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RESEARCH ARTICLE

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# Long-term abacus training gains in children are predicted by medial temporal lobe anatomy and circuitry

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## Abstract

Abacus-based mental calculation (AMC) is a widely used educational tool for enhancing math learning, offering an accessible and cost-effective method for classroom implementation. Despite its universal appeal, the neurocognitive mechanisms that drive the efficacy of AMC training remain poorly understood. Notably, although abacus training relies heavily on the rapid recall of number positions and sequences, the role of memory systems in driving long-term AMC learning remains unknown. Here, we sought to address this gap by investigating the role of the medial temporal lobe (MTL) memory system in predicting long-term AMC training gains in second-grade children, who were longitudinally assessed up to fifth grade. Leveraging multimodal neuroimaging data, we tested the hypothesis that MTL systems, known for their involvement in associative memory, are instrumental in facilitating AMC-induced improvements in math skills. We found that gray matter volume in bilateral MTL, along with functional connectivity between the MTL and frontal and ventral temporal-occipital cortices, significantly predicted learning gains. Intriguingly, greater gray matter volume but weaker connectivity of the posterior parietal cortex predicted better learning outcomes, offering a more nuanced view of brain systems at play in AMC training. Our findings not only underscore the critical role of the MTL memory system in AMC training but also illuminate the neurobiological factors contributing to individual differences in cognitive skill acquisition.

Ye Xie and Hyesang Chang contributed equally to this study.

**KEYWORDS**
abacus, individual difference, longitudinal cognitive intervention, medial temporal lobe, mental calculation, multi-modal neuroimaging

**Research Highlights**

- We investigated the role of medial temporal lobe (MTL) memory system in driving children's math learning following abacus-based mental calculation (AMC) training.
- AMC training improved math skills in elementary school children across their second and fifth grade.
- MTL structural integrity and functional connectivity with prefrontal and ventral temporal-occipital cortices predicted long-term AMC training-related gains.

## 1 | INTRODUCTION

Since its introduction in the 1200s, the abacus has stood the test of time as an educational tool for mastering mental arithmetic (Butterworth, 2006; Li et al., 2016; Wang et al., 2013). It provides a platform for efficient mental calculations; individuals proficient in abacus demonstrate the ability to solve complex arithmetic problems involving large numbers and multiple operations with remarkable speed and accuracy (Hatano & Osawa, 1983) (Figure 1A shows an example of abacus-based calculation). Although abacus-based mental calculation (AMC) training has been shown to effectively enhance arithmetic skills in children (Du et al., 2014; Ku et al., 2012), little is known about the neurocognitive mechanisms that drive long-term AMC learning gains. To address this knowledge gap, we used a multimodal brain imaging approach and multiyear longitudinal assessments to examine children's mathematical problem-solving abilities in relation to AMC training. Understanding whether the integrity of brain structure and functional circuits predicts long-term AMC training gains can provide valuable insights into brain-based biomarkers of individual differences in response to interventions. Findings also have the potential to enhance the development of mathematical abilities in childhood, which may serve as a foundation for future academic and professional achievements (Butterworth et al., 2011; Geary et al., 2017; Iuculano & Menon, 2018; National Mathematics Advisory Panel, 2008; PISA, 2017).

Proficient use of the abacus involves the rapid recall of number positions and sequences and integration of multiple mnemonic functions (Frank & Barner, 2012; Hanakawa et al., 2003; Hatano & Osawa, 1983; Stigler, 1984), a cognitive process intricately linked to associative memory systems in the brain. There is growing evidence for a critical role of the medial temporal lobe (MTL) learning and memory system, encompassing the hippocampus and parahippocampal gyrus, in children's arithmetic problem solving and learning (Chang et al., 2019, 2022; Cho et al., 2011, 2012; De Smedt et al., 2011; Fias et al., 2013; Menon, 2016; Peters & De Smedt, 2018; Qin et al., 2014; Rivera et al., 2005; Rosenberg-Lee et al., 2018; Supekar et al., 2013). Notably, a previous study found that morphometry and intrinsic connectivity of the hippocampus prior to training predicted arithmetic performance gains after 8 weeks of short-term math fact retrieval training in children (Supekar et al., 2013). In another study, the intrinsic connectivity of the hippocampus predicted learning in response to 4 weeks of fundamental number sense training in children, which suggests a wide role for the MTL system in math learning (Chang et al., 2022). This finding was further solidified by meta-analysis of 14,371 studies which identified hippocampal circuits as canonical learning pathways across multiple study contexts (Chang et al., 2022).

Superior math abilities in experienced abacus users are thought to arise from structured mnemonic representations of numbers as exceptional memory for sequence of numbers has been observed in these individuals (Hatano & Osawa, 1983). Enhanced ability to process and access representations of numbers is thought to underpin proficient use of abacus (Cui et al., 2020; Yao et al., 2015). Furthermore, fluent use of abacus involves integration of multiple cognitive processes, including number representation, math facts, and abacus principles (Frank & Barner, 2012; Hanakawa et al., 2003; Stigler, 1984), which is closely aligned with the pivotal role of the MTL system in the formation of integrated memory representations (Menon, 2016; Zeithamova & Bowman, 2020). Despite the strong conceptual link between mnemonic functions and skilled abacus use, there has been a lack of systematic investigation into the predictive role of the MTL learning and memory system in long-term AMC training gains. This critical gap in literature leaves unanswered questions about whether established functions of the MTL system may be broadly applicable to mathematical learning contexts that are not explicitly linked to fact retrieval.

In the current study, we investigated the neural underpinnings of long-term gains in math abilities associated with AMC training in elementary school aged children. Children enrolled in the study were either assigned to receive AMC training in addition to math classes (Supplementary video data) or continued with their regular math classes as a control group. After one year of AMC training, 45 second grade children aged 7–9 years completed structural and functional MRI scans. The control group comprised 26 age-, gender-, and IQ-matched children completed all aspects of the study except for the AMC training. To evaluate long-term learning gains, we assessed children's learning rates using standardized math tests from their second to fifth grade in elementary school (Figure 1B).

