Inter-brain coupling reflects disciplinary differences in real-world classroom learning

■ **Authors**

Jingjing Chen[1, 6], Penghao Qian[2], Xinqiao Gao[3], Baosong Li[4,3], Yu Zhang[5] & Dan Zhang[1, 6]

■ **Affiliations**

1 Dept. of Psychology, School of Social Sciences, Tsinghua University, China
2 College of Information and Electrical Engineering, China Agricultural University, China
3 Beijing No. 19 High School, Beijing, China
4 College of Education, Zhejiang Normal University, Jinhua, China
5 Institution of Education, Tsinghua University, China
6 Tsinghua Laboratory of Brain and Intelligence, Tsinghua University, Beijing, China

* Corresponding authors:
Dan Zhang, dzhang@tsinghua.edu.cn, +86-10-62796737
Yu Zhang, zhangyu2011@tsinghua.edu.cn, +86-10-62785686

Abstract

Classroom learning is one of the most critical scenarios in educational practices worldwide. Classroom learning was always organized into different disciplines (such as Math or language courses) in educational practice. However, we know little about how disciplinary differences are manifested in students' neural dynamics supporting successful classroom learning. In order to address this question, we investigated disciplinary differences during the successful classroom learning from the framework of hard and soft disciplines by recording thirty-four high-school students' EEGs simultaneously during their regular Chinese (a soft discipline) and Math (a hard discipline) courses across a whole semester. One's theta-band inter-brain coupling to all other classmates during both the Chinese and Math courses was found to be positively correlated with their learning outcomes in Math. In contrast, one's alpha-band inter-brain coupling to their excellent peers was positively correlated with their learning outcomes in Chinese. These results demonstrated the value of inter-brain coupling as neural correlates of successful classroom learning and highlighted excellent peers as a candidate to represent successful learning for soft disciplines. Our findings provide real-world neuroscience evidence for understanding disciplinary differences and suggest possibly different neurocognitive mechanisms to support successful learning in different disciplines.

Keywords:

disciplinary difference, learning process, inter-brain coupling, real-world classroom, EEG

Introduction

Classroom learning, where dozens of students learn together under the guidance of a teacher in a classroom, is one of the most representative scenarios for human beings' daily learning activities. Due to its practical importance for personal development, classroom learning has drawn consistent attention from the fields of education and psychology[1–3]. It has also been considered an ideal starting point for real-world neuroscience[4].

In practice, classroom learning has always been organized into different disciplines according to the learning contents (e.g., Math, history, physics, or language courses), and it is widely acknowledged that different disciplines would require different learning strategies and approaches. The hard-soft dimension is possibly one of the most influential frameworks regarding disciplinary differences[5]. Hard disciplines (e.g., math, natural science, engineering, and technology) are known for the relatively hierarchical, linear knowledge structure and straightforward, uncontentious teaching contents. Soft disciplines are usually associated with loose-structured, non-linear knowledge and contents that require more constructive and interpretative activity (e.g., history, philosophy, language courses)[5–7]. The differences between hard and soft disciplines in the classroom have been proven to influence teachers' teaching goals and shape students' learning strategies and approaches toward successful learning[8,9]. For instance, it has been proposed that students prioritize fixed knowledge from teachers when learning hard disciplines than their soft counterparts[10]. Nevertheless, it should be noted that the disciplinary differences of successful learning have mainly been studied indirectly by inferring the learning process using data from expert evaluation, retrospective self-reports, learning outcomes, etc.[7,10,11]. There is a dearth of empirical studies directly addressing the learning process itself[12].

The neuroscience methods have demonstrated their potential as a powerful tool to directly capture the learning process by recording the corresponding neural activity in an objective and non-intrusive way[13,14]. Moreover, the development of the portable EEG devices further suggested the potential to record students' brain activity during their learning process in real-classroom settings[13,15–17], thus supporting a direct investigation of the disciplinary differences in successful classroom learning. With portable EEG devices, students' sustained attention, situational interests, engagement, and relationship with teachers have been successfully assessed during their classroom learning process for disciplines such as math or biology in recent studies[4,18–20]. Compared to the laboratory-based studies, the real-classroom studies are advantageous for their high ecological validity, as it is difficult to fully simulate real disciplinary learning in the laboratories. Nevertheless, it should be emphasized that these studies have only included one single discipline per study. We know little about how disciplinary differences are manifested in students' neural dynamics supporting successful classroom learning.

