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Teacher-student synchrony distinguishes students with high and low improvement in the same classroom

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Abstract

Individual differences in learning outcomes persist among students receiving identical instruction. Using functional near-infrared spectroscopy (fNIRS) hyperscanning, we investigated teacher-student inter-brain coherence (IBC) during mathematics instruction in fifty-eight triads (one instructor, two third-grade students). Triads were classified as uniform (similar student improvement) or diverse (differential improvement). We tested whether enhanced IBC reflects conceptual alignment or teacher-student communicative dynamics. Our results favored the latter. Within uniform triads, teacher-student IBC predicted learning gains; within diverse triads, higher-improving students showed greater IBC with teachers, but this correlated with teacher-rated challenging behaviors rather than learning outcomes. Our findings suggest that heightened neural synchrony indexes adaptive instructional attention toward struggling learners, who achieve superior gains through increased teacher engagement. Teacher-student communicative behavior is a strong factor in explaining students' learning differences, supporting the socio-affective foundations of mathematics learning and advancing understanding of interpersonal neural mechanisms supporting individualized instruction.

1 Introduction

Even when students learn within the same classroom environment, substantial variance in learning outcomes persists. Recent advances in neuroimaging hyperscanning, which monitors brain activity across multiple individuals simultaneously, have enabled investigation of the neural mechanisms underlying social learning in authentic classroom settings[1–6]. This approach yields findings with greater ecological validity for multi-person neuroscience[7,8], compared to traditional single-person paradigms that examine individuals in isolation. While prior studies have predominantly utilized science-related concepts as learning materials (e.g., astronomy), young learners at the onset of formal education engage with diverse knowledge types beyond conceptual understanding, including procedural knowledge and problem-solving strategies[9,10]. Mathematics learning uniquely demands the simultaneous integration of multiple knowledge types[11], making it an ideal domain for examining individual differences in learning and their associated neural correlates within teacher-student dyads.

Neuroimaging hyperscanning quantifies inter-brain coherence (IBC; also termed inter-brain synchrony) between individuals, capturing the temporal and spectral alignment of neural activity patterns[12]. Prior studies have often reported increased IBC between teacher-student and student-student dyads during instruction, with some studies reporting positive correlations between IBC magnitude and learning outcomes[2,10,13,14]. Two explanations have been proposed for the increased IBC. The conceptual alignment explanation posits that students attend to instructional content, process the information, and construct knowledge to achieve shared understanding with their teachers[15,16]. Supporting evidence includes temporal dynamics wherein students' neural responses lag teachers' by about 300 milliseconds in Alpha-band signals using electroencephalography (EEG)[14] and 10 seconds in hemodynamic signals using functional near-infrared spectroscopy (fNIRS)[2,13]. These time-lagged neural associations of the

teacher and students predict individual differences in learning outcomes[2,13,14]. Additional support derives from findings that students exhibiting greater IBC with high-performing peers or domain experts demonstrated better learning outcomes[4,17], suggesting enhanced content comprehension during instruction.

The second explanation emphasizes communicative behaviors as drivers of IBC during social learning[18], which subsequently modulate students' learning outcomes. Classroom learning involves complex interpersonal dynamics wherein pedagogical factors, such as teachers' collaborative expertise[19], concept contextualization[10], and interactive feedback patterns[6], all shape knowledge acquisition. Implicitly, teachers may differentiate teaching strategies by monitoring students' engagement indicators, disruptive behaviors, and responsiveness[20], dynamically adjusting their approach to optimize student engagement. In line with this teacher-student communication explanation, teacher-rated and student-rated interpersonal closeness correlated with teacher-student IBC[1,5], while their social bonding positively predicted IBC increases[21]. Thus, variations in teacher-student IBC may reflect teachers' adaptive instructional modification, such as offering timely encouragement and differentiated attention, in response to individual students' behaviors, indirectly enhancing their learning performance.

The present study provides empirical tests of these explanations for the relationships between teacher-student IBC and individual differences in learning outcomes. First, we *hypothesized* that students within the same classroom exhibiting comparable learning improvements would show similar IBC patterns with their teacher. In contrast, students with diverse learning outcomes would show distinct IBC profiles. We further *hypothesized* that if the conceptual alignment explanation is correct, IBC may index shared conceptual understanding between teachers and students, such that IBC patterns would predict post-instruction learning outcomes among students within the same classroom. Alternatively, given that the teacher-student communication explanation posits that IBC predominantly reflects moment-to-moment social interaction, its fluctuations would correlate with students' real-time classroom performance instead of cumulative learning improvements, signaling teachers' implicit instructional adaptations and individualized attention allocation.

We examined these hypotheses using mathematics instruction with school-aged children for two reasons. First, despite extensive hyperscanning research on conceptual and motor learning, mathematically-integrated content remains underexplored. Mathematics learning presents unique cognitive demands requiring simultaneous processing of symbolic, procedural, and conceptual information. Second, school-aged children represent an optimal population given their developing self-regulation capacities[22,23] and immature inhibitory control[24,25]. These developmental characteristics yield more spontaneous behavioral responses in naturalistic learning environments, providing teachers with clearer observable indicators of comprehension and engagement compared to adult or college-student learners who may mask confusion or disengagement.

2 Methods

This study was approved by local ethics committee (information masked for peer review), adhering to the Declaration of Helsinki. Informed consent was obtained from all adult participants and parents/guardians of child participants. Compensation was HKD $100 per hour.

2.1 Participants

Sixty-five triads were recruited, each designed to include one adult instructor and two third-grade students. Each student participated in a single lab visit involving two instructional sessions on different topics (*fraction* and *perimeter*), while instructors were randomly selected from the adult participant pool and taught one or more sessions. Recruitment was conducted via local social media and peer referrals. Inclusive criteria included: 1) no history of neurological or psychological disorders, 2) adult participants capable of delivering mathematical instruction, 3) children enrolled in mainstream third-grade education, 4) Hong Kong residency, and 5) Cantonese as primary language.