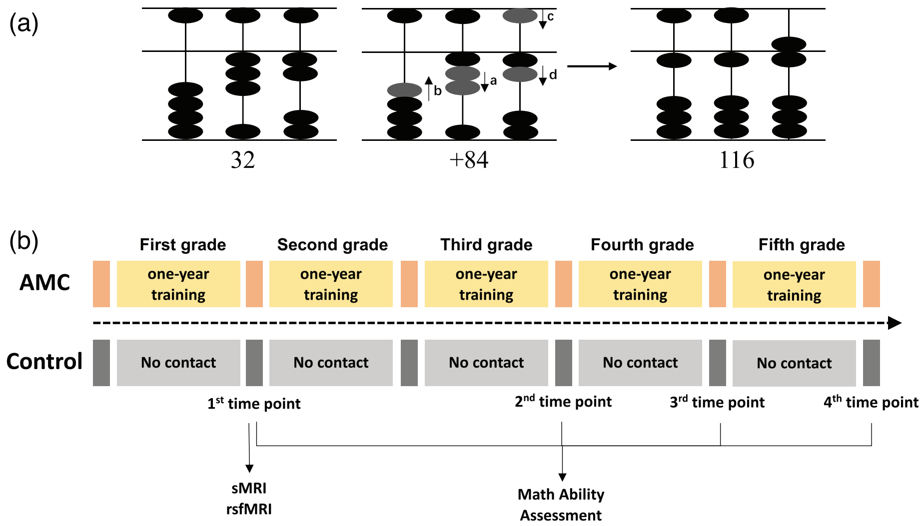


**FIGURE 1** Sample abacus calculation procedure and the study design. (A) *An example of abacus calculation of 32 + 84*. The three columns from the right to left represent digits of ones, tens and hundreds. Each of the beads located in the upper part of the abacus represents five when pushed down while each of the beads in the lower part of the abacus represents 1 when pushed up. To achieve the calculation of 32+84, (a) two beads in the tens-digit column were pushed down (↓) and (b) one bead in the hundreds-digit column was pushed up (↑) (adding eight equals adding 10 minus 2). Then, (c) one bead in the upper part of the ones-digit column was pushed down (↓) and (d) one bead in the lower part of the ones-digit column was pushed down (↓) (adding four equals adding 5 minus 1). The result of this calculation was 116. (B) *The study design*. Participants were assigned to abacus-based mental calculation training (AMC) or control group at the beginning of their first grade. Children in the AMC group completed up to 5 years of longitudinal training in school (2 h each week) from the beginning of their first grade. Structural and resting-state functional MRI scans were collected at the 1st time point (after 1-year training). Math ability was assessed from the 1st time point to the 2nd, 3rd, or 4th time point (after 3–5 years of training) (see Material and Methods for more details). The control group completed all aspects of the study except for AMC training.

Our primary objective was to determine whether the MTL learning and memory system drives individual differences in learning outcomes following AMC training. Building on our prior findings of the critical role of the MTL in math learning (Chang et al., 2022; Supekar et al., 2013) and its general function in binding and consolidating memory representations (Menon, 2016; Zeithamova & Bowman, 2020), we hypothesized that gray matter volume and functional connectivity of the MTL would predict learning gains in the AMC group, but not the control group. We further extended our analysis to examine the potential role of the posterior parietal cortex (PPC), a brain region implicated in numerical cognition and visuospatial attention (Butterworth & Walsh, 2011; Hubbard et al., 2005; Menon & Chang, 2021) as well as performance in experienced abacus users (Du et al., 2013; Li, Hu et al., 2013). Specifically, we aimed to establish whether the MTL and PPC systems contribute to learning gains in a similar or distinct manner in the context of long-term AMC training.

## 2 | MATERIAL AND METHODS

### 2.1 | Participants

A total of 105 children (abacus-based mental calculation [AMC] group: $n$ = 57; control group: $n$ = 48) from The Chinese Abacus Training Project (CATP; see Supplementary methods for details) participated in the current study. Participants in the AMC group received AMC training in addition to regular math classes from the beginning of their first grade to the end of fifth grade, while participants in the control group continued receiving regular math classes. Children in the control group were provided with additional learning of conventional study materials, such as calculation and reading, for the equivalent duration as additional learning of abacus in the AMC group. Participants' math ability assessments were administered from the 1st time point (see Figure 1B for the study design), which corresponded to the beginning of their second grade, to the 2nd, 3rd, and 4th time points in the following four years. Starting math ability assessments from the 1st time point ensured that participants have acquired fundamental knowledge about arithmetic operations and visuospatial reasoning to complete the assessments (see *Math ability assessments* for more details). Participants' neuroimaging data were acquired at the 1st time point.

To address questions about longitudinal predictors of math learning, we included participants who completed both (1) the neuroimaging session at the 1st time point (beginning of the 2nd grade in elementary school) and (2) math ability assessments at the 1st time point and at least one additional math ability assessment between 2nd and 4th time points. Among a total of 105 participants enrolled in the study (AMC: $N$ = 57; control: $N$ = 48), 10 participants (AMC: $n$ = 5; control: $n$ = 5) were not able to complete neuroimaging session or had poor structural imaging quality; 23 participants (AMC: $n$ = 7; control: $n$ = 16) had incomplete math ability assessments; and 1 participant in the control group was missing demographic information. As a result, 71 participants (AMC: $n = 45$; control: $n = 26$) were included in behavioral and structural neuroimaging data analysis. AMC and control groups were well matched in terms of age ($p = 0.89$), gender ($p = 0.42$), and IQ ($p = 0.38$) at the 1st time point. Demographic characteristics are shown in Table S1.

Considering potential loss to follow up in AMC and control groups in the current study, we additionally confirmed that data were missing at random by examining whether math ability at the 1st time point in each group was equivalent between participants who completed the current study and those who dropped out from the study after the 1st time point. Among those who had math ability scores at the 1st time point, there was no significant difference in math ability between participants who completed the study and those who dropped out from the study (AMC group: completed: $n = 45$, $M \pm SD$: $53.65 \pm 8.82$; dropout: $n = 10$, $M \pm SD$: $52.10 \pm 9.02$; $t(53) = -0.50$, $p = 0.62$; control group: completed: $n = 26$, $M \pm SD$: $49.42 \pm 7.33$; dropout: $n = 20$, $M \pm SD$: $48.02 \pm 9.06$; $t(44) = -0.58$, $p = 0.57$).

For functional MRI (fMRI) data analysis, five participants from the AMC group and five participants from the control group were further excluded due to high head motion (displacement > 3 mm or rotation > 3°). A total of 40 participants in the AMC group and 21 participants in the control group were included in fMRI data analysis, with the two groups well-matched in terms of age, gender, and IQ at the 1st time point (all $ps > 0.05$).

The final sample size of the training group for structural and functional MRI analysis ($N = 40$–$45$) was determined adequate (estimated power > 85%) for brain-behavior association analysis based on previous neuroimaging studies of math intervention in children (range of Cohen's $d$: 1.0–1.2) (Iuculano et al., 2015; Supekar et al., 2021). Due to the modest sample size in the control group, our brain-behavior association analysis focused on the training group.

All participants had normal or corrected-to-normal vision and none reported any history of hearing loss, neurological or psychiatric disorders, or requirements for special educational assistance. The study was approved by Zhejiang University in China. All procedures followed were in compliance with the guidelines of the Helsinki Declaration. All the parents (or other guardians) of the participants provided written informed consents.

## 2.2 | Abacus training protocol

Participants in the AMC group completed up to 5 years of training from the beginning of their first grade to the end of their third, fourth or fifth grade (duration of training: $M \pm SD = 4.36 \pm 0.48$ years) in an elementary school in Qiqihar, Heilongjiang Province of China. AMC training involved teaching participants how to add, subtract, multiply, or divide numbers with the abacus with both hands (see Figure 1A for an example of the abacus calculation procedure). The training session occurred for 2 h each week throughout the school year (approximately 320 h for the full 5-year training after excluding absence due to vacations, examinations, and other school events).

