Student-teacher inter-brain coupling causally predict academic achievement over semesters

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Abstract:
Student-teacher interactions are fundamental to educational success. Leveraging advancements in hyperscanning technology, this study employs longitudinal EEG data to examine the causal effects of student-teacher inter-brain coupling on academic achievements. The findings indicate that enhanced coupling in the high-beta frequency band can positively predict improved academic performance in both Chinese and math subjects. Our analysis also suggests that student-teacher coupling has a unique and significant predictive advantage for Chinese achievement compared to inter-brain coupling among students. This study underscores the causal impact of student-teacher inter-brain coupling on learning based on robust evidence from real classroom settings, confirming its ecological validity.

Introduction

Human learning fundamentally occurs through interactions with the environment, with student-teacher interactions in the classroom playing a pivotal role. These interactions are crucial not only for individual academic outcomes but also serve as vital conduits for transmitting cultural values and knowledge across generations[1-4]. Hyperscanning technology, characterized by the simultaneous collection of neural activity data from multiple individuals in real-world settings, has made significant contributions to the study of brain mechanisms underlying these social interactions[5-10]. By positing the teacher as a central reference point, the inter-brain approach offers a nuanced perspective on this educational interplay[11]. Empirical studies leveraging hyperscanning have linked inter-brain coupling between teachers and students with successful educational dialogues, consistently associating this neural synchronization with academic achievement[4, 5]. However, these studies are predominantly conducted in controlled laboratory settings, which may not fully capture the complexities of real-world classroom dynamics, thus limiting their ecological validity[12, 13]. With the development of wearable electroencephalogram (EEG) and guided by the perspective of inter-brain coupling, recent hyperscanning studies have begun to move towards real-world classroom scenarios, primarily focus on inter-brain coupling among students[14-17]. The portability, ease of use, and low operational cost of wearable EEG devices are anticipated to facilitate the longitudinal recording of data in classroom settings,

providing a rich, comprehensive description and analysis of learning processes.

Understanding the impact of inter-brain coupling on academic performance through such longitudinal data is crucial for deciphering the complex processes of learning, which in turn can lead to the development of more effective educational interventions and assessment strategies[18, 19]. Current research predominantly identifies correlations, leaving room for ambiguity due to potential reciprocal influences between student-teacher interaction and student achievement[20]. For instance, a positive correlation between student-teacher interaction and academic achievement does not necessarily indicate that better interaction leads to improved outcomes; it could also result from teachers' preferential engagement with higher-performing students[21, 22]. Establishing causal relationships within this framework requires the collection and analysis of longitudinal data, an area yet unexplored by hyperscanning studies[23-25]. Leveraging insights from econometrics, we have formulated both *dynamic* and *static* frameworks to elucidate the causal connection between student-teacher inter-brain coupling and learning outcomes[26-28]. The dynamic model primarily scrutinizes how variations in the student-teacher coupling influence subsequent shifts in leaning outcomes, encapsulating the temporal aspect of their interaction. And the static model assesses the impact of student-teacher coupling levels on learning outcomes at a given point. In the dynamic model, we have incorporated baseline coupling values to mitigate potential biases linked to teacher preferences. Considering the inherent difficulty for teachers to anticipate changes in student performance, the dynamic model inherently suggests a more definitive causal direction from the student-teacher coupling dynamics to learning outcomes.

In our study, we utilized wearable EEG devices to longitudinally collect neurophysiological data from both teachers and students across multiple semesters during real Chinese and math classes in a middle school setting. For each participant, the average levels of student-teacher inter-brain coupling as well as the standardization scores, which represent the students' learning outcomes, were calculated for each half-semester (i.e., one *period*). Then the *dynamic* and *static* models were established to investigate the causal relationship between student-teacher inter-brain coupling and learning outcomes. The linear mixed-effects model was employed to account for variations among individuals and across different *periods*. Our results demonstrate that student-teacher coupling in both Chinese and math classes can causally predict improvements in academic performance, particularly within the high-beta frequency band (18-30 Hz). Additionally, the mean value and improvement of student-teacher coupling can also predict students' learning outcomes, with the effect extending into the subsequent period. This investigation is at the forefront in exploring the causal dynamics between student-teacher coupling and learning outcomes, enhancing the current understanding of effective learning from a neural perspective.

Results

In this study, forty-eight first-year middle school students (22 males; aged 12-14) and

four teachers (two teaching Chinese and two teaching math) underwent EEG recordings during Chinese and math classes spanning three semesters, each lasting four months. EEG recordings were carried out for one week each month, capturing 1-2 daily sessions of both Chinese and math classes, with each session lasting 40 minutes. Prior to each session, students were equipped with EEG headbands, participated in usual class activities, and completed a brief questionnaire immediately following each session (*Fig. 1a, b*).

The research employed the total interdependence (TI) value to quantify the student-teacher inter-brain coupling, conducting analyses across multiple frequency bands. For each student, the student-teacher TI value was calculated between that student and their respective teacher during each class session (*Fig. 1c*). These TI values were then averaged and standardized for each half-semester, operationally defined as one *period* (*Fig. 1d*). Learning outcomes were assessed through half-semester examinations, with scores provided by the school administration and normalized against the entire student cohort within the school. Higher normalized scores indicated better performance. The differences in TI values and normalized scores were calculated between two consecutive *periods*, and this analysis was extended across various frequency bands including broadband (1-40 Hz), delta (1-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), low beta (13-18 Hz), high-beta (18-30 Hz), and gamma (30-40 Hz) frequency bands.