Environmental constraints resulted in incomplete data collection: seven triads included only one student due to weather-related cancellations, no-shows, or illness, while three additional triads completed only the perimeter session due to time limitations. The final dataset comprised 58 fraction sessions and 55 perimeter sessions, involving 24 instructors (mean ± standard deviation (SD) of age: 34.9 ± 9.8 years, 4 males) and 116 students (mean ± SD of age: 8.2 ± 0.5 years, 64 males). Instructors represented diverse teaching backgrounds, ranging from pedagogical novices to experienced educators. No prior relationships existed between instructors and students.

2.2 Teaching Materials and Procedure

We selected *perimeter* and *fraction* as representative mathematical topics requiring distinct cognitive processes. Perimeter calculations demand addition and multiplication, while fostering spatial reasoning through shape analysis[26]. Fraction learning involves division and multiplication operations, providing foundational understanding of ratios and proportions[27]. These topics, typically introduced in fourth-grade curricula, were unfamiliar to our third-grade participants, minimizing prior knowledge effects. Instructional materials were pedagogically adapted for third-grade comprehension and designed for 15-minute delivery. Standardized slides presenting concepts, formulations, and worked examples were prepared in traditional Chinese script. All instructors familiarized themselves with materials before teaching sessions, with instruction delivered in Hong Kong Cantonese.

Each experimental session followed a fixed sequence across two mathematical topics (counterbalanced across triads): resting baseline (3 minutes), pre-test (5 minutes max), instruction (about 10 minutes), and post-test (5 minutes max) (see Fig. 1a). During baseline, participants closed their eyes and minimized movement to reduce fNIRS motion artefacts. Pre- and post-tests were completed individually without peer interaction. Although instructors were allocated 10 minutes for content delivery, natural variations in teaching pace were permitted. The experimental environment simulated authentic classroom conditions (see Fig. 1b). Instructors were encouraged to interact with students (e.g., asking questions and sharing short stories related to the concept), with students free to ask questions throughout instruction.

2.3 Behavioral Data Collection and Analyses

2.3.1 Learning Improvement: Pre- and Post-test Scores

Learning assessments evaluated prior knowledge and instructional effectiveness through matched pre- and post-tests. Each 10-item quiz comprised at least two conceptual understanding questions (multiple-choice format) and calculation problems (open-response format). Two quiz versions with comparable difficulty were counterbalanced as pre-test and post-test across triads (see supplementary materials, Appendix A). Scoring assigned one point per correct response (maximum: 10 points).

Learning outcomes were quantified for each test taken by each student on each topic using normalized gain scores: (post-test - pre-test score) divided by the maximum possible improvement (i.e., 10 – pre-test score), accounting for ceiling effects among high-performing students. Gain values of 1 indicate maximum improvement, whereas values ≤ 0 indicate no improvement or performance decline. Students achieving perfect pre-test scores (N = 4 fraction session; N = 3 perimeter session) were excluded from gain analyses due to absence of improvement potential. Student dyads within triads were classified as exhibiting 'uniform' or 'diverse' learning patterns based on gain score differences. The SD of learning improvements across all students in each session was first calculated. Then, the two students within the same triad who showed differences in learning improvement larger than 0.9 SD in the fraction session and 0.85 SD in the perimeter were classified as having 'diverse' improvements, with the remaining students be classified as having 'uniform' improvements. These SD cutoffs ensured comparable sample sizes between groups within each session.

2.3.2 Student-Teacher Interaction Questionnaire: In-class Performance Rating

Post-instruction assessments captured multiple dimensions of the teaching-learning interaction. Instructors completed the Teacher Self-Efficacy Scale (TSES)[28] and rated each student's classroom behavior on 7-point Likert scales across four dimensions: attentiveness, observable interest, disruptive behaviors, and academic struggles. These dimensions were developed through consultation with an experienced local teacher and reviewed by an educational professional. Internal consistency analysis using R Studio Package *psych*[29] yielded Cronbach's alpha of 0.7, indicating good reliability.

2.4 fNIRS Data Acquisition and Analyses

2.4.1 fNIRS data acquisition

For fNIRS data acquisition, we focused on the left (l) and right (r) medial frontal cortex (lMFC and rMFC) and temporoparietal junction (lTPJ and rTPJ), as IBC with MFC and TPJ have been reported to be associated with students' learning outcome[2,13,30]. The fNIRS data were collected using one continuous-wave NIRS instrument (NIRSport2 devices, NIRx medical technologies, LLC) per participant, with 16 sources and 16 detectors, which provided 42 regular channels per participant. To reduce the noise in

fNIRS data, such as systemic responses from the extracerebral tissue[31], eight short channels were included that have been shown to greatly improve fNIRS signal quality in adults[32] and young children[25,33]. The locations of light sources and detectors were arranged according to the standard 10–10 system. The optodes were held by an elastic NIRScap of predetermined size based on each child's head circumference. Channels were clustered into four brain regions: the lMFC and rMFP (each with 9 channels), lTPJ and rTPJ (each with 10 channels).

2.4.2 fNIRS data analyses

The fNIRS data were imported into and analyzed in MATLAB (version 2024b; The MathWorks, Natick, MA) with scripts from HOMER2 software[34] and written by the authors. The preprocessing pipeline on the regular channels consisted of (a) removing step-like noises, (b) converting light intensity to optical density, and (c) calculating the concentration changes in the hemoglobin with children's ages taken into account[35]. After preprocessing, the IBC in each triad between the teacher and two students was measured by calculating the wavelet transform coherence (WTC) for the change in oxygenated hemoglobin signals[12]. The WTC measures cross-correlations between two signals in the frequency and time domains that uncover locally phase-locked components between two signals and has been widely used to reveal IBC[12,36]. We decided to involve limited noise-reduction methodology in the preprocessing, as the WTC method has been reported to be quite robust to motion artifacts in the fNIRS data[12]. To mark inter-brain ROI connections, we used $ROI_1{}^T$-$ROI_2{}^S$ to stand for the connection between the ROI_1 in the teacher and the ROI_2 in the student. To examine IBC between teacher-student across conditions, we focused on two lecture-specific frequency of interest (FOIs): [0.291 0.489] Hz, [0.137 0.173] Hz. Please see supplementary materials for a detailed description of how the two FOIs were determined. Further analyses were focused on IBC of the two FOIs combined.