Participants in the AMC group first learned the principles of abacus operation and performed calculations with a physical abacus. They were then asked to solve arithmetic problems by visualizing the operation of beads in abacus in their mind. During this period, finger movements were allowed to assist with imaginary movements of beads (see Supplementary video data). They were then asked to calculate quickly and accurately via visualization of abacus calculations without finger movements. Throughout the course of this long-term training, difficulty levels were adjusted in a stepwise manner to improve their AMC skills gradually. Even after participants acquired the skill to perform mental arithmetic without the use of physical abacus, they continued to receive training on the physical abacus to facilitate learning of increasingly difficult problems. All participants in the AMC group passed the basic level of the qualification examination of the Chinese Abacus and Mental Arithmetic Association at the 1st time point (after one-year training), which included serial addition and subtraction of six numbers (e.g., $89 + 8 - 6 + 2 - 46 + 7$). Participants continuously improved at later time points. With long-term practice, they were able to automatically process and manipulate numerical representations on the mental abacus, allowing them to achieve rapid and precise mental arithmetic performance without the physical apparatus. By the end of 5 years of training (4th time point), most participants in the AMC group achieved high levels of the qualification examination, which involves serial addition and subtraction of 10 numbers (e.g., $9847 - 625 + 56 - 1839 + 716 + 2943 + 807 + 61 + 325 - 40$) and large multiplication (e.g., $496 \times 357$) and division (e.g., $26670 \div 381$) problems.

## 2.3 | Cognitive assessments

### 2.3.1 | IQ assessment

Participants' intelligence quotient (IQ) was assessed by the Chinese version of the Combined Raven's test (Dong et al., 2007). Raw scores were standardized based on the age norm of Chinese urban children for each participant.

### 2.3.2 | Math ability assessment

Participants' math ability was assessed by the Chinese version of a standardized math test, *The Heidelberger Rechentest* (Haffner et al., 2005; Li & Wu, 2004; Wu & Li, 2005). This test assessed participants' overall math skills, including arithmetic and visuospatial math ability components, which are two aspects of math ability closely related to AMC training. The arithmetic component consisted of six time-limited subtests (maximum number of problems, time limit): addition (40 problems, 1 min), subtraction (40 problems, 1 min), multiplication (40 problems, 1 min), division (40 problems, 1 min), filling in missing number in equations (40 problems, 2 min), and number comparisons (40 problems, 1 min). The visuospatial math ability component consisted of five time-limited subtests, including length estimation (24 problems, 3 min), cube counting (28 problems, 3 min), number sequencing (20 problems, 3 min), object counting (21 problems, 1 min), and connecting numbers (10 problems, 2 min). The final score was converted into *t*-scores according to Chinese national norms based on grade, which ranked the child's math ability among their peers.

Math ability was assessed at four time points: (1) after a year of training; (2) after three years of training; (3) after four years of training; and (4) after five years of training (see Figure 1B for the study design). Considering that participants did not receive training in multiplication and division in the first grade, these two subtests were not tested in the 1st time point but in the following three time points when these arithmetic operations were practiced. All participants included in data analysis completed the math ability assessment at the 1st time point. In the AMC group, math ability was assessed twice in three participants, three times in 26 participants, and four times in 16 participants. In the control group, math ability was assessed three times in four participants, and four times in 22 participants. To account for varying number of math ability scores acquired at different time points across participants, time points and corresponding math ability scores were entered into a hierarchical linear mixed effects model (Bates et al., 2015) in each group. The slope of each individual in this model was used as learning gains in math ability across time points for each participant. Group differences were tested by two sample *t*-tests.

## 2.4 | Structural and functional MRI data acquisition

Structural and resting-state functional MRI data were acquired from all participants using a 1.5-T scanner (Achieva, Philips) with 8-channel head coil. High-resolution structural images were obtained using a 3-dimensional fast field sequence with following parameters: TR = 25 ms, TE = 4.6 ms, flip angle = 15°, FOV = 256 mm × 256 mm, acquisition matrix = 256 × 256, reconstruction voxel size = 1 × 1 × 1 $mm^3$, 150 slices in the sagittal plane.

Resting-state functional images were acquired for 6 min using a single-shot echo planar imaging (EPI) sequence with the following parameters: TR = 2000 ms, TE = 50 ms, flip angle = 90°, FOV = 230 mm × 230 mm, matrix = 64 × 64, slice thickness/gap = 5 mm/0.8 mm, 22 interleaved ascending slices covering the whole brain.

## 2.5 | Voxel-based morphometry (VBM)

T1-weighted images were manually aligned to conventional anterior commissure (AC)—posterior commissure (PC) space with landmarks including the AC, PC and midsagittal plane and analyzed with the Computational Anatomy Toolbox (CAT) implemented (http://www.neuro.uni-jena.de/cat/) in the Statistical Parametric Mapping (SPM12) software (https://www.fil.ion.ucl.ac.uk/spm/software/spm12/). The analysis procedure included skull stripping, segmentation of images into gray matter, white matter and cerebrospinal fluid probability images, and spatial normalization of gray matter images to a customized gray matter template in standard Montreal Neurological Institute (MNI) space. Gray matter probability maps were thresholded at 0.1 to minimize inclusion of incorrect tissue types. The images were modulated with Jacobian determinants and after segmentation they were smoothed with an isotropic Gaussian Kernel (8 mm full-width half maximum [FWHM]). Finally, whole brain regression analysis was performed within each group with gray matter volume as an independent variable, learning gains as a dependent variable, and total intracranial volume (TIV) and math ability at the 1st time point as covariates of no interest. Statistical threshold was set as height threshold of $p < 0.005$ and extent threshold of $p < 0.05$ (70 voxels) based on Monte Carlo simulations within a gray matter mask. This statistical threshold was chosen to balance Type I and Type II errors in the current study, considering that larger sample sizes are typically needed to detect effects with a more stringent threshold (Carter et al., 2016). To address potential concern about lenient height threshold of $p = 0.005$, additional height threshold of $p = 0.001$ (uncorrected) is provided for significant regions at $p < 0.005$, $k > 70$ in Supplementary Tables. Anatomical locations of brain regions were identified by AAL (Tzourio-Mazoyer et al., 2002), Harvard–Oxford atlas (Desikan et al., 2006), and Juelich histological atlas (Eickhoff et al., 2005). Follow-up correlation and regression analyses examined the relationship between gray matter volume of regions of interest (ROIs; clusters identified from whole brain analysis) and learning gains, controlling for the TIV and math ability at the 1st time point.

## 2.6 | fMRI data processing and analysis

The first five functional images were discarded to allow for signal equilibrium. Images were preprocessed and analyzed using the CONN toolbox (Whitfield-Gabrieli & Nieto-Castanon, 2012). The preprocessing procedure included following steps: realign and unwrap, slice timing, segmentation, and normalization, and 6 mm FWHM Gaussian kernel smoothing. In addition to the six motion parameters and their first derivatives, WM signals and CSF signals were removed with CompCor method (Behzadi et al., 2007). This component-based noise correction method reduces physiological and extraneous noise and provides interpretative information on correlated and anticorrelated functional brain networks. The time series was detrended and a 0.01–0.08 Hz band-pass filter was applied.