Descriptive statistics of learning outcomes and student-teacher coupling values are presented in Figure 2. Figure 2a and 2b display the distribution of Chinese and math scores across different *periods*, respectively, showing no significant differences in score distribution across *periods* ($F_{Chinese}(3,84) = 1.02, p = 0.388$; $F_{math}(5,228) = 0.22, p > 0.05$) show no significant differences. Figure 2c presents the student-teacher coupling values of Chinese class across all periods and various frequency bands, revealing no significant differences ($F_{broadband}(2,66) = 0.57, p > 0.05$; $F_{delta}(2,65) = 0.27, p > 0.05$; $F_{theta}(2,66) = 1.65, p > 0.05$; $F_{alpha}(2,65) = 1.44, p > 0.05$; $F_{lowbeta}(2,65) = 2.31, p > 0.05$; $F_{highbeta}(2,65) = 2.29, p > 0.05$; $F_{gamma}(2,65) = 0.58, p > 0.05$). Figure 2d illustrates the student-teacher coupling values in math class across all periods and frequency bands, with no significant differences observed ($F_{broadband}(4,132) = 0.33, p > 0.05$; $F_{delta}(4,132) = 0.58, p > 0.05$; $F_{theta}(4,132) = 0.50, p > 0.05$; $F_{alpha}(4,132) = 2.77, p > 0.05$; $F_{lowbeta}(4,133) = 0.18, p > 0.05$; $F_{highbeta}(4,132) = 0.49, p > 0.05$; $F_{gamma}(4,132) = 2.14, p > 0.05$).

Student-teacher inter-brain coupling causally predicted students' academic improvement

The study first employed a dynamic model, applying the improvements in learning outcomes (ΔScores) between the two adjacent *periods* as the outcome variable, and the student-teacher coupling values (TI values) and changes in student-teacher coupling values (ΔTI values) as predictors. After controlling for the baseline TI values, the analysis showed that ΔTI values significantly impacted the improvement in both

Chinese (Fig 3a) and math scores (Fig 3b). For Chinese, ΔTI in broadband and high-beta frequency bands can positively predicted the improvements in Chinese scores ($\beta_{\Delta broadbandTI} = 0.374, p = 0.040$; $\beta_{\Delta highbetaTI} = 0.457, p = 0.008$), whereas for math, ΔTI in high-beta frequency bands positively predicted the improvements in math scores ($\beta_{\Delta highbetaTI} = 0.187, p = 0.043$). These findings suggest that more pronounced increases in student-teacher TI values can causally predict greater academic improvements. TI values also possess a predictive effect on academic improvement. For Chinese, TI values in the broadband and high-beta frequency bands similarly exhibit a significant positive predictive effect on score increases ($\beta_{broadbandTI} = 0.461, p = 0.019$; $\beta_{highbetaTI} = 0.542, p = 0.001$). For math, TI values in the broadband, delta, and high-beta bands are all capable of positively predicting increases in scores ($\beta_{broadbandTI} = 0.464, p = 0.001$; $\beta_{deltaTI} = 0.291, p = 0.020$; $\beta_{highbetaTI} = 0.218, p = 0.039$). This implies that higher coupling values with teachers can also account for the progress in learning outcomes. The results of the model fit are depicted in Figure 3c (Chinese) and Figure 3d (math). To explore whether student-teacher coupling values with significant impacts could predict Δscores across multiple subsequent periods, we employed TI and ΔTI to predict Δscores with lags ranging from 0 to 4 *periods*. For instance, if ΔTI represents the change in TI values from *period* 1 to *period* 2, then with a lag period of 0, the corresponding dependent variable would be the change in scores from *period* 1 to *period* 2, yielding results consistent with those shown in Figures 3a and 3b. When the lag period is set to 1, the dependent variable shifts to the change in scores from period 2 to period 3. The outcomes are depicted in Figure 3e (Chinese) and 3f (math), indicating that student-teacher coupling does not have a predictive effect on subsequent changes in academic performance. All significant results stem from instances where both the model's p-values and the permutation test's p-values are significant. The model outcomes and the results of the permutation tests are presented in *Table S1* and *Figure S1* of the *Supplementary Information*.

Student-teacher inter-brain coupling predicted students' academic achievement

A static model was then developed to supplement the analysis of the predictive role of student-teacher coupling in learning outcomes. This model utilized the learning outcome (Scores) of each *period* as the outcome variable, and the student-teacher coupling values (TI values) and changes in student-teacher coupling values (ΔTI values) as predictors. For both Chinese (Fig. 4a) and math (Fig. 4b), the student-teacher coupling can predict learning outcomes. Broadband TI and high-beta TI positively predict Chinese scores ($\beta_{broadbandTI} = 0.428, p = 0.037$; $\beta_{highbetaTI} = 0.435, p = 0.047$), while broadband TI and Δgamma TI significantly predict math scores ($\beta_{broadbandTI} = 0.404, p = 0.021$; $\beta_{\Delta gammaTI} = 0.369, p = 0.016$). The model fit results of significant frequency bands are presented in figure 4c and 4d. These findings demonstrate that higher TI values and their growth correlate with better academic achievements. Subsequently, we performed predictions using TI and ΔTI for scores with lags ranging from 0 to 4 *periods*. The significant predictive effect diminishes after one lagged period, with high-beta TI and Δhigh-beta TI demonstrating a significant

predictive effect on Chinese scores for the one lagged period ($\beta_{highbetaTI} = 0.468, p = 0.037$; $\beta_{\Delta highbetaTI} = 0.556, p = 0.008$). These results reveal that high-beta inter-brain coupling can effectively predict Chinese scores for the next period, but fails to predict performance in periods beyond that. The model outcomes and the results of the permutation tests are presented in *Table S2* and *Figure S1* of the *Supplementary Information*.

Student-class/excellence inter-brain coupling predicted students' academic achievement