2.5 Statistical analyses

We first tested that students within the triads exhibiting comparable learning improvements (i.e., uniform group) would show similar IBC patterns with their teacher. In contrast, those with diverse learning outcomes within the triads (i.e., diverse group) would show distinct IBC profiles, with the student who had higher improvement synchronizing better with the teacher during the instruction compared to the student with lower improvement. Then, we examined whether IBC increases reflected conceptual alignment or communicative dynamics by examining correlations with learning outcomes vs. teacher-rated classroom behaviors. Since students had significantly higher pre-test scores ($t(112) = 7.19$, $p < 0.001$) and more learning improvement ($t(107) = 3.36$, $p = 0.001$) for perimeter, compared to fraction, the following analyses were conducted separately by topic.

Four-step statistical analyses were conducted to test the hypotheses. In step 1, we combined the two lecture-related FOIs (FOI1 and FOI2) and calculated the cumulative IBC between the 5th and 80th percentiles for each condition. We then compared the cumulative IBC in the training session against the resting condition across every pair of ROIs to identify the ROIs that showed significant task-related

increases in IBC. A Benjamini-Hochberg method[37] was used to correct the false discovery rate (FDR) for the p-values across the maximum of 16 significant connections per session. Among the ROIs identified in step 1, we did three more steps of analysis. In step 2, we compared teacher-student IBC between paired students, separately analyzing uniform and diverse dyads. In step 3, within diverse dyads, correlational analyses examined relationships between teacher-student IBC and individual learning improvements. In step 4, we investigated how teacher-rated student behaviors were associated with teacher-student IBC and/or students' learning improvements.

An exploratory analysis examined uniform dyads across all 16 ROI pairs, testing correlations between teacher-student IBC and both learning improvements and teacher-rated student behaviors. Multiple comparisons were corrected using the Benjamini-Hochberg procedure[37].

3 Results

3.1 Behavioral measures of learning improvement

The learning improvements (normalized gains) of students were reported. After excluding sessions with missing data and students achieving ceiling pre-test scores (10/10), the final analysis included 49 complete triads (Fig. 2), equally distributed between diverse (N = 24) and uniform (N = 25) learning improvement groups per topic. Students in the diverse and uniform groups did not differ in their learning improvement in fraction ($t(96) = 0.58$, $p = 0.56$) or perimeter ($t(96) = 0.73$, $p = 0.47$). To evaluate potential confounds from differential prior knowledge, we compared pre-test scores between the two groups. No significant differences emerged for fraction ($t(96) = 1.07$, $p = 0.29$) or perimeter ($t(96) = 1.03$, $p = 0.31$), confirming equivalent baseline knowledge across groups.

3.2 fNIRS measures of IBC

3.2.1 Instruction-induced increases in teacher-student IBC

For each teacher-student ROI pair, we compared cumulative IBC during the instruction against the other conditions per topic. During instruction, IBC significantly exceeded baseline, pre-test, and post-test levels across all ROI connections ($p_{adjusted} < 0.01$), except for comparison between the fraction instruction and pre-test conditions in $rTPJ^{T}$-$lTPJ^{S}$ (Fig. 3, see complete statistics in **Table S1** and **Table S2** of the supplementary materials). These findings demonstrate that active instruction substantially enhances teacher-student neural synchrony, potentially reflecting social interaction dynamics, students' neural entrainment to teacher's speech, and their shared state of knowledge.

When examining cumulative IBC, teachers' lMFC and rMFC regions showed elevated IBC during both pre-test and post-test phases compared to the resting baseline for fraction instruction only, although most of the comparisons were not significant after multiple comparison correction (see supplementary

materials). This pattern could be due to 'mere presence'—whereby mutual awareness, even without explicit interaction, modulates IBC relative to the eyes-closed baseline condition.

3.2.2 Differential IBC patterns distinguish high- and low-improving students

We investigated whether teacher-student IBC during instruction differed between paired students within uniform vs. diverse improvement dyads across all ROIs. Within uniform dyads, no ROI pairs showed significant IBC differences between two students sharing similar learning gains. Conversely, diverse dyads revealed systematic IBC differences: students demonstrating higher learning gains exhibited significantly greater teacher-student IBC than their lower-gaining peers across four ROI connections during perimeter instruction ($p_{adjusted} < 0.05$): $lMFC^{T}$-$rTPJ^{S}$, $rMFC^{T}$-$rTPJ^{S}$, $lTPJ^{T}$-$rTPJ^{S}$, and $rTPJ^{T}$-$rTPJ^{S}$ (Fig. 4). This finding supports our first hypothesis that within the same triad students with similar learning outcomes showed comparable IBC, whereas students with more diverse learning outcomes exhibit different IBC in the same instructional context.

Significant differences were only observed in the perimeter instruction but not in the fraction instruction (Fig. 4), potentially due to their differences in topic difficulty. Indeed, students scored higher in the baseline knowledge, as reflected by pre-test score ($t(112) = 7.19$, $p < 0.001$) and greater learning improvement ($t(107) = 3.36$, $p = 0.001$) for perimeter than for fraction. The absence of differentiated IBC patterns during fraction instruction suggests that the topic may be too challenging for third-grade students to learn within such a short session, such that they did not show any distinct teacher-student IBC patterns.

3.2.3 IBC correlates with teacher perceptions but not learning outcomes

To evaluate competing hypotheses regarding IBC mechanisms (concept alignment vs. teacher-student communication), we performed correlational analyses to test the relationship between teacher-student IBC increases and learning outcomes within diverse dyads for the pairs of ROIs showing significant differences (Fig. 4). Teacher-student IBC increase refers to the difference between IBC during instruction and IBC during baseline. Contrary to the conceptual alignment hypothesis, no significant correlation was found between IBC increases and normalized learning gains for any ROI pair showing significant differences.