Functional connectivity analysis was conducted by the CONN toolbox. Our analysis focused on medial temporal lobe (MTL) and posterior parietal cortical (PPC) regions implicated in math learning (Supekar et al., 2013) and numerical cognition and visuospatial attention (Menon & Chang, 2021), respectively. MTL and PPC ROIs were obtained from the structural regression analysis in the AMC group and were used as seed ROIs in seed-to-voxel functional connectivity analysis in each subject. Whole brain regression analysis was performed for each group to investigate whether functional circuits of the ROIs are predictive of learning gains, with math ability at the 1st time point as a covariate of no interest. Statistical threshold was set at height threshold of $p < 0.005$ and extent threshold of $p < 0.05$ (70 voxels) based on

Monte Carlo simulations with gray matter mask of Anatomical Automatic Labelling (AAL) 90 regions (Tzourio-Mazoyer et al., 2002). This statistical threshold was chosen to balance Types I and II errors in the current study, considering that larger sample sizes are typically needed to detect effects with a more stringent threshold (Carter et al., 2016). To address potential concern about lenient height threshold of $p = 0.005$, additional height threshold of $p = 0.001$ (uncorrected) is provided for significant regions at $p < 0.005$, $k > 70$ in Supplementary Tables. Significant clusters were determined after gray matter masking. Anatomical locations of brain regions were identified by AAL, Harvard–Oxford atlas, and Juelich histological atlas.

Follow-up ROI analysis was performed to visualize results and ensure the findings were not driven by outliers and to confirm group differences in relation between functional connectivity and learning gains for each ROI. ROIs were clusters showing significant results from whole brain analysis.

## 2.7 | Confirmatory cross-validation analysis

A machine-learning approach combining balanced cross-validation and linear regression (Cohen, 2010; Supekar et al., 2013) using the Python regressioncv toolbox (https://github.com/poldrack/regressioncv) was applied to examine the robustness of predictive ability of gray matter volume and functional circuits of MTL ROIs. Brain measure (gray matter volume or functional connectivity of MTL regions) and learning gains in math ability were included as independent and dependent variables in a linear regression algorithm after regressing out covariates of no interest (TIV and/or math ability at the 1st time point). A cross-validation procedure was performed by dividing the data into four folds so that the distribution of dependent and independent variables was balanced across folds. Using a leave-one-out method, a linear regression model was built using three folds and used the left-out fold to predict the data. By repeating this procedure four times, *r(pred, actual)*, the correlation between the values predicted by regression model and the observed values, was computed to represent how well the independent variable predicts the dependent variable. Nonparametric permutation testing (1000 samples) was used to assess the statistical significance of the regression algorithm. Parallel analysis was conducted for PPC ROIs.

# 3 | RESULTS

## 3.1 | The abacus-based mental calculation (AMC) group showed greater long-term learning gains than the control group

We first examined whether AMC training resulted in significantly greater learning gains after a year of training, compared to the control group, who only attended business-as-usual math classes during the same period. After a year training (at the 1st time point; see also Figure 1B), the AMC group performed significantly better on the com-

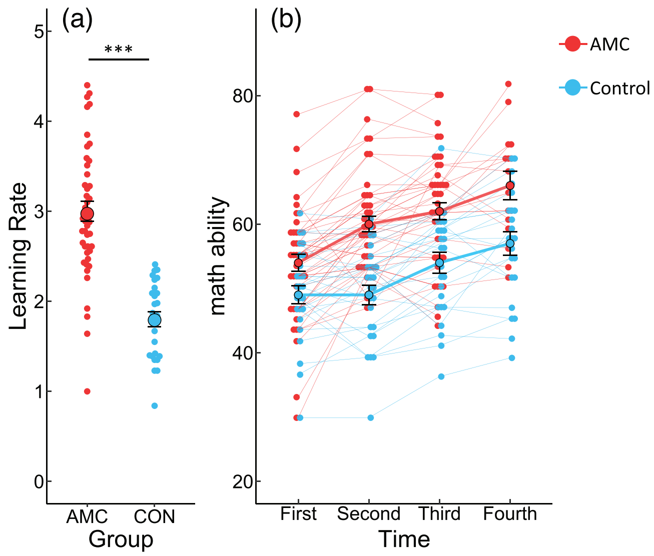


**FIGURE 2** Behavioral results. (A) *Learning gains from the 1st time point*. Each individual's slope in a hierarchical linear mixed effects model (see Material and Methods) was used to determine learning gains in math ability from the 1st time point (see also Figure 1B) for each participant. The abacus mental calculation training (AMC) group showed higher learning gains in math ability than the control group. Individual data points are shown in red (AMC group) and blue (control group) dots. Group means are shown in red (AMC group) and blue (control group) circles with black outlines. Error bar represents standard error of the mean. ***, $p < 0.001$. (B) *Individual learning trajectories in each group*. Each individual's score on math ability assessments at each time point is shown in red (AMC group) and blue (control group) dots. Red and blue lines connecting the dots display individual learning trajectories in the AMC and control groups, respectively. Group means for math ability assessments at each time point are shown in red (AMC group) and blue (control group) circles with black outlines. Error bar represents standard error of the mean.

posite score of standardized math ability tests than gender-, age-, and IQ-matched control group (AMC group: $M \pm SD = 53.65 \pm 8.82$; control group: $M \pm SD = 49.42 \pm 7.33$; $t(69) = 2.07$, $p = 0.042$, paired $t$-test). This finding indicates significant improvements in general math ability after one year of AMC training when compared to only participating in regular math classroom activities.

To examine long-term AMC training gains spanning multiple years, we then assessed the rate of learning on standardized math ability tests across second and fifth training years in the AMC group, compared to the control group. As math ability scores were acquired at various time points between second and fifth training years, time points and corresponding math ability scores were entered into a hierarchical linear mixed effects model (Bates et al., 2015) in each group. Participant-specific slopes in this model were then used as a measure of individual learning rates. Learning rates were significantly higher in the AMC training group than the control group (Figure 2A; AMC group: $M \pm SD = 2.97 \pm 0.73$; control group: $M \pm SD = 1.79 \pm 0.44$; $t(69) = 7.54$, $p < 0.001$, paired $t$-test). Participants in both groups showed considerable individual differences in learning rates (coefficient of variation: AMC group: 0.24, control group: 0.24; Figure 2B). These results

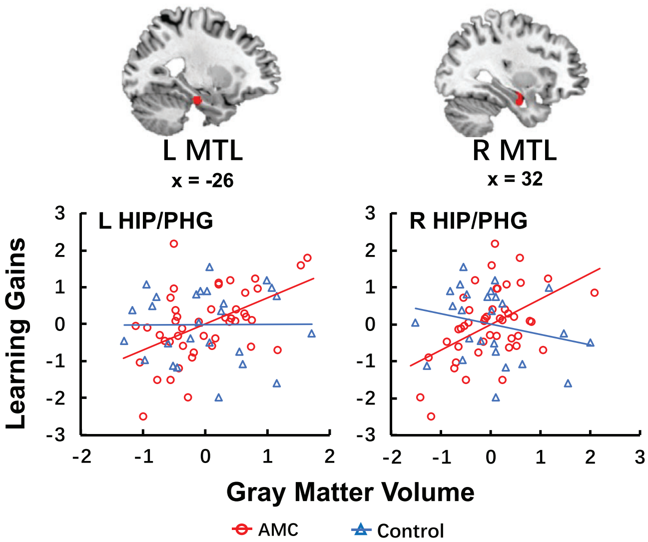


**FIGURE 3** Gray matter volume of medial temporal lobe (MTL) regions predicts learning gains in math ability in the abacus mental calculation training (AMC) group. Results are based on a whole-brain voxel-based morphometry (VBM) regression analysis with total intracranial volume (TIV) and controlling for math ability at the 1st time point as covariates of no interest (height threshold $p < 0.005$; extent threshold $p < 0.05$, 70 voxels). HIP = hippocampus; PHG = parahippocampal gyrus; L = left; R = right.

demonstrate significantly greater long-term math learning gains in the AMC group than the control group.

