multiplication. Cognitive development was highlighted as being supported by the strengthening of posterior parietal–temporal circuits and a gradual decoupling from prefrontal scaffolding.

Structural integrity and functional integration of the medial temporal lobe (MTL) and posterior parietal cortex (PPC) were predictors of long-term skill acquisition in children trained with the abacus. Gray matter structural covariance across networks predicted longitudinal arithmetic progress, while early cortical surface plasticity in parietal and frontal regions provided structural correlates of developing mathematical abilities.

Findings also highlight the role of large-scale brain networks. Functional maturation, expressed as increased segregation of modules such as the default mode network (DMN) and frontoparietal network (FPN), supported arithmetic development. Expertise in symbolic numbers refined the quantity representation system in the IPS, while hippocampal–neocortical reorganization underpinned the transi-

Table 1: Characterization of the study samples

Feature	Nº studies	Studies
Sample size (n)		
Small (10–29)	4	McCaskey et al. (2018); McCaskey et al. (2020); Kuhl et al. (2020); Xie et al. (2024)
Medium (30–50)	13	Dumontheil & Klingberg (2011); Qin et al. (2014); Evans et al. (2015); Price et al. (2016); Demir-Lira et al. (2016); Suárez-Pellicioni & Booth (2018); Battista et al. (2018); McCaskey et al. (2018); McCaskey et al. (2020); Schwartz et al. (2020); Kuhl et al. (2021); Suárez-Pellicioni et al. (2021); Suárez-Pellicioni et al. (2021b); Ren et al. (2024); Xie et al. (2024)
Large (>50)	2	Fraga-González et al. (2022); Wang et al. (2022)
Population		
Dyscalculia	2	McCaskey et al. (2018); McCaskey et al. (2020)
Typically development (mixed risk for dyscalculia)	1	Kuhl et al. (2021)
Typically development (mixed dyslexia risk)	1	Fraga-González et al. (2022)
Typical development	15	Dumontheil & Klingberg (2011); Evans et al. (2015); Emerson & Cantlon (2015); Price et al. (2016); Demir-Lira et al. (2016); Suárez-Pellicioni & Booth (2018); Battista et al. (2018); McCaskey et al. (2018); McCaskey et al. (2020); Schwartz et al. (2020); Kuhl et al. (2020); Kuhl et al. (2021); Suárez-Pellicioni et al. (2021); Suárez-Pellicioni et al. (2021b); Fraga-González et al. (2022); Wang et al. (2022); Ren et al. (2024); Xie et al. (2024)
Age at T1		
3–5 years	3	Emerson & Cantlon (2015); Kuhl et al. (2020); Kuhl et al. (2021)
6–8 years	7	Qin et al. (2014); Emerson & Cantlon (2015); Evans et al. (2015); Price et al. (2016); Battista et al. (2018); Kuhl et al. (2020); Fraga-González et al. (2022); Wang et al. (2022); Xie et al. (2024)
9–10 years	12	Dumontheil & Klingberg (2011); Qin et al. (2014); Evans et al. (2015); Price et al. (2016); Demir-Lira et al. (2016); Suárez-Pellicioni & Booth (2018); Battista et al. (2018); McCaskey et al. (2018); McCaskey et al. (2020); Schwartz et al. (2020); Kuhl et al. (2021); Suárez-Pellicioni et al. (2021); Suárez-Pellicioni et al. (2021b); Ren et al. (2024); Xie et al. (2024)
11–14 years	9	Dumontheil & Klingberg (2011); Demir-Lira et al. (2016); Suárez-Pellicioni & Booth (2018); Battista et al. (2018); Schwartz et al. (2020); Suárez-Pellicioni et al. (2021); Suárez-Pellicioni et al. (2021b); Fraga-González et al. (2022); Wang et al. (2022); Ren et al. (2024)