To further understand the unique role of student-teacher inter-brain coupling in predicting learning outcomes, this study conducted analogous analyses on student-student inter-brain coupling. The predictive effects on learning outcomes were compared when referencing different group brain activities. To this end, we compared the predictive effectiveness on scores and Δscores when using the class average level and excellent students as references (*Fig. 5*). The specific model outcomes are presented in *Table S3 and S4* of the *Supplementary Information*. The results indicate that high-beta and gamma TI values of student-class coupling negatively predict ΔChinese scores ($\beta_{\Delta deltaTI} = 0.222, p = 0.019$). For math, ΔTI across broadband, alpha, low-beta, and gamma bands, along with student-class coupling in alpha and low-beta bands of student-class coupling, positively predict Δmath scores ($\beta_{\Delta broadbandTI} = 0.185, p = 0.044$; $\beta_{alphaTI} = 0.214, p = 0.027$; $\beta_{\Delta alphaTI} = 0.346, p = 0.001$; $\beta_{lowbetaTI} = 0.198, p = 0.037$; $\beta_{\Delta lowbetaTI} = 0.272, p = 0.003$; $\beta_{\Delta gammaTI} = 0.259, p = 0.007$). For student-excellece coupling, only Δgamma TI can positively predict Δmath scores ($\beta_{\Delta gammaTI} = 0.352, p = 0.010$). In terms of predicting learning outcomes, ΔTI in delta band and low-beta TI of student-excellence coupling exhibit a positive predictive capability for Chinese scores ($\beta_{\Delta deltaTI} = 0.193, p = 0.028$; $\beta_{lowbetaTI} = 0.276, p = 0.029$). For math scores, student-class coupling shows a strong predictive capacity. Except for Δalpha TI and Δhigh-beta TI, all other student-class coupling positively predict math outcomes ($\beta_{broadbanTI} = 0.387, p = 0.000$; $\beta_{\Delta broadbandTI} = 0.265, p = 0.001$; $\beta_{deltaTI} = 0.321, p = 0.000$; $\beta_{\Delta deltaTI} = 0.182, p = 0.008$; $\beta_{thetaTI} = 0.456, p = 0.001$; $\beta_{\Delta thetaTI} = 0.284, p = 0.007$; $\beta_{alphaTI} = 0.172, p = 0.038$; $\beta_{lowbetaTI} = 0.453, p = 0.000$; $\beta_{\Delta lowbetaTI} = 0.325, p = 0.000$; $\beta_{highbetaTI} = 0.277, p = 0.005$; $\beta_{gammaTI} = 0.262, p = 0.012$; $\beta_{\Delta gammaTI} = 0.257, p = 0.003$). Furthermore, broadband TI and Δgamma TI, within student-excellence coupling positively predict math scores ($\beta_{broadbandTI} = 0.271, p = 0.012$; $\beta_{\Delta gammaTI} = 0.322, p = 0.005$). The results highlight the distinctiveness between subjects and underscore the unique predictive value of student-teacher coupling.

Discussion

This study investigates the impact of student-teacher inter-brain coupling values on learning outcome in real Chinese and math classes over six *periods* (i.e., three semesters) at a middle school. By utilizing longitudinal data, we have demonstrated a causal impact of student-teacher inter-brain coupling on learning outcomes. Specifically, the student-

teacher TI and ΔTI values within the broadband and high-beta frequency bands were found to positively predict the improvement in Chinese academic achievement, while TI values across broadband, delta, and high-beta bands, along with Δhigh-beta TI, positively predict Δmath scores. Furthermore, higher broadband and high-beta TI values were predictive to Chinese scores, while increased broadband TI and Δgamma TI were linked to better math performance. The predictive capacity of student-teacher coupling extended into subsequent semesters, suggesting a sustained impact on academic success. This study also reveals that for Chinese subjects, student-teacher coupling was more predictive than inter-brain coupling among students. These findings highlight the unique and significant role of student-teacher inter-brain coupling in academic performance, providing insights into the underlying neurophysiological mechanisms that facilitate effective student-teacher interactions.

Importantly, this research is pioneering in its confirmation that classroom-based student-teacher inter-brain coupling can predict learning outcomes, marking the first evidence of a causal link within the fields of educational science and cognitive neuroscience. This suggests that students who engage more effectively with their teachers are likely to experience academic improvements. The neural signatures observed in the high-beta frequency bands corroborate previous findings in both educational contexts and broader cognitive neuroscience[29, 30], solidifying and expanding these observations to establish causality. Additionally, our exploration of the lagged effects of this predictive capability reveals that it accurately forecasts performance improvements only for the most recent 1-2 periods (i.e., two to four months), implying a closed relationship between coupling and academic achievement within a reasonable duration.

This study consistently demonstrated a positive predictive effect on both learning outcomes and their improvements, suggesting that students who interact more effectively with their teachers tend to achieve better outcomes. Specifically, in the Chinese subject, the high-beta frequency band was consistently significance in predicting both learning outcomes and their improvement, and it also significant forecasted improvement in math scores. Extensive research has linked the beta frequency band to various cognitive functions, including working memory[31, 32], language processing[33], reward processing and long-term memory[34]. The high-beta frequency, in particular, is believed to play a more significant role in top-down information processing[35-37]. Furthermore, the immature brain development of early adolescents results in distinct patterns of brain activity compared to late adolescents and adults. Specifically, the brain activity of middle school students is more vibrant, exhibiting higher power across all frequency bands, particularly in fast wave activity such as the high-beta bands[38, 39]. This suggests that the high-beta frequency band plays a critical role in the sophisticated cognitive activities typical of early adolescents.

This study conducted a comparative analysis of academic performance predictions based on student-teacher inter-brain coupling versus inter-brain coupling among

students, thereby affirming the unique value of student-teacher coupling. Prior research has demonstrated the predictive effectiveness of student-class coupling in high school math and biology class, as well as the capacity of student-excellence coupling to forecast Chinese performance[14, 15]. This study found that student-class coupling for math learning offers superior predictive performance. In the contrast, compared to coupling among students, student-teacher coupling displays unique neural signatures (e.g. significant in high-beta band student-teacher coupling for Chinese), highlighting the distinctive patterns inherent in student-teacher interactions. Additionally, in predicting improvements in Chinese performance, student-teacher coupling shows enhanced predictive capability, as indicated by higher R-squared values in models utilizing student-teacher coupling (*See Table S1-4*).

Several limitations of this study warrant mention. First, while the research provides neurophysiological evidence of classroom learning across different disciplines through inter-brain coupling, the specific pathways of influence and the broader neurophysiological implications require further investigation and empirical validation. Second, factors such as teaching style, content, and other classroom dynamics might influence the neurophysiological data, necessitating additional exploration. Additionally, this study faced a significant loss of data samples due to the inherent noise of real classroom settings. However, to the best of our knowledge, this dataset is unique in featuring neurophysiological data collected longitudinally from both teachers and students in real classroom environments. This aspect significantly enhances the ecological validity of the study and underscores the importance of longitudinal data in educational neuroscience.

In conclusion, this study explored the profound causal impact of student-teacher interactions on learning outcomes within real classroom environments, offering neurophysiological insights. Our findings highlight the pivotal role of these interactions in enhancing effective learning, as analyzed from a neuroscientific perspective. By affirming the critical importance of student-teacher dynamics in academic success, this research further uncovers the intricate mechanisms underlying human learning, enriching our understanding of the cognitive foundations of education.