## 3.2 | Gray matter volume of the medial temporal lobe (MTL) predicts individual differences in long-term math learning gains in the AMC group

Next, to address our main question about the brain basis of individual differences in long-term learning gains in response to AMC training, we used voxel-based morphometry (VBM) to determine whether structural integrity of the MTL at the 1st time point could predict longitudinal learning gains.

Using a whole brain regression analysis, we found that gray matter volume in multiple brain regions was associated with learning gains in the AMC group. Here, gray matter volume of the bilateral MTL, PPC, postcentral gyrus, and orbitofrontal gyrus and the left putamen, right posterior cingulate cortex, right superior temporal gyrus, and left ventral temporal-occipital cortices (VTOC) showed a positive association with learning gains (Table S2). Gray matter volume of the bilateral inferior frontal gyrus, left middle frontal gyrus, and left fusiform gyrus showed a negative association with learning gains.

Our ROI analysis focused on the MTL (left hippocampus and parahippocampal gyrus; peak MNI coordinate: [−26, −21, −23]; right hippocampus and parahippocampal gyrus [32, −9, −24]), implicated in math learning (Supekar et al., 2013) (Figure 3). We found that gray matter volume of the left MTL and the right MTL was positively correlated with math learning gains in the AMC group (left MTL: $r = 0.49$, right MTL: $r = 0.48$), but not in the control group ($ps > 0.22$), with significant between-group differences in brain-behavior associations ($ps < 0.04$; Table S6). To further examine predictive ability of structural measures, we performed additional cross-validation analysis using machine learning algorithms. Gray matter volume of both the left MTL [$r(pred, actual) = 0.42$, $p < 0.001$] and the right MTL [$r(pred, actual) = 0.40$, $p < 0.001$] predicted learning gains in the AMC group, but not in the control group ($ps > 0.22$), with significant group differences in prediction power ($ps < 0.04$). Additional analysis controlling for IQ showed similar results (Supplementary Results).

Together, these results demonstrate that structural integrity of the MTL is predictive of long-term math learning gains in response to AMC training.

## 3.3 | Gray matter volume of the posterior parietal cortex (PPC) predicts individual differences in long-term math learning gains in the AMC group

Next, to contrast to the role of the MTL, among regions in which gray matter volume was associated with learning gains in the AMC group, our ROI analysis focused on the PPC (left intraparietal sulcus and superior parietal lobule [−26 −62 45] right intraparietal sulcus and supramarginal gyrus [44 −48 47]), implicated in numerical cognition and visuospatial attention (Menon & Chang, 2021) (Figure S1).

Correlation analysis revealed that gray matter volume in the left PPC and right PPC was positively correlated with learning gains in the AMC group (left PPC: $r = 0.46$; right PPC: $r = 0.48$), but not in the control group ($ps > 0.40$), with significant between-group differences in brain-behavior associations ($ps < 0.04$; Table S6). Confirmatory analysis using machine learning approach showed that gray matter volume of both the left PPC [$r(pred, actual) = 0.38$, $p < 0.001$] and the right PPC [$r(pred, actual) = 0.41$, $p < 0.001$] predicted the learning gains in the AMC group, but not in the control group ($ps > 0.63$), with significant group differences in prediction power ($ps < 0.002$). Additional analysis controlling for IQ showed similar results (Supplementary Results).

Together, these results demonstrate that structural integrity of the PPC is predictive of long-term math learning gains in response to AMC training.

## 3.4 | Greater functional connectivity of the MTL predicts long-term math learning gains in the AMC group

Our next goal was to determine whether functional connectivity of the MTL predicts individual differences in long-term math learning gains with AMC training, and to identify target brain areas associated with this prediction. We performed a whole brain regression analysis with intrinsic connectivity of the MTL as the independent variable, learning gains as the dependent variable, covarying out math ability at the 1st time point. Specifically, we focused on left and right hemisphere MTL regions whose structural integrity predicted learning gains.