Table 2: Characterization of the Experimental Designs

Feature	Nº studies	Studies
Intervention		
Abacus-based mental calculation (AMC) training	1	Xie et al. (2024)
Grapheme-phoneme identification intervention	1	Fraga-González et al. (2022)
Time points		
2	15	Qin et al. (2014); Dumontheil & Klingberg (2011); Emerson & Cantlon (2015); Evans et al. (2015); Price et al. (2016); Demir-Lira et al. (2016); McCaskey et al. (2018); Suárez-Pellicioni & Booth (2018); McCaskey et al. (2020); Schwartz et al. (2020); Kuhl et al. (2020); Kuhl et al. (2021); Suárez-Pellicioni et al. (2021); Suárez-Pellicioni et al. (2021b); Wang et al. (2022); Ren et al. (2024); Xie et al. (2024)
4	3	Evans et al. (2015); Battista et al. (2018); Xie et al. (2024)
5	1	Fraga-González et al. (2022)
Neuroimage Type		
Task-based fMRI	10	Qin et al. (2014); Dumontheil & Klingberg (2011); Emerson & Cantlon (2015); Demir-Lira et al. (2016); Battista et al. (2018); McCaskey et al. (2018); Suárez-Pellicioni & Booth (2018); Schwartz et al. (2020); Suárez-Pellicioni et al. (2021); Wang et al. (2022)
Resting-state fMRI	3	Evans et al. (2015); Kuhl et al. (2021); Xie et al. (2024)
Structural MRI	7	Evans et al. (2015); Price et al. (2016); Kuhl et al. (2020); McCaskey et al. (2020); Suárez-Pellicioni et al. (2021); Wang et al. (2022); Ren et al. (2024); Xie et al. (2024)
EEG	1	Fraga-González et al. (2022)
fMRI Task Type		
Single-digit multiplication (correctness judgment)	3	Qin et al. (2014); Suárez-Pellicioni et al. (2021); Wang et al. (2022); Ren et al. (2024)
Simple subtraction (true/false)	1	Demir-Lira et al. (2016)
Single-digit additions	2	Qin et al. (2014); Battista et al. (2018)
Dot Comparison (ANS)	2	Demir-Lira et al. (2016); Suárez-Pellicioni & Booth (2018)
Numerical Order Judgment (ascending/descending)	1	McCaskey et al. (2018)
Transitive Relations	1	Schwartz et al. (2020)
Visuospatial Working Memory Task	1	Dumontheil & Klingberg (2011)
Category Matching (numbers, faces, shapes, words)	1	Emerson & Cantlon (2015)
Mathematical Tasks (Behavioral)		
Calculation (WJ-III)	2	Price et al. (2016); Schwartz et al. (2020)
Numerical Operations (WIAT-II)	2	Evans et al. (2015); Battista et al. (2018)
Math Fluency (Rapid Calculation)	3	Demir-Lira et al. (2016); Suárez-Pellicioni & Booth (2018); Schwartz et al. (2020)
Specific Multiplication (CMAT subtest)	3	Suárez-Pellicioni et al. (2021); Wang et al. (2022); Ren et al. (2024)
Applied Problems & Math Reasoning	3	Evans et al. (2015); Price et al. (2016); Schwartz et al. (2020)
Number Line Estimation	2	McCaskey et al. (2018); McCaskey et al. (2020)

tion from counting strategies to efficient memory-based problem solving.

Socioeconomic status (SES) was identified as a neural predictor of math growth, with high-SES children relying more on verbal systems (IFG) and low-SES children on spatial systems (PSPL/Precuneus). Neuroimaging data from working memory tasks were better predictors of identifying children at risk of future low academic performance in mathematics than behavioral working memory measures alone.

Finally, structural abnormalities in numerical processing regions and atypical frontoparietal connectivity before formal schooling were predictors of children who were later diagnosed with developmental dyscalculia.

Anatomical Neural Correlates: In summary, the neural correlates highlighted in the reviewed studies include parietal, frontal, temporal, and occipital regions. A total of 25 cortical regions were identified across the reviewed studies, which are represented in Figure 2.