Methods

Participants.

Forty-eight first-year middle school students (22 males; 12-14 years old) and four teachers (two Chinese teachers and two math teachers) from two separate classes (23 students from class 1; 25 students from class 2) from a middle school in Beijing participated in the study. All participants and their legal representatives provided informed consent, and the study was approved by the Department of Psychology at Tsinghua University (THU201708).

Three students were discarded from the analysis due to the unsatisfactory EEG retention rates (>80% of epochs were removed, see more details in the “Data preprocessing” section). As a result, 45 participants were included in the analyses.

Data Collection.

EEG data.

The EEG data collection took place in real classroom environment and spanned a total duration of 12 months, covering three academic semesters. Data acquisition extended over four months per semester, with each half-semester identified as a distinct 'period'. Within these periods, data collection took place for a week every month, during which one to two sessions were recorded daily from two separate student classes. Specifically, for Class 1, 62 math and 59 Chinese sessions were recorded, while Class 2 accounted for 55 math and 50 Chinese sessions. Each lesson had a duration of 40 minutes, during which the teachers conducted their planned teaching activities, and students engaged in their regular learning tasks. Both students and teachers equipped themselves with the EEG headbands before each session and removed them subsequently, as directed by the research team.

EEG data were captured using a dual-channel headband featuring dry electrodes, specifically positioned at the Fp1 and Fp2 regions of the frontal cortex. The data recording occurred at a sampling rate of 250 Hz, employing the Brainno device (SOSO H&C, South Korea). The reference electrode was clipped to the right ear, serving as the ground for Fpz.

Student's learning outcomes.

Data on the students' academic achievement were gathered through their midterm and final examination scores in Chinese and math over three semesters, encompassing a total of six examinations, provided by the school administration.

Data Processing.

Student's learning outcome preprocessing.

We utilized standardized ranking information to represent students' learning outcomes, enabling a consistent and equitable comparison of student performance across various exams and cohort sizes. Students were first ranked on a scale from 1 to *N*, where *N* represents the total number of students in the cohort. The highest-performing student was assigned a rank of 1, progressing sequentially to the student with the lowest score, who received the rank of *N*. This approach effectively mitigating the issues of score saturation and truncation and highlights the relative performance among students, enhancing the robustness of the model. This initial ranking was subsequently standardized using a specific formula:

$$Score = \frac{(N+1) - Initial\ Rank}{N} \tag{1}$$

Where $Score$ denotes students' standard score of students, representing their academic achievement. N denotes the total number of students, and the $Initial\ Rank$ indicates the ranking of individual student within the cohort. The $Score$ ranges between 0 and 1, with higher values signifying better performance.

EEG data preprocessing.

The EEG data for each student were preprocessed through a five-step procedure for both channels, consistent with methodologies employed in previous studies[15, 40]. The preprocessing steps included the identification of missing data, robust detrending, band-pass filtering, waveform segmentation, and ocular artifact mitigation. Subsequently, the data from each channel were segmented into 30-second epochs. For a single 40-minute class session, this resulted in a total of 160 epochs across both channels for every student (*Fig. S2*).

Additionally, 33 of the participants were also participates in a separate research project, during which eyes-open and eyes-closed EEG data in resting states were collected. The spectral analysis was conducted on resting state data. The spectrum of the eye-closed data prominently featured a peak in the alpha frequency band, thereby affirming the reliability of the collected EEG data (*Fig. S3*).

Student-teacher Inter-brain Coupling Calculation.

This study employs the total interdependence values (TI) for assessing student-teacher, student-class and student-excellence inter-brain coupling. This approach relies on the coherence of two signals within the frequency domain, which has been validated for its efficacy in real classroom environments[40]. The utility of TI values as a metric for inter-brain coupling has been increasingly recognized in a variety of real-world contexts, including concert hall, and classroom[14, 15, 41, 42]. The computation of TI values is as follow:

$$TI_{xy} = -\frac{2}{f_s}\sum_{i=1}^{N-1} \ln\left(1 - C_{xy}^2(i\Delta f)\right)\Delta f \qquad (2)$$

where C_{xy} denotes the spectral coherence of the signal at the frequency f, computed by the Welch method. Here, f_s denotes the sampling rate, and N represents the number of data points between 0 and the Nyquist sampling rate $f_s/2$. The frequency resolution Δf is computed employing the relation $\frac{f_s}{2(N-1)}$. In this analysis, TI values were computed across the EEG's broad frequency spectrum, ranging from 1 to 40Hz. Calculations also incorporated individual frequency bands: delta (1-4Hz), theta (4-8Hz), alpha (8-13Hz), low beta (13-18Hz), high-beta (18-30Hz), and gamma (30-40Hz).

Within each session, the TI value for each student-teacher pair was determined by averaging the TI values across all epochs that successfully matched between the student and teacher, considering data from both recording electrodes (as shown in *Figure 1C*). A *'segment'* was defined as a matched epoch, recognized as such only when it included artifact-free and valid data from both the teacher and the student. A minimum threshold was established, requiring that only student-teacher pairs with at least six valid segments were to be included[14, 15]. For Chinese classes, the average proportion of valid student-teacher coupling segments for each session was 50.2%, while for math classes, it was 46.6% (*Fig. S4*).

Student-class inter-brain coupling.
The student-class inter-brain coupling value for a given student is computed as the mean of all TI values between this student and the rest of the class of each session. For Chinese, the average proportion of valid student-class coupling segments for each session was 50.5%, while for math, it was 50.4% (*Fig. S4*).

Student-excellence inter-brain coupling.
The student-excellence inter-brain coupling value for a given student is computed as the mean of all TI values between this student and the top four student in the class. For Chinese, the average proportion of valid student-class coupling segments for each session was 45.0%, while for math, it was 40.4% (*Fig. S4*).

Following this, the inter-brain coupling values within each *period* (i.e., half-semester) were averaged for each student. To ensure the quality of the data, student samples with valid sessions constituting less than 20% within a *period* were omitted from the analysis. These averaged TI values were then normalized to a range of [0, 1] for each frequency band.