We further examined whether teachers' impressions of students were associated with teacher-student IBC increase. Indeed, increased IBC between teachers' bilateral MFC and TPJ with students' rTPJ positively correlated with ratings of disruptive behavior, disinterest, and academic struggle (higher scores indicating greater difficulties, Fig. 5). Importantly, these correlations were driven by students with more improvement, as teacher-rated difficulties of more-improving students positively correlated with IBC between more-improving students' rTPJ and teachers' lMFC ($r(24) = 0.51$, $p = 0.012$), rMFC ($r(24) = 0.46$, $p = 0.024$), and rTPJ ($r(24) = 0.36$, $p = 0.081$). These results suggest that teachers allocated more

attention to more-improving students who struggled more in the classroom, manifested as heightened neural synchrony (i.e., IBC), indirectly resulting in higher learning outcomes, compared to less-improving students in the same classroom, supporting the teacher-student communication hypothesis.

Exploratory analyses within uniform dyads revealed topic-specific patterns. During perimeter instruction, teacher-student IBC increase correlated with students' learning improvement in $lTPJ^{T}$-$lMFC^{S}$ ($r(47) = 0.31$, $p = 0.03$), $lTPJ^{T}$-$lTPJ^{S}$ ($r(47) = 0.42$, $p = 0.003$), and $lTPJ^{T}$-$rTPJ^{S}$ ($r(47) = 0.37$, $p = 0.009$). However, only $lTPJ^{T}$-$lTPJ^{S}$ remained significant after multiple comparison correction ($p_{adjusted} = 0.042$), with $lTPJ^{T}$-$rTPJ^{S}$ showing a marginal significance ($p_{adjusted} = 0.071$) (see Fig. 6). Teacher ratings of student classroom behaviors (i.e., disruptive behavior, disinterest, and academic struggle) correlated with teacher-student IBC increase for $lMFC^{T}$-$rMFC^{S}$ ($r(47) = 0.30$, $p = 0.036$) and $rMFC^{T}$-$rMFC^{S}$ ($r(47) = 0.30$, $p = 0.033$), though neither survived multiple comparison corrections ($p_{adjusted} = 0.28$).

4 Discussion

The current study examined neural mechanisms underlying individual differences in mathematics learning outcomes (from concept learning to problem-solving in two topics, fraction and perimeter) among third-grade students in triadic classroom settings. By examining teacher-student neural synchrony during instruction in fractions and perimeter, we provide novel insights into how inter-brain coherence differentiates students with varying learning improvement within identical instructional contexts.

4.1 Enhanced teacher-student synchrony characterizes high-improving students

To establish the instructional specificity of IBC from fNIRS hyperscanning measures, we compared teacher-student neural synchrony across experimental conditions. IBC during active instruction significantly exceeded levels observed during rest, pre-test, and post-test phases across all ROI pairs, eliminating mere presence effects[38,39] and confirming instruction-specific neural coupling. This aligns with extensive hyperscanning studies about enhanced IBC during pedagogical interactions[40].

Our triadic design enabled direct comparison of IBC patterns between students experiencing identical instruction but achieving different learning outcomes. Student dyads with uniform learning improvements exhibited comparable teacher-student IBC patterns across all ROI connections (Fig. 4). In contrast, within the student dyads receiving the same instruction yet with diverse learning improvements, those with higher learning improvement (S_h) showed greater IBC between their rTPJ and teachers' bilateral MFC and TPJ regions, compared to those with lower learning improvement (S_l). This differentiation specifically occurred during perimeter instruction, where students showed greater baseline knowledge and learning potential. These results establish that IBC can distinguish students

with differential learning success within shared instructional environments, extending previous evidence linking teacher-student synchrony to learning outcomes[10].

4.2 IBC reflects communicative dynamics rather than conceptual alignment

We also tested the hypotheses whether IBC was a neural marker of conceptual alignment when co-constructing knowledge[2,13] or a neural marker of social engagement[1,21]. Our correlation analyses among ROI pairs showed significantly greater teacher-student IBC among students with higher learning improvement, compared to those with lower learning improvement. Within diverse-outcome dyads, teacher-student IBC was positively associated with teacher ratings of student classroom behaviors, but not with students' learning improvement. Counterintuitively, the students exhibiting more challenging behaviors (e.g., more disruptive behaviors and less interest) showed a higher IBC with the teacher, particularly involving teachers' bilateral MFC and TPJ regions synchronized with students' rTPJ. These findings reflected that teachers allocated disproportionate attention to students displaying learning difficulties, continuously monitored their comprehension, mentalized their cognitive states, and adjusted instructional approaches accordingly[41,42]. This adaptive teaching process may likely occur in the present study, where there were only two students in the session. Such adaptive attention involves theory-of-mind processing[43] and joint attentional system (TPJ) of both the teacher and students[44]. Teachers might more contingently respond to the students with disruptive behaviors in a small class, and hence their social bonds were strengthened. The IBC represents interpersonal social bonding between the teacher and students in real-life interaction, highlighting the socio-affective nature of the neural mechanism underlying small-group classroom learning[21].

Prior studies reported increased synchrony between the instructor's PFC and students' MFC when learning a song[45] or conceptual knowledge[2,13]. Further, IBC with the MFC but not TPJ was predictive of students' performance, suggesting that MFC may be a hub of knowledge construction among students[2]. However, this was not aligned with the results of the present study. First, within the diverse dyads, there was an absence of association between teacher-student IBC and students' learning improvement. Second, within the uniform dyads, teacher-student IBC in teacher's lTPJ and students' lTPJ ($p_{adjusted}$ = 0.042) and rTPJ ($p_{adjusted}$ = 0.071) were associated with students' learning improvement (Fig. 6). The ROIs involved (left and right TPJ) were from the attentional network but not the MFC or the lateral prefrontal areas, where neural markers of successful learning were consistently found in social learning studies[2,10,13,45,46].