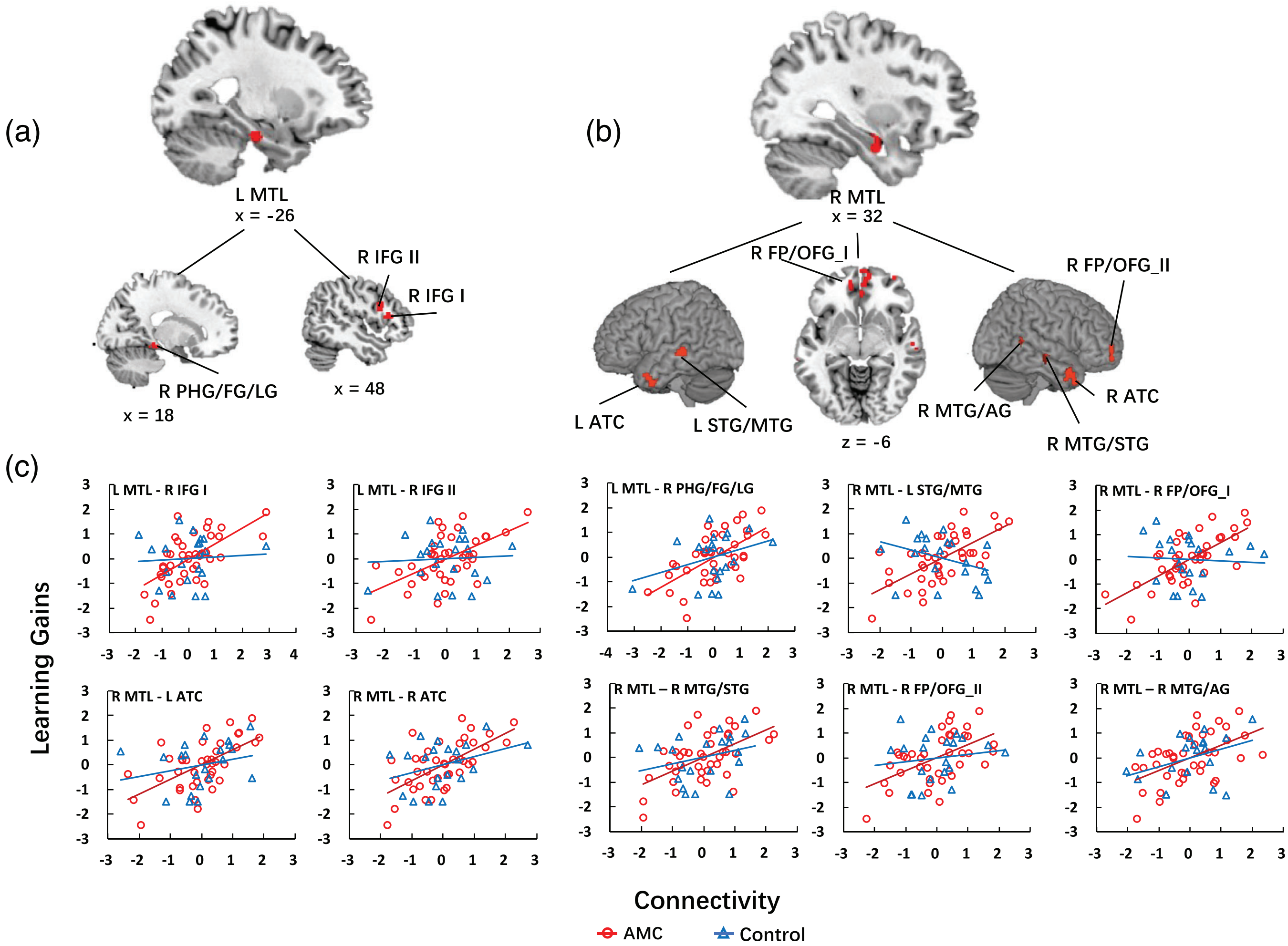


**FIGURE 4** Functional connectivity of medial temporal lobe (MTL) regions positively predicts learning gains in math ability in the abacus mental calculation training (AMC) group. A-B. Functional connectivity of the (A) left and (B) right MTL with frontal and temporal cortical regions was positively associated with learning gains in the AMC group. C. Scatter plots of the relation between MTL functional circuits and learning gains. Results are based on a whole-brain functional connectivity regression analysis controlling for math ability at the 1st time point as covariate of no interest (height threshold $p < 0.005$; extent threshold $p < 0.05$, 70 voxels; gray matter mask applied). No significant brain-behavior association was observed in the control group for the target regions identified in the AMC group. AG = angular gyrus; ATC = anterior temporal cortex; FG = fusiform gyrus; FP = frontal pole; IFG = inferior frontal gyrus; LG = lingual gyrus; MTG = middle temporal gyrus; OFG = orbitofrontal gyrus; PHG = parahippocampal gyrus; STG = superior temporal gyrus; L = left; R = right.

We found that functional connectivity of the left MTL with the right inferior frontal gyrus and right parahippocampal, fusiform and lingual gyri (Figure 4A; Table S3) and functional connectivity of the right MTL with the right orbitofrontal gyrus, bilateral middle temporal gyrus, and bilateral anterior temporal cortex (Figure 4B; Table S3) were positively correlated with learning gains in the AMC group (*rs* > 0.52), but not in the control group (*rs* < 0.38) (Figure 4C). Significant between-group differences in brain-behavior associations were found for connectivity of the left MTL with the right inferior frontal gyrus and right parahippocampal, fusiform and lingual gyri, and connectivity of the right MTL with the left middle temporal gyrus and right orbitofrontal gyrus (*ps* < 0.03) (Table S6). Additional analysis of functional connectivity of regions in which gray matter volume was related to learning also revealed that connectivity of frontal and VTOC regions was associated with learning (Supplementary Results). These results suggest functional circuits between MTL and frontal and VTOC regions support long-term learning gains.

Confirmatory analysis using a machine learning approach showed that functional connectivity of the left MTL with the right parahippocampal, fusiform and lingual gyri [*r(pred, actual)* = 0.58, $p < 0.001$] and the right inferior frontal gyrus [I: *r(pred, actual)* = 0.59, $p < 0.001$; II: *r(pred, actual)* = 0.51, $p < 0.001$] predicted learning gains in the AMC group. Functional connectivity of the right MTL with the bilateral middle and superior temporal gyri [left: *r(pred, actual)* = 0.60, $p < 0.001$; right: *r(pred, actual)* = 0.49, $p < 0.001$], bilateral anterior temporal cortex [left: *r(pred, actual)* = 0.54, $p < 0.001$; right: *r(pred, actual)* = 0.59, $p < 0.001$], right middle temporal and angular gyri [*r(pred, actual)* = 0.45, $p = 0.002$] and right frontal pole and orbitofrontal gyrus [I: *r(pred,* *actual)* = 0.65, $p < 0.001$; II: *r(pred, actual)* = 0.46, $p = 0.002$] predicted learning gains in the AMC group. No such relationships were observed in the control group (*ps* > 0.10). Significant group difference in prediction power was found for all these brain regions (*ps* < 0.04) expect for connectivity between the right MTL and right middle temporal and angular gyri ($p = 0.11$). Taken together, these results suggest that MTL functional circuits contribute to long-term learning gains in response to AMC training.

### 3.5 | PPC circuits predict reduced long-term math learning gains in the AMC group

Finally, considering the involvement of the PPC in visuospatial attention and numerical problem solving (Ansari, 2008; Arsalidou et al., 2018; Butterworth & Walsh, 2011; Hubbard et al., 2005; Menon & Chang, 2021; Nieder, 2016; Peters & De Smedt, 2018), we further examined whether functional connectivity of the PPC identified from whole brain VBM analysis was correlated with learning gains in response to AMC training. Here, we found that functional connectivity of the left PPC with the left superior parietal lobule and right orbitofrontal gyrus (Figure 5A; Table S4) and functional connectivity of the right PPC with the bilateral fusiform gyrus, bilateral middle occipital gyrus, left precentral gyrus, bilateral inferior frontal gyrus, and right calcarine (Figure 5B; Table S4) were negatively correlated with learning gains in the AMC group (*rs* < −0.52) (Figure 5C). Follow-up correlation analyses showed that in the control group, no significant association between functional connectivity of the PPC and learning gains was observed in the target regions identified from the AMC group (Figure 5C; |*rs*| < 0.30, *ps* > 0.19), except for left precentral and inferior frontal gyri (*rs* = −0.52, *ps* < 0.016). There were significant between-group differences in brain-behavior associations for all identified target regions (*ps* < 0.05), except for left precentral and inferior frontal gyri and the right calcarine (*ps* > 0.12).

Confirmatory analysis using machine learning approach further examined the predictive role of PPC circuits in learning. Functional connectivity of the PPC with all identified target regions predicted learning gains in the AMC group [*rs(pred, actual)* > 0.46, *ps* < 0.002]. In the control group, the relationship was not significant for all target regions (*ps* > 0.19), except for left precentral and inferior frontal gyri [*rs(pred, actual)* > 0.38, *ps* < 0.019]. Significant group differences in prediction power were found for all these brain regions (*ps* < 0.05), except for left precentral and inferior frontal gyri (*ps* > 0.26).

To further explore whether functional connectivity of PPC regions predicts long-term learning gains in a similar way as functional connectivity of MTL regions, we performed a multiple regression analysis with average positive or negative functional connectivity for each brain region as predictor and learning gains as dependent variable. Here we found that functional circuits of the right MTL positively predicted learning ($b = 3.27$, $se = 0.77$, $t = 4.25$), and functional circuits of the PPC negatively related to learning (left PPC: $b = -1.48$, $se = 0.44$, $t = -3.38$; right PPC: $b = -2.20$, $se = 0.61$, $t = -3.62$; Table S5).

Together, these results show that, in contrast to findings that stronger MTL functional circuitry is associated with better learning, stronger functional circuits of the PPC are associated with weaker learning following long-term abacus training.