Regression Analysis.
Linear mixed-effects (LME) models were fitted to the data to investigate the relationship between student-teacher TI and academic achievement, which allow to effectively partition the overall variation of the dependent variable into components corresponding to different levels of data hierarch[43]. According to the dependent variables, two kinds of models are designed. The *dynamic model* (equations 5-6) uses the difference in test score between *period* t and the previous *period* as the dependent variable, representing the improvement of learning achievement, while the *static model* (equations 7-8) uses standardized test score as dependent variable. Given the potential non-independence of EEG data within each individual students or time *period*, the two categorical variables are employed to classify the observations into separate groups, to account for correlated observations in the data[44].

The intraclass correlation analysis.
The intraclass correlation coefficient (ICC) was first calculated for each categorical variable, in order to determine if it is appropriate to include the corresponding random effect. The formula of ICC is as follows:

$$ICC = \frac{Var_{between}}{Var_{between} + Var_{within}} \tag{3}$$

where $Var_{between}$ denotes the between-group variation of the dependent variable, and Var_{within} denotes the within-group variation. The ICC value is between 0 and 1, where a higher ICC value indicates larger distinctions between groups. An ICC value above 0.05 highlights noteworthy intraclass correlation that should be considered[45].

Prediction of academic improvement.
The *dynamic* model is applied in order to investigate whether student-teacher coupling

can causally predicted student academic achievement. The investigation aimed to explore whether the increase in TI values could dynamically affect changes in academic achievement after controlling for the initial impact of TI. In pursuit of this, the model integrated both the baseline TI values and their incremental growth as independent variables, with the growth of standardized scores as the dependent variable in the analysis.

The *dynamic* models are:

$$\Delta Score_{it} = Score_{it} - Score_{i(t-1)} = \beta_0 + \beta_1 frequencyTI_{i(t-1)} + \beta_2 \Delta frequencyTI_{it} + u_i + \mathrm{u_t} + \varepsilon_{it} \quad (4)$$

where $\Delta Score_{it}$ denotes the improvement of students' academic achievement; $\mathrm{Score_{it}}$ represents the standardized score of student i in period t, and $\mathrm{Score_{i(t-1)}}$ denotes the standardized score of the same student i in the preceding period, $t-1$; $frequencyTI_st_{i(t-1)}$ indicate the vector of student-teacher TI values of student i in *period* $t-1$ in different frequency bands (i.e., broadband, delta, theta, alpha, low-beta, high-beta, and gamma bands); $\Delta frequencyTI_{it}$ is the difference between $frequencyTI_{it}$ and $frequencyTI_{i,t-1}$; u_i is the individual fixed ability (or say, random effect of student), u_t is the period fixed characteristics (or say, random effect by period), and ε_{it} denotes the random error term.

ICC was calculated first. For ΔChinese score, the ICC for student individual (ICC_{stu_id}) was 0.000 and for *period* factor (ICC_{period}) was 0.000. In the case of Δmath score, ICC_{stu_id} was 0.000, and ICC_{period} was 0.137. As a result, in the prediction of ΔChinese scores, the individual factor was treated as the random effect. For the prediction of Δmath scores, the period factor was treated as the random effect.

Prediction of student's academic achievement.

The study then investigates the influence of student-teacher inter-brain coupling on the students' learning outcome. The inter-class correlation analysis (ICC) was first conducted to refine the regression models. For Chinese score, the ICC for individual student (ICC_{stu_id}) was 0.796, and for *period* (ICC_{period}) it was 0.000; For math score, ICC_{stu_id} was 0.625, and ICC_{period} was 0.000. Thus, only the individual level was treated as random effect in the analysis.

The *static* models were designed as:

$$Score_{it} = \beta_0 + \beta_1 frequencyTI_{st_{i(t-1)}} + \beta_2 \Delta frequencyTI_{st_{it}} + u_i + \varepsilon_{it} \quad (5)$$

where all the symbols are consistent with those defined before (*See formula 4*).

Prediction of student's academic achievement over multiple lagged *periods*.

To investigate whether the student-teacher coupling has a long-term predictive effect on score and Δscore, this study utilized current TI and ΔTI to predict scores over multiple lagged *periods*. The formula is as follow:

$$\Delta Score_{i(t+lag\ period)} = \beta_0 + \beta_1 frequencyTI_{i(t-1)} + \beta_2 \Delta frequencyTI_{it} + u_i + \varepsilon_{it} \quad (6)$$

$$Score_{i(t+lag\ period)} = \beta_0 + \beta_1 frequencyTI_{i(t-1)} + \beta_2 \Delta frequencyTI_{it} + u_i + \varepsilon_{it} \quad (7)$$

where $lag\ period$ denotes the number of *periods* by which the score lags behind ΔTI, $Score_{i(t+lag\ period)}$ is the achievement of student i in *period* $t + lag\ period$; and other symbols are consistent with before (*See formula 4, 5*). For example, if the $lag\ period$ is set to 2, and t equals 3, this implies predicting the score for the 5th period using the TI from the 2nd period and the ΔTI from the 2nd to 3rd period.

We conducted nonparametric permutation tests to further verify the correlation between inter-brain coupling and learning outcomes. To assess the significance of our findings, we generated 5,000 random permutations of the independent and dependent variables and calculated the distribution of predicted coefficients from these shuffled datasets. By comparing the original coefficient values with those generated from the 5,000 shuffled versions, we evaluated the robustness of our results. Results with p-values less than 0.05 from both parametric and nonparametric tests are considered significant[46].