This divergence could likely be due to four reasons. First, previous studies investigated conceptual knowledge[2,13], while we had our participants learn mathematics (perimeter and fractions), during which they not only practiced basic arithmetic operations (addition, subtraction, multiplication, and division), but also transferred the knowledge acquired from the session to solve novel problems. Second, the current study examined *a priori* ROIs, following previous fNIRS hyperscanning studies on conceptual

learning. However, mathematical reasoning engages fronto-insular-parietal networks[47–49], which was potentially beyond our ROI coverage (Fig. 1) and might not be captured by fNIRS technology due to its limited spatial resolution. Third, prior findings were mostly based on college-aged young adults, while the present study focused on third graders, who have not been given sufficient attention in fNIRS literature, despite their substantial time being spent in classroom learning with their teachers and peers in mathematical education[50,51]. Fourth, prior studies involving instructor-learn interactions[6,13,46] aggregated data across different participant dyads. This methodological design was susceptible to confounding variables, such as teachers' varying instructing/lecturing skills and efficacy, and distractions from the environment, which could affect the IBC results. To avoid these confounds, we conducted within-triad analysis by comparing students within the same dyads with the same or different learning outcomes.

4.3 Limitations

Several methodological constraints warrant consideration. Teacher ratings of student behavior, despite ecologically valid, may vary with instructors' experience and perceptual biases. Our diverse teacher sample, though representative of real-world variation, introduces potential rating inconsistencies. Besides, the absence of systematic behavioral coding during instruction limits our understanding of specific interactive behaviors distinguishing high- and low-improving students. Future studies should incorporate objective behavioral measures and moment-to-moment interaction coding to clarify communicative mechanisms underlying differential IBC patterns.

4.4 Implications and future directions

In conclusion, we reveal that teacher-student neural synchrony during mathematics instruction reflects dynamic communicative processes rather than mere conceptual alignment. This neural coupling appears to index teachers' adaptive responses to individual student needs, with enhanced synchrony characterizing students who struggle behaviorally yet achieve greater learning gains through increased instructional attention. These insights underscore the interactive nature of classroom learning and highlight the importance of responsive teaching in supporting diverse learners within shared instructional environments.

Our findings carry significant implications for mathematics education and classroom practice. First, the findings that enhanced teacher-student neural synchrony was due to communicative behaviors during social learning[1,5,52], characterize students receiving more instructional attention from the teacher suggests that small-group instruction may naturally facilitate adaptive teaching through clearer behavioral feedback signals. Also, observable student behaviors could serve as critical signals guiding teachers' attention allocation and instructional adaptation, which may potentially enhance students' learning outcomes.

Second, the topic-specific nature of our findings; that is, significant effects for perimeter but not fractions, highlights the importance of matching instructional time to content complexity. Educational

interventions should consider extending instruction time for challenging topics like fractions (e.g., or third graders), where brief exposures may be insufficient for establishing differentiated neural engagement patterns. This aligns with mathematics education research highlighting the need for sustained, iterative instruction for abstract concepts[11].

Future research should examine how IBC patterns scale to larger classroom settings[1,2], especially young children who struggle in the classroom but not attended to by the teachers, for instance children with elevated autistic traits[39]. Investigating whether explicit training in behavioral monitoring enhances teachers' ability to identify and support at-risk learners could yield strategies for improving mathematics education. Longitudinal studies tracking how teacher-student neural synchrony evolves across extended instructional periods would further test whether initial IBC differences predict long-term learning.

Declarations

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Author contributions

XZ: Conceptualization; Analysis and interpretation; Writing – original draft, review & editing.

XCH: Conceptualization; Data acquisition; Writing – original draft

LYX: Conceptualization; Data acquisition; Project Administration; Writing – original draft

CST: Conceptualization; Writing – original draft, review & editing.

PCMW: Conceptualization; Funding acquisition; Resources; Supervision; Writing – review & editing.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Data availability: The study reported in this article was not preregistered. The summary (de-identified) data supporting the conclusions of this article are stored on Open Science Framework and available for peer review through the following link. https://osf.io/rh9ev/files

Code availability: The underlying code for this study is available in Open Science Framework and can be accessed via this link https://osf.io/rh9ev/files.