## 4 | DISCUSSION

Leveraging data acquired from elementary-school-aged children in a five-year longitudinal study, we investigated the role of the medial temporal lobe (MTL) learning and memory system in predicting long-term gains from abacus-based mental calculation (AMC) training. We found that children who underwent AMC training showed greater long-term math learning gains than their well-matched peers in the control group who did not receive the training. Critically, individual differences in training-induced learning gains were predicted by structural integrity and functional connectivity of the MTL. Specifically, MTL functional connectivity with distributed frontal and ventral temporal-occipital cortical (VTOC) regions were predictive of subsequent growth in math abilities in the AMC training group. In contrast, functional connectivity of the posterior parietal cortex (PPC), a brain region consistently implicated in visuospatial attention and numerical cognition, was associated with lower longitudinal gains in math abilities. Our findings underscore the pivotal role of the MTL in long-term math learning via AMC training and provide insights that could inform pedagogical strategies for optimizing learning outcomes.

### 4.1 | Predictive role of the MTL in children's abacus-based math learning

The MTL is well-established as a central hub for learning and memory processes (Burgess et al., 2002; Collin et al., 2017; Eichenbaum, 2000; Horner & Doeller, 2017). Extending prior research emphasizing the involvement of the MTL in the learning and retrieval of math facts in both children and adults (Bloechle et al., 2016; Chang et al., 2019; Cho et al., 2011, 2012; De Smedt et al., 2011; Klein et al., 2019; Qin et al., 2014; Rosenberg-Lee et al., 2018; Supekar et al., 2013), we found that larger gray matter volume of the MTL predicted children's long-term math learning gains following AMC training. This convergence of evidence underscores the pivotal role of structural integrity of the MTL in individual differences in math skill acquisition across time periods and learning contexts.

Additionally, functional connectivity analyses revealed that coupling of the MTL with multiple prefrontal and VTOC regions predicted AMC training gains. Previous studies have suggested that abacus training induces plasticity of structural connectivity (Hu et al., 2011) and resting-state intrinsic functional connectivity (Xie et al., 2018; Xu et al., 2023; Zhang et al., 2021) as well as alteration in activation patterns of fronto-parietal and VTOC regions (Wang et al., 2017, 2019). MTL-prefrontal cortical functional circuits are thought to be crucial for long-term memory consolidation (Japee et al., 2015; Leung et al., 2002; Song et al., 2019) and has been shown to facilitate arithmetic fact

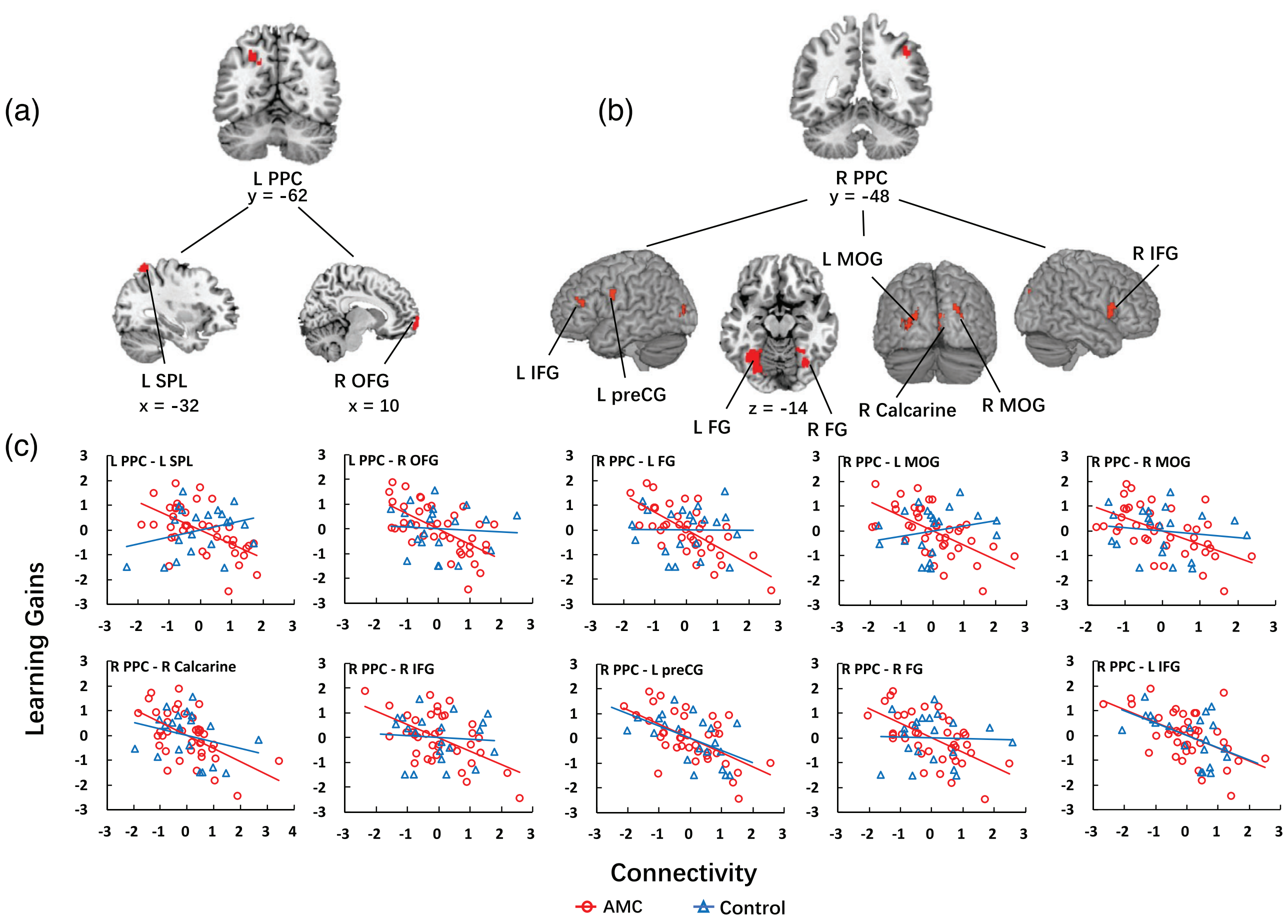


**FIGURE 5** Functional connectivity of posterior parietal cortex (PPC) regions negatively predicts learning gains in math ability in the abacus mental calculation training (AMC) group. A-B. Functional connectivity of the (A) left and (B) right PPC with multiple cortical regions was negatively associated with learning gains in the AMC group. C. Scatter plots of the relation between PPC functional circuits and learning gains. Results are based on a whole-brain functional connectivity regression analysis with math ability at the 1st time point as covariate of no interest (height threshold $p < 0.005$; extent threshold $p < 0.05$, 70 voxels; gray matter mask applied). No significant brain-behavior association was observed in the control group for the target regions identified in the AMC group, except for left precentral and inferior frontal gyri. FG = fusiform gyrus; IFG = inferior frontal gyri; MOG = middle occipital gyrus; OFG = orbitofrontal gyrus; preCG = precentral gyrus; SPL = superior parietal lobule; L = left; R = right.

retrieval in children (Cho et al., 2011; Menon, 2016; Qin et al., 2014). VTOC regions, including fusiform and lingual gyri, of which connectivity with the MTL was predictive of learning gains in the AMC group, have been implicated in a wide range of numerical tasks including quantity discrimination and mental arithmetic (Arsalidou & Taylor, 2011; Chen et al., 2021; Iuculano et al., 2018; Skagenholt et al., 2022). Furthermore, greater engagement and plasticity of the fusiform gyrus has been reported in AMC trained individuals, which provides convergent evidence for its role in representing numbers on mental abacus, which is associated with proficient abacus use (Hanakawa et al., 2003; Li, Wang, et al., 2013; Weng et al., 2017; Zhou et al., 2022). Our finding highlights the role of functional coupling of the MTL with medial VTOC regions in facilitating math skill acquisition via AMC training.