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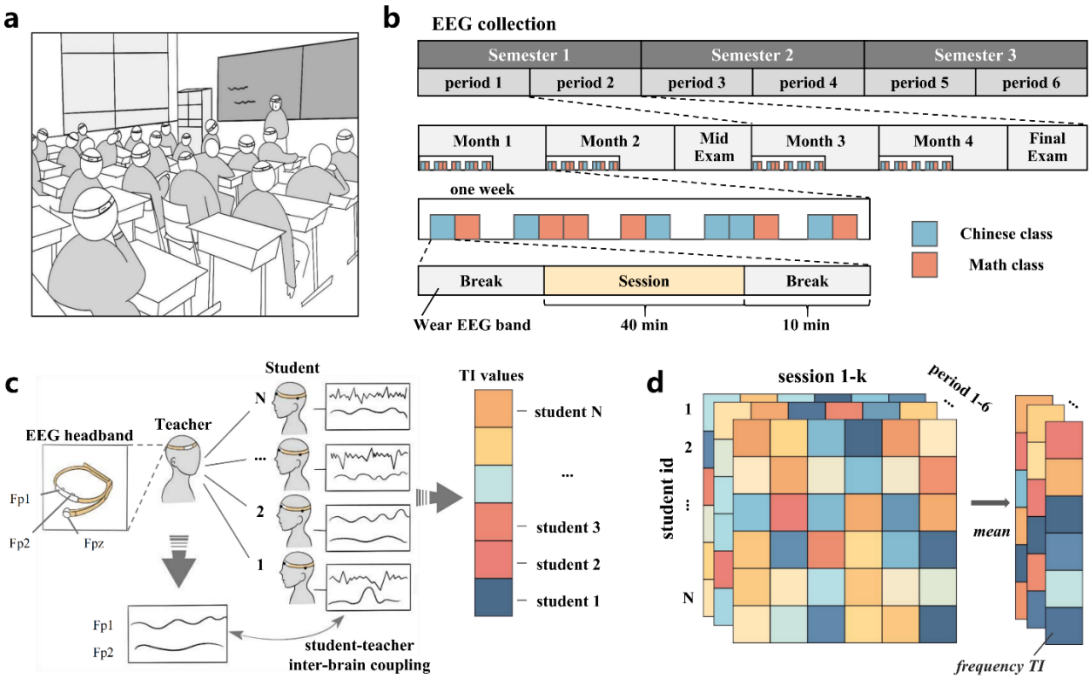

Fig 1. An Illustration of data collection process. **a,** Schematic representation of data acquisition in a real classroom setting. **b,** Outline of the data collection process. **c,** An illustration of the calculation of student-teacher inter-brain coupling of each session. **d,** An illustration of the student-teacher inter-brain coupling for each *period*. The TI value is calculated for each student per session, then averaged across all sessions within each *period*.

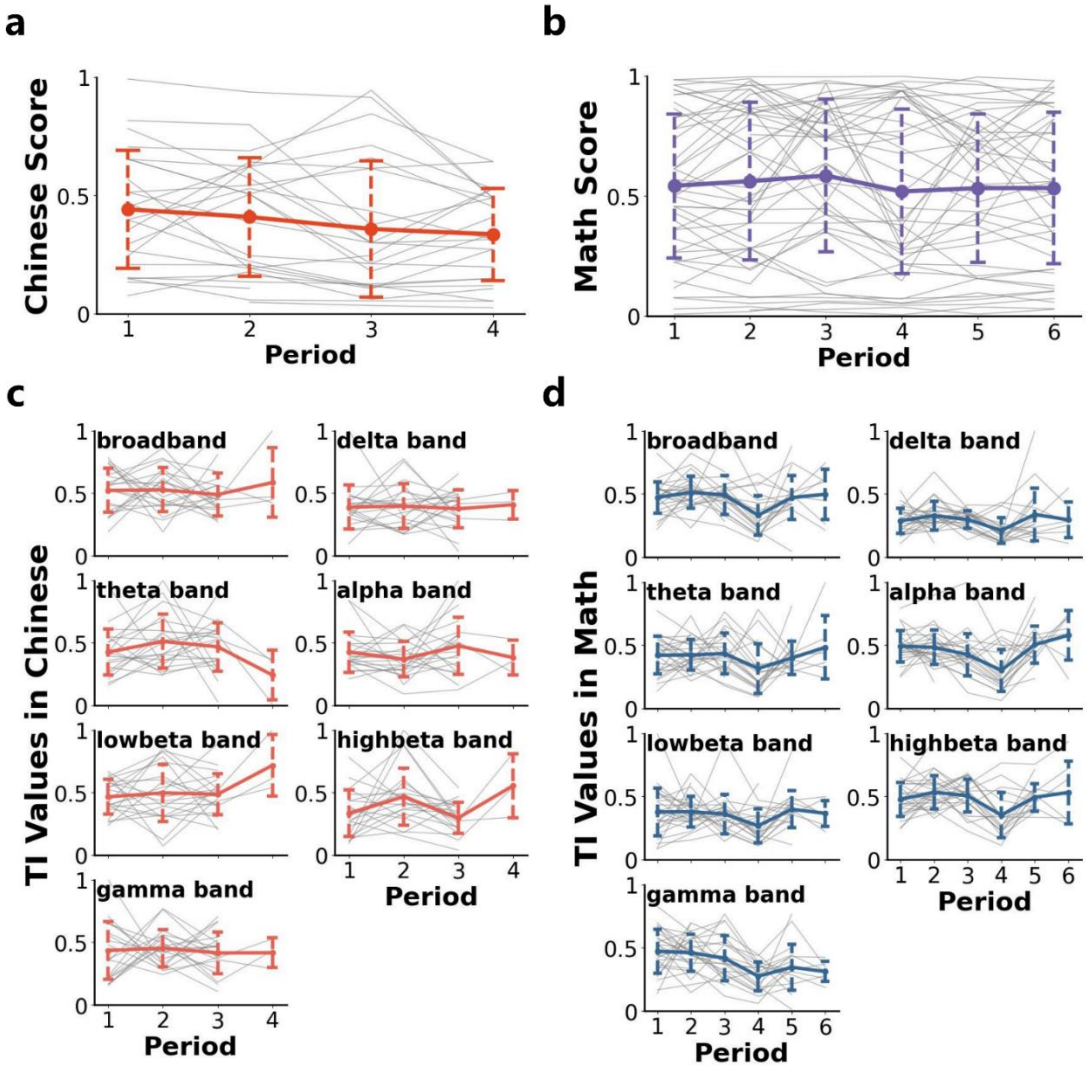

Fig 2. Descriptive statistics of learning outcomes and student-teacher coupling values across *periods*. **a,** The average scores for Chinese, with the upper and lower limits indicating standard deviation. **b,** The average scores for math. **c,** Average TI values for Chinese across each period, with upper and lower limits representing the standard deviation. **d,** Average TI values for math across each period.