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Figures

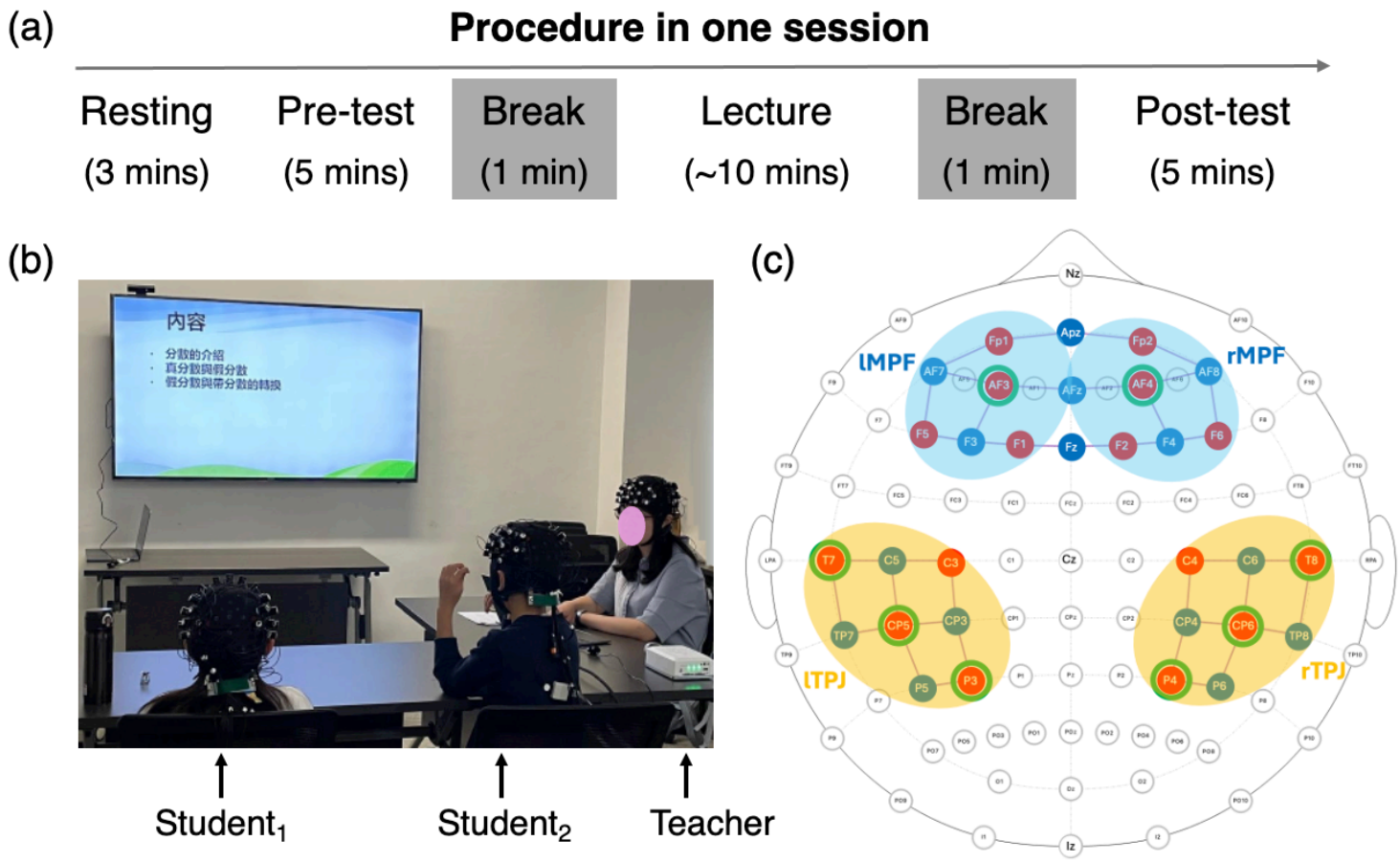


Figure 1

Summary of study schematic. Panel (a) shows the testing procedure in one session; two sessions were conducted, one for fraction and one for perimeter, in a counterbalanced order across participants. Panel (b) shows the simulated classroom. Panel (c) shows the montage, that is, the locations of and connections between fNIRS light sources (red; n = 16), regular light detectors (blue; n = 15), and short-channel detectors (green; n = 8), which was created with NIRSite Version 2.0.

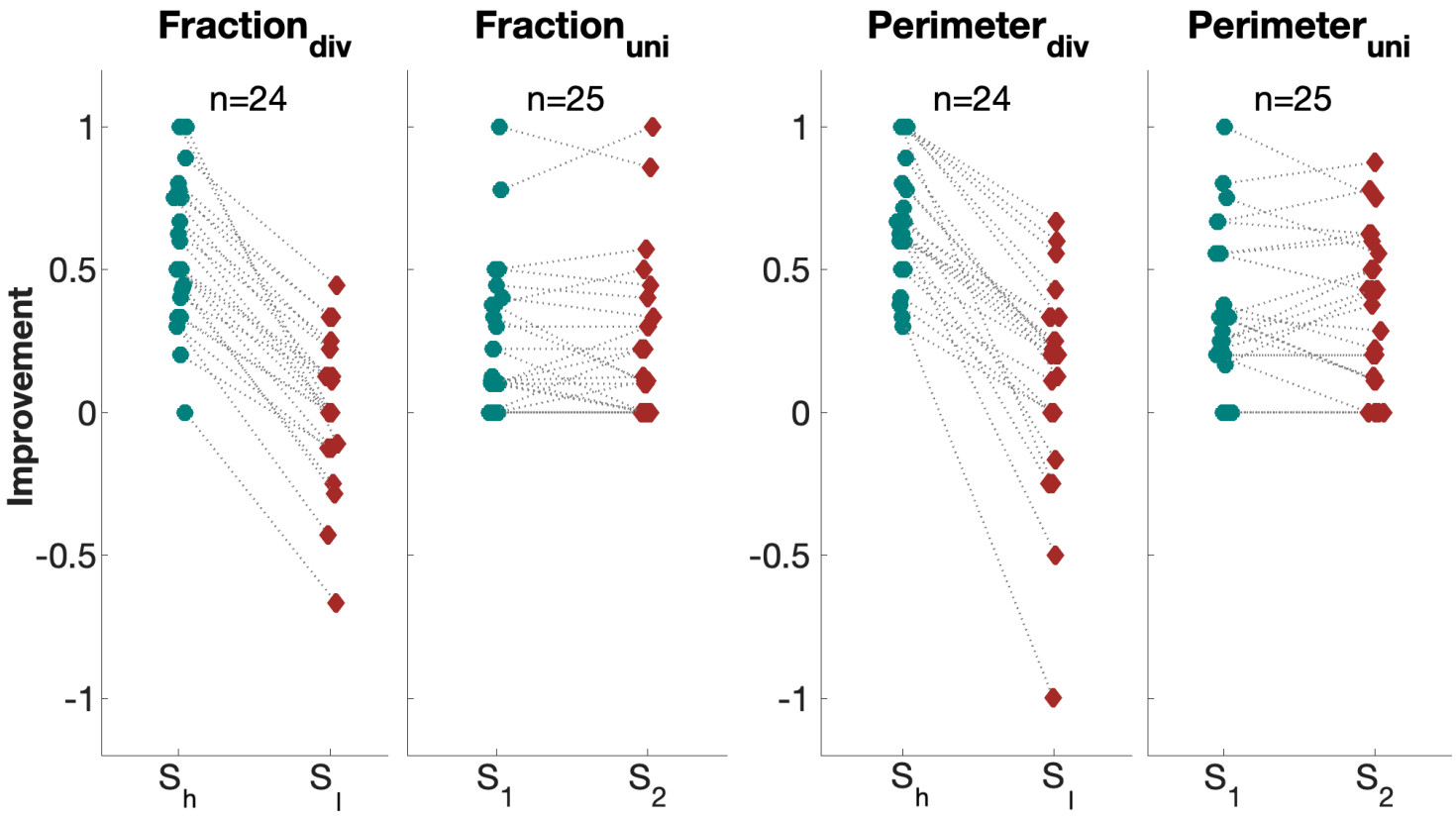


Figure 2

Behavioural measures of learning improvement on the topics of fraction and perimeter. For each topic, teacher-student triads were divided into those with diverse (div) or uniform (uni) learning improvements. Based on students' improvement, the two students within the diverse dyads were labelled as higher- (S_h) and lower- improvement (S_l) students, and S_1 and S_2, in the uniform dyads, respectively.