In summary, these results suggest that the functional integration of the MTL memory system with prefrontal and VTOC systems facilitates efficient long-term consolidation of math skills through AMC training. More broadly, our study provides evidence that the MTL's role extends beyond arithmetic fact retrieval and short-term learning to longitudinal development of problem-solving skills associated with AMC training.

### 4.2 | Influence of PPC on long-term gains in abacus-based math learning

Given the vital role of the PPC in visuospatial attention and numerical cognition (Butterworth & Walsh, 2011; Hubbard et al., 2005; Menon & Chang, 2021), we additionally examined the potential role of the PPC in AMC training gains. Understanding distinct roles of the medial temporal lobe (MTL) and the posterior parietal cortex (PPC) in abacus-based math skill acquisition is vital for several reasons. First, it enables a more comprehensive understanding of the neurocognitive mechanisms underpinning the development of numerical problem-solving skills. Each of these brain regions has been previously implicated in different aspects of mathematical learning, but their roles in the specific context of AMC training have not been elucidated. Second, contrasting the roles of the MTL and PPC can provide insights into how different neural circuits may be preferentially engaged to drive AMC learning.

Consistent with previous studies (De Smedt et al., 2019; Price et al., 2016), the structural integrity—specifically, the gray matter volume—of the PPC was positively correlated with mathematical learning gains following AMC training in children. Interestingly, these PPC regions did not emerge as targets in functional circuits involving the MTL at a whole-brain level, underscoring their distinct roles in long-term abacus learning. Instead, our analysis of functional connectivity of the PPC with other parietal, frontal, and VTOC regions revealed a negative correlation with long-term math learning gains in the AMC group. This finding is consistent with prior research suggesting that hyperconnectivity between the PPC and other brain regions negatively impacts math abilities (Abreu-Mendoza et al., 2021; Jolles et al., 2016; Price et al., 2018; Rosenberg-Lee et al., 2015). Moreover, similar to present findings, a recent arithmetic training study also observed reduced involvement of parietal circuits and increased engagement of hippocampal circuits associated with learning, which has been linked to reduced reliance on procedure based processing and increased use of retrieval based problem-solving strategy (Fias et al., 2021). These findings are broadly consistent with the notion that practice may lead to reduced effort and greater automaticity (Ericsson et al., 2018; Wang et al., 2013). The inverse relationship between PPC circuit engagement and learning outcomes further highlights the important role of strong MTL circuits in driving long-term learning gains in response to AMC training.

In summary, the contrasting roles of the MTL and PPC in abacus-based math skill acquisition provides a more comprehensive understanding of the neurocognitive mechanisms and underscores the pivotal role of the MTL in long-term math learning, further highlighting its importance relative to the PPC in the context of AMC training.

### 4.3 | Associative memory as a mechanism for skill acquisition in abacus-based learning

Our findings collectively indicate that the structural integrity and intrinsic connectivity of the MTL plays a critical role in the acquisition of mathematical skills through abacus-based training in elementary school children. Our finding is consistent with prior research showing that the hippocampus, a key component of the MTL, is instrumental in the formation and consolidation of long-term memory (Schapiro et al., 2019). Importantly, the hippocampus has been identified as a unique structure for forming associations between multidimensional cognitive spaces and facilitating generalized learning (Tavares et al., 2015; Theves et al., 2019). This ability to form associations is particularly relevant in the context of AMC, which necessitates the integration of visuospatial representations of numbers with multiple cognitive processes involved in arithmetic operations, both of which aspects are essential for math problem-solving. Aligned with our findings, MTL circuits have been shown to play an important role in forming new associations and concepts (Ren et al., 2020). Connections between the MTL and frontal and temporal cortical regions likely serve as the neural basis for the integration of diverse cognitive processes. Such integration appears to be crucial for facilitating effective skill acquisition through AMC training.

#### 4.3.1 | Limitation and future directions

While our study offers valuable insights into the role of the MTL learning and memory system in predicting long-term gains from abacus training, it also has several limitations that warrant attention. First, we acknowledge that while we longitudinally assessed math ability encompassing arithmetic calculation and visuospatial processing and its underlying neural correlates in long-term- AMC-trained children, these math assessments may have limited implications for the development of broader math achievement. Assessments including more complex math problem solving may help explore potential transfer of AMC training to broader math ability. Second, although we focused on the MTL and contrasted its role with the PPC—two regions critical for associative memory and numerical cognition respectively—we did not extensively explore the functional roles of other brain regions or neural circuits involved. Future research should employ task-based fMRI studies to illuminate how additional brain areas may contribute to abacus learning. Third, the modest sample size in our study, stemming from the time and resource-intensive nature of collecting longitudinal data with children, is also a limitation. The lower retention rate in the control group could have resulted in reduced statistical power to detect potential predictors of learning in this group compared to the training group. To partially address this concern, we employed a cross-validation approach that demonstrated the robustness of our predictive models based on structural and resting-state functional brain features.

Future studies may benefit from classroom-based intervention studies combined with neuroimaging data acquired before and after training. Such a design would provide a more comprehensive characterization of learning and brain plasticity as well as neural substrates associated with concurrent ability in children (Rosenberg-Lee et al., 2018). Finally, inclusion of an active control group that receives a different form of cognitive training could help clarify whether the observed changes are uniquely tied to abacus training or to other aspects of cognitive skill development.

## 5 | CONCLUSION

Our study expands our understanding of the neurocognitive mechanisms underlying long-term mathematical learning in response to AMC training. We demonstrate that the structural integrity and functional connectivity of the medial temporal lobe is a robust predictor of long-term learning gains in children undergoing AMC training. We suggest that the hippocampal learning-memory system interacts with frontal and temporal regions to integrate representations across multiple cognitive domains to drive long-term learning. More generally, our study provides insights into sources of individual differences in cognitive skill acquisition and response to interventions, which may serve as a critical step towards the development of brain-based markers of efficient learning.

## AUTHOR CONTRIBUTIONS

Ye Xie, Hyesang Chang, Vinod Menon, and Feiyan Chen designed study and wrote the first draft of the paper; Ye Xie, Yi Zhang, Chunjie Wang, and Fengji Geng conducted experiments and acquired data; Ye Xie, Hyesang Chang, Chunjie Wang, Yuan Zhang, and Lang Chen analyzed data; Ye Xie, Hyesang Chang, Yi Zhang, Chunjie Wang, Yuan Zhang, Lang Chen, Fengji Geng, Yixuan Ku, Vinod Menon, and Feiyan Chen edited the paper.

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## CONFLICT OF INTEREST STATEMENT

The authors declare no competing interests.

## DATA AVAILABILITY STATEMENT

All data analyzed in the manuscript were from Chinese Abacus Training Project (CATP). Please contact the corresponding author, Feiyan Chen (chenfy@zju.edu.cn), for additional information.

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## SUPPORTING INFORMATION

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