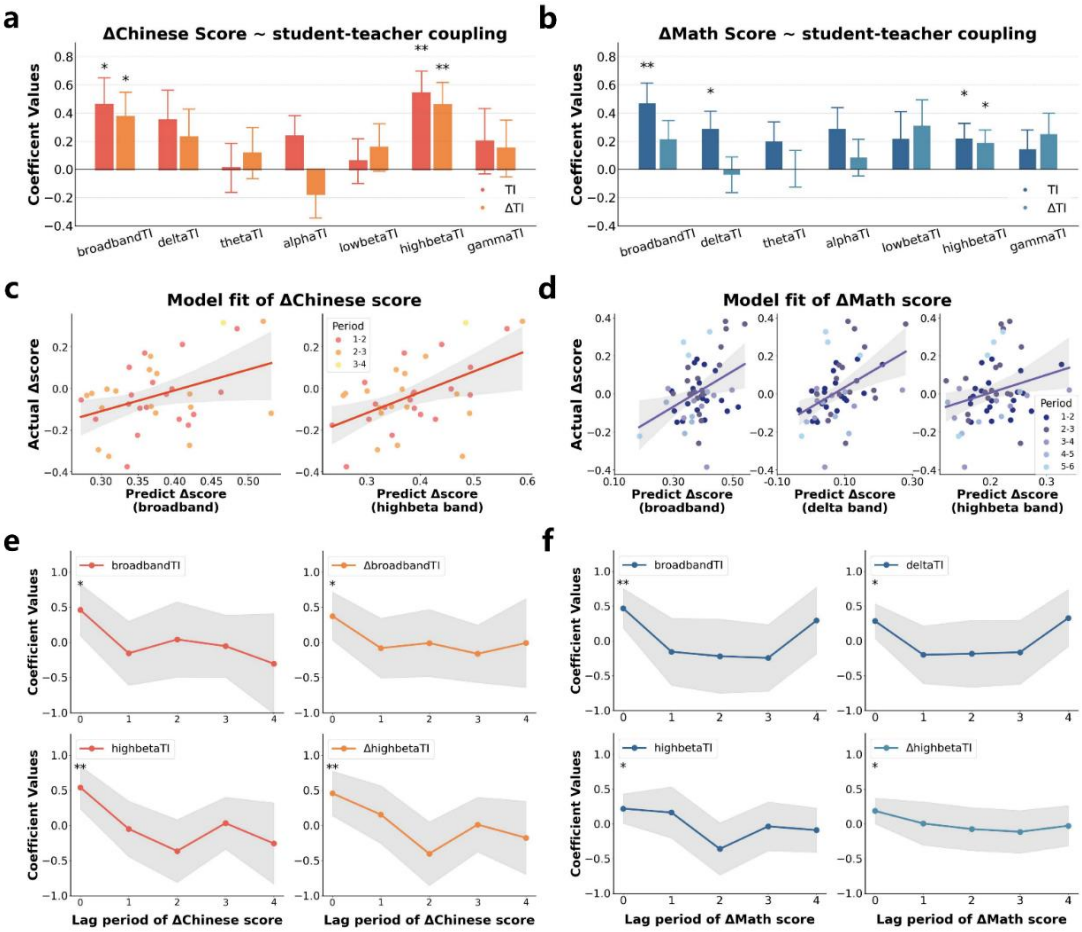

Fig 3. Coefficients for predicting improvement of Chinese and math scores based on student-teacher coupling across different frequency bands. **a,** Prediction results for Chinese improvement based on student-teacher coupling, N=37. The horizontal axis represents TI values and ΔTI values across different frequency bands, while the vertical axis corresponds to the associated coefficient values. Asterisks denote significant correlation, *$p < 0.05$, **$p < 0.01$. **b,** Prediction results for math improvement based on student-teacher coupling, N=54. **c,** Model fit results for predicting ΔChinese score. The horizontal axis denotes predicted Δscore, while the vertical axis represents the actual values of Δscores. Data points from different *periods* are denoted by distinct colors. **d,** Model fit results for predicting Δmath score. **e,** Coefficient values for predicting multi-period ΔChinese score. The horizontal axis indicates the lag period, while the vertical axis represents the coefficient values. The shaded areas represent the 95% confidence intervals. **f,** Coefficient values for predicting multi-period Δmath score.