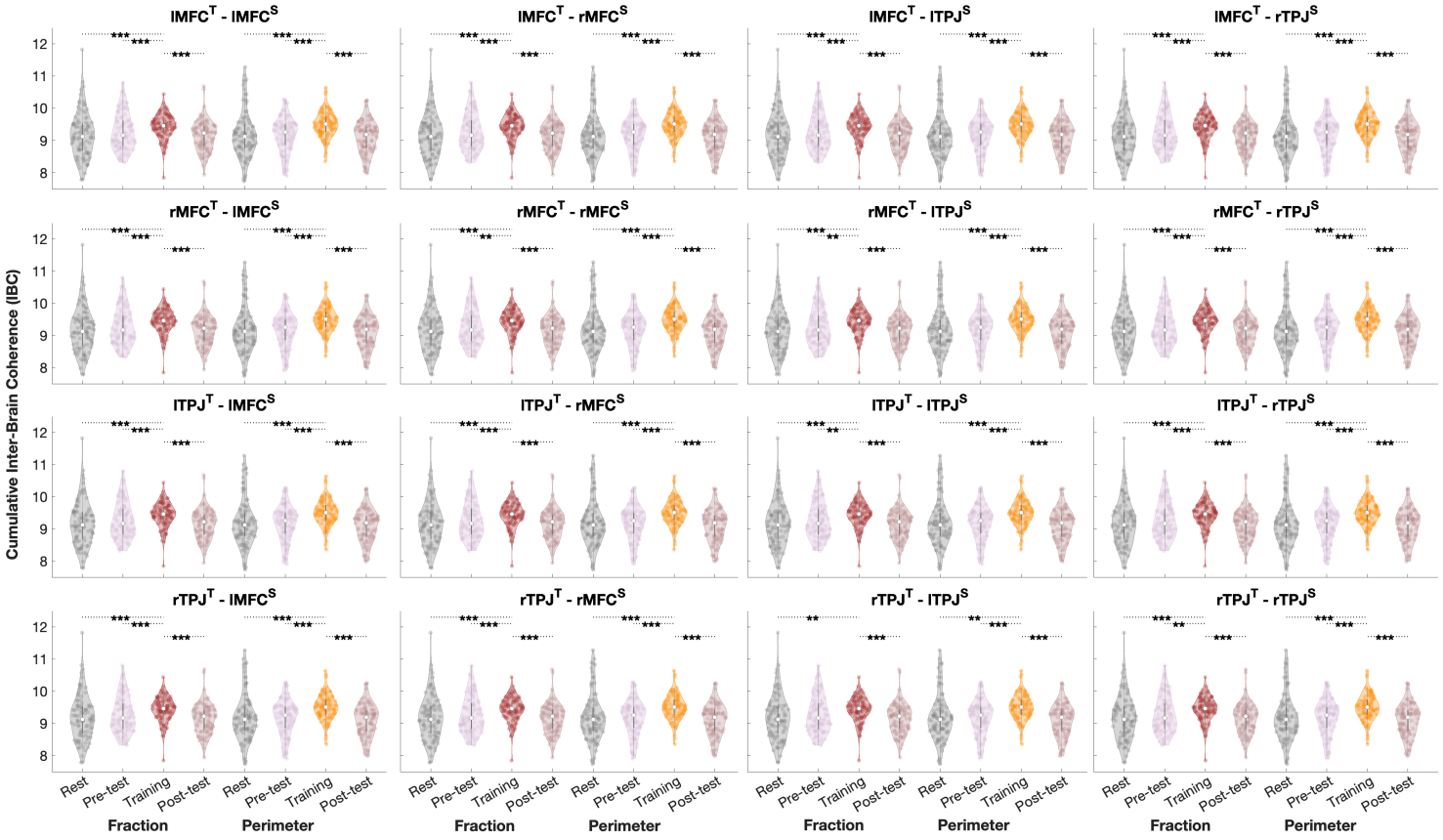


Figure 3

Teacher-student inter-brain coherence (IBC) across conditions. Violin plots show the cumulative inter-brain coherence across percentiles per condition. The white dots indicate the group median per condition. Asterisk signs show the significance when comparing the IBC values in during the lecture against the resting, pre-test, and post-test conditions, with '**' for adjusted $p < 0.01$, and '***' for adjusted $p < 0.001$.