Specifically, parietal regions cited inclucded the superior parietal lobule (SPL/IPS); supramarginal gyrus (SMG); inferior parietal lobule (angular gyrus); precuneus and postcentral gyrus.

Frontal regions included the superior frontal gyrus (dlPFC); pars opercularis (vlPFC/IFG); pars triangularis (IFG); rostral middle frontal gyrus (MFG); caudal middle frontal gyrus (MFG/premotor); frontal pole, lateral orbitofrontal cortex (OFC); caudal anterior cingulate cortex (ACC) and the precentral gyrus (premotor).

Temporal regions included the superior temporal gyrus (STG); middle temporal gyrus (MTG); inferior temporal gyrus (ITG); temporal pole; parahippocampal gyrus (PHG) and fusiform gyrus.

Occipital regions included the cuneus, lingual gyrus and lateral occipital cortex (MOG). Finally, other regions such as the insula, hippocampus, thalamus, and putamen were also highlighted in the results of the studies reviewed here.

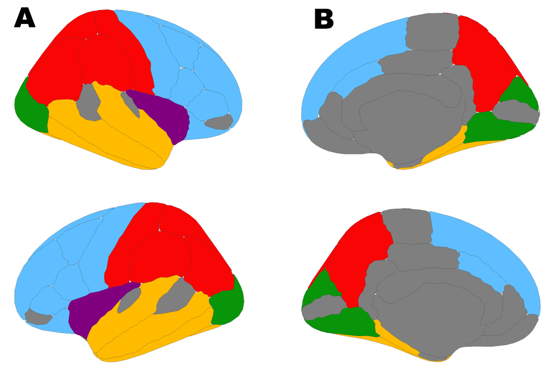

Figure 2: Brain regions mentioned in the results of 19 longitudinal neuroimaging studies of mathematical cognition in children. (A) Lateral view of the brain, with the right hemisphere shown at the top and the left hemisphere at the bottom. (B) Medial view, with the right hemisphere at the top and the left hemisphere at the bottom. Brain regions are displayed following the Desikan–Killiany atlas and are color-coded by anatomical location: parietal regions (red), frontal regions (blue), temporal regions (orange), occipital regions (green), and Insula (purple).

Discussion and Conclusions

This review synthesized current evidence on longitudinal neuroimaging studies of mathematical cognition in school-aged children, highlighting a dynamic, multi-component system that evolves from structural foundations into functionally specialized networks.

In summary, a key limitation is the scarcity of longitudinal studies; most available evidence comes from cross-sectional designs, which, although more established, cannot capture developmental trajectories. Even among the few longitudinal studies identified, neuroimaging data were often collected only once, limiting the construction of predictive models of structural and functional change over time.

The most frequently used neuroimaging technique was MRI. However, MRI environments are often aversive for young children, which limits the generalization of findings to naturalistic learning contexts and the ecological validity of the findings.

The WEIRD population bias also persists, particularly in longitudinal work, though recent cross-sectional studies suggest progress, such as the studies of Fonseca et al. (2025) and Bezuidenhout et al. (2026). Extending such advances to longitudinal designs that incorporate cultural and socio-economic diversity will be essential for a broader understanding of longitudinal development of mathematical cognition and its neural correlates.

Future research should prioritize the development of robust longitudinal predictive models, conducted in naturalistic contexts and with greater sociocultural representation. Techniques such as functional near-infrared spectroscopy (fNIRS), combined with EEG, may offer more feasible and ecologically valid approaches for studying young children in realistic educational settings.

This review has several limitations that should be mentioned. Some relevant studies may have been missed because search strings did not explicitly include terms such as numerosity or arithmetic fluency; the six-page limit required a brief synthesis of the results; despite the systematic search strategy and clearly defined inclusion and exclusion criteria, the screening and selection process involved only one independent reviewer, which may have introduced bias. Addressing these weaknesses, the next step will be a full systematic review following the PRISMA checklist to ensure methodological rigor and comprehensiveness.

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