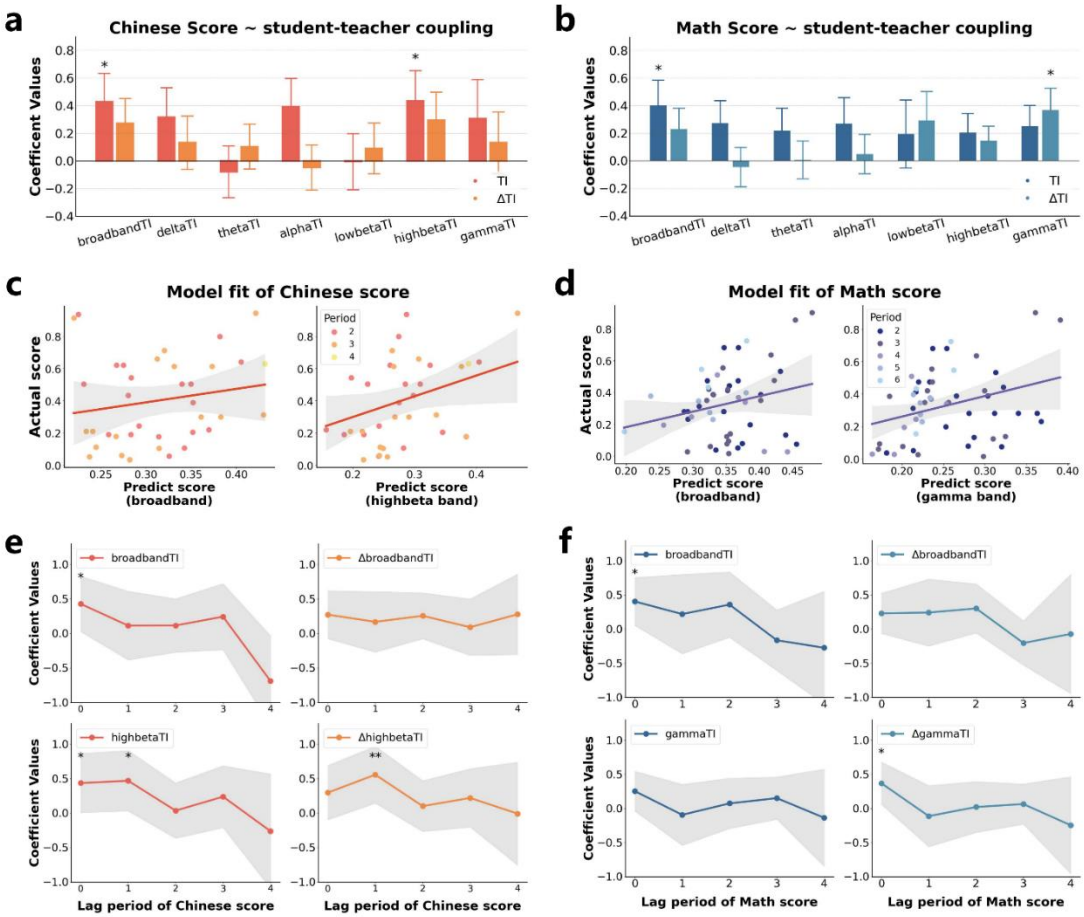

Fig 4. Coefficients for predicting Chinese and math learning outcomes based on student-teacher coupling across different frequency bands. **a,** Prediction results for Chinese score based on student-teacher coupling, N=37. **b,** Prediction results for math learning outcomes based on student-teacher coupling, N=54. **c,** Model fit results for predicting Chinese score. **d,** Model fit results for predicting math score. **e,** Coefficient values for predicting multi-period Chinese score. **f,** Coefficient values for predicting multi-period math score.

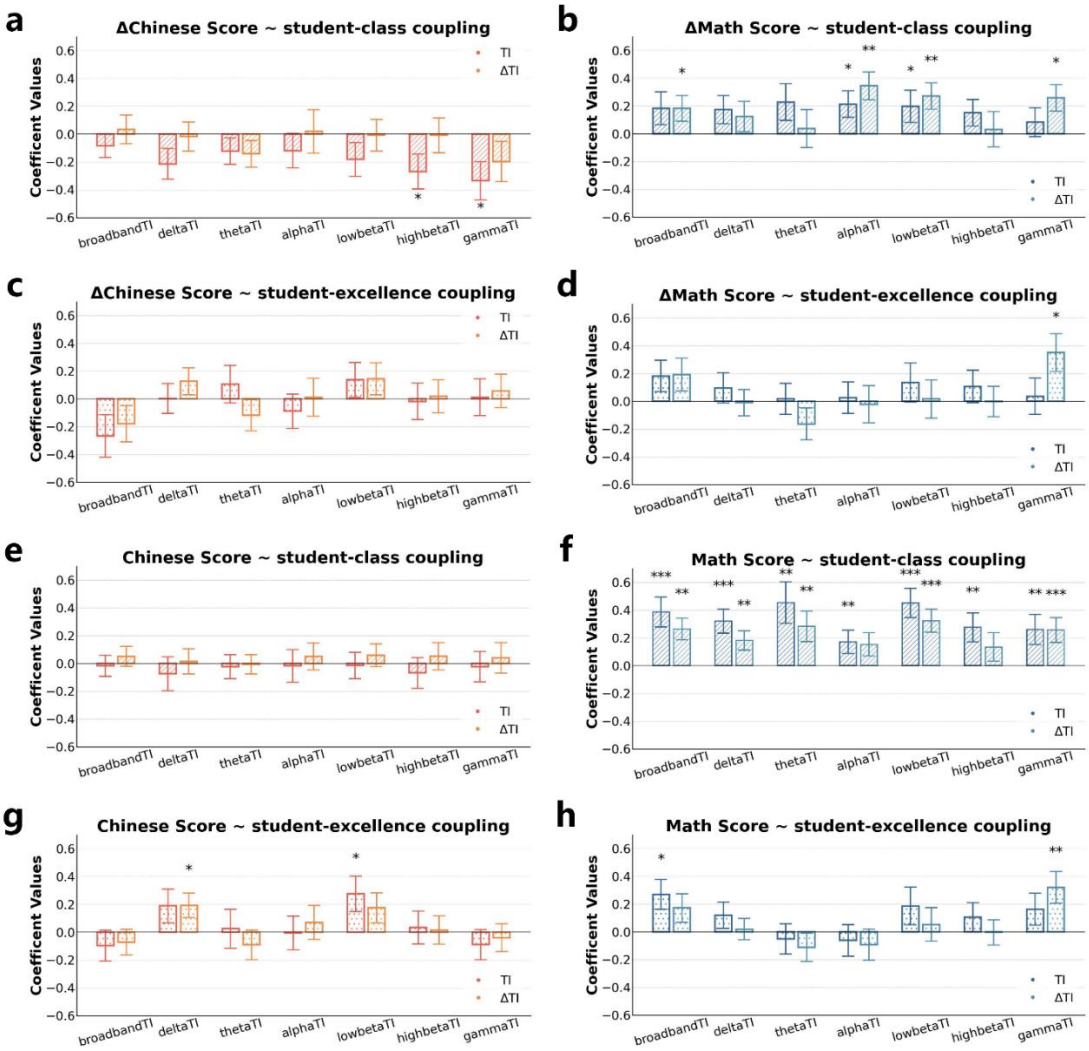

Fig 5. Coefficients for predicting Chinese and math learning outcomes based on student-class coupling and student-excellence coupling across different frequency bands. **a,** Prediction results for ΔChinese score based on student-class coupling, N = 149. **b,** Prediction results for Δmath score based on student-class coupling, N = 156. **c,** Prediction results for ΔChinese score based on student-excellence coupling, N = 120. **d,** Prediction results for Δmath score based on student-excellence coupling, N = 162. **e,** Prediction results for Chinese score based on student-class coupling, N = 149. **f,** Prediction results for math score based on student-class coupling, N = 156. **g,** Prediction results for Chinese score based on student-excellence coupling, N = 120. **h,** Prediction results for math score based on student-excellence coupling, N = 162.