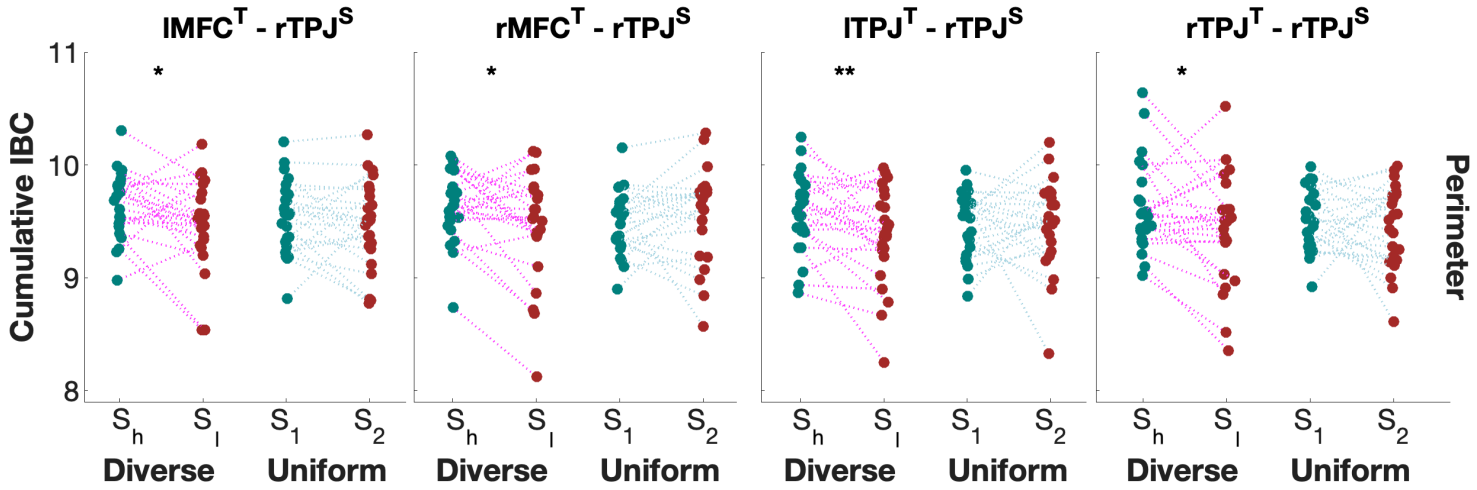


Figure 4

Pairs of regions of interest (ROIs) showing differences between students with higher- and lower improvement.

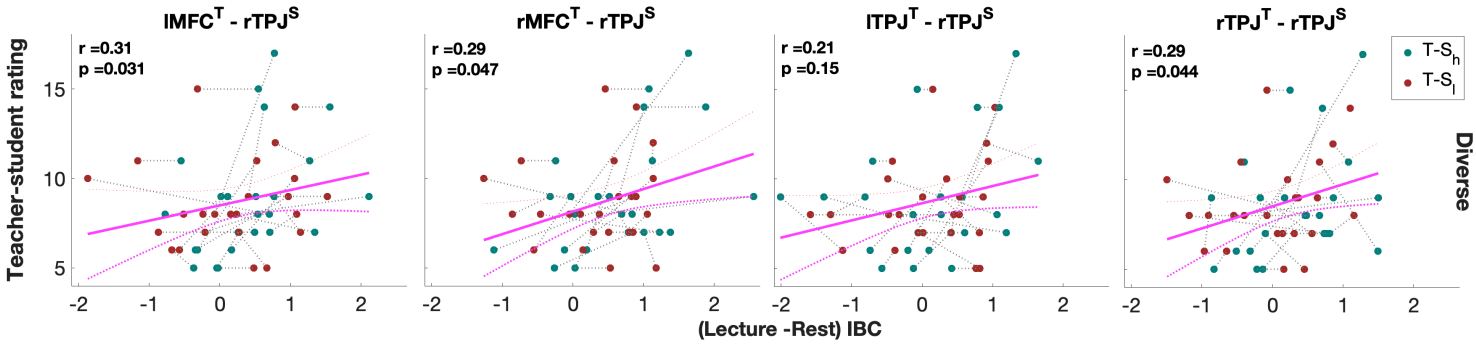


Figure 5

Behavior and inter-brain coherence (IBC) correlations in the diverse group.

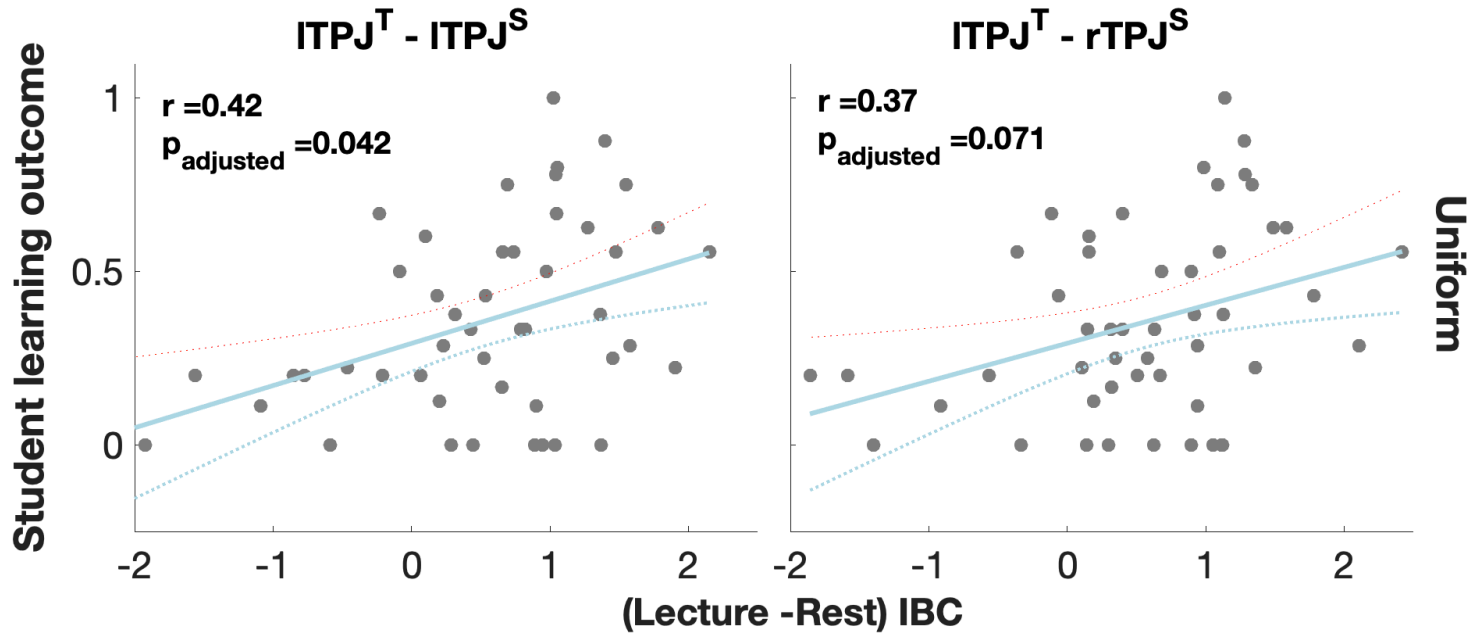


Figure 6

inter-brain coherence (IBC) predicted students' learning improvement in the uniform group.

Supplementary Files

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- Supplementarymaterials20250904.docx