The emerging inter-brain coupling analysis suggested a feasible tool to investigate the neural dynamics during successful classroom learning[21–24]. Previous neuroscience methods might identify the neural correlates of successful disciplinary learning by

extracting the neural activity related to a certain learning event compared to a baseline[25]. Unlike the traditional methods, the inter-brain approach identifies the neural correlates of interest by investigating the inter-brain neural coupling among the people who receive the same complex stimuli[26–28] or are involved in the same interacting scenarios[29–35]. Hereby, the inter-brain approach is well suited for analyzing real-classroom data, as all students in the classroom are situated in the same learning environment. The inter-brain coupling analysis has been shown to be capable of characterizing the neural dynamics during typical learning scenarios such as lectures, videos, and group discussions[4,36–38]. Moreover, one student's neural coupling to other students has been reported as an efficient neural indicator for evaluating individuals' learning processes. For example, the average inter-brain EEG coupling from one student to all their peers or classmates (termed as 'student-class coupling' in the following) has been found to be positively correlated with their class engagement during a biology course[4] and their memory retention performance during a biology and chemistry course[37].

Despite these positive findings, it is worth noting that in most available student-student neural coupling studies, the disciplines investigated are hard ones, such as biology, computer science, and physics[4,20,36,37,39]. While inter-brain analysis provided a promising candidate to investigate how disciplinary differences are manifested in students' neural dynamics supporting successful classroom learning, no single inter-brain study to date has addressed the issue of disciplinary differences. Interestingly, the state-of-the-art findings on the learning of hard disciplines have highlighted the functional importance of student-class coupling. Higher coupling strength is associated with a better learning state and outcome[4,36–38]. Therefore, it seemed promising to consider the 'class average' neural activity for representing a successful learning process. As the learning of hard disciplines is straightforward and non-ambiguous (e.g., the exact application of fixed mathematical rules)[40], it is plausible to assume that the students are expected to exhibit consistent neural activity across students. Hereby, averaging might facilitate the extraction of the neural activity shared across students that could effectively represent the 'desired' and fixed learning routine aligned with the teaching contents. However, as soft and hard disciplines vary in the learning approaches they favored[41], the successful learning of soft disciplines might follow a different routine where more scope for creativity and cultural interest are cherished compared with the hard disciplines[7]. Accordingly, the possibly different learning routines towards success might undermine the importance of 'class average' in the context of soft disciplines.

Excellent peers could serve as an alternative candidate reference to represent a successful learning process. Here, excellent peers (termed as 'excellence' in the following) refer to the students in a class with top learning outcomes. As good learning outcomes have long been associated with an effective learning routine[42], it is reasonable to take excellence as a good representative of successful learning. Compared to the 'class average', the excellence could be a better candidate for a successful learning

process of soft disciplines, given a potentially different learning routine. While it could be challenging to compare these two representatives (i.e., 'class average' vs. excellence) for successful learning with conventional single-brain-based methods, the inter-brain approach enables us to directly compare them. Specifically, it is quite straightforward to compute student-class coupling and student-excellence coupling similarly. Comparing the student-class coupling and student-excellence coupling during the learning of soft and hard disciplines may give us insights into disciplinary differences in learning.

The present study aimed to investigate how disciplinary differences are manifested in students' neural correlates of successful classroom learning by recording EEGs from a group of high-school students in China during their regular classroom learning for a whole semester. Math and Chinese (the mother tongue learning in China) were chosen as representative courses for the hard discipline and soft discipline, respectively, as they are two of the most important compulsory courses before college in China. Based on the state-of-the-art understanding of disciplinary learning[4,36,37], we hypothesized that the 'class average' might effectively represent the successful learning process during Math courses (a hard discipline). In contrast, excellent peers could be an effective representation of the successful learning process of Chinese (a soft discipline). Correspondingly, the student-class coupling was expected to be correlated with the final exam scores of Math courses, and the student-excellence coupling was expected to be correlated with the final exam scores of Chinese courses. To describe neural activity for learning more precisely, these two inter-brain couplings were calculated separately for EEGs at different frequency bands. No clear hypothesis regarding the difference in an involved EEG frequency band was formulated due to limited evidence to date. Any discovery would promote our understanding of the neural mechanism behind disciplinary differences in the real-world classroom learning process.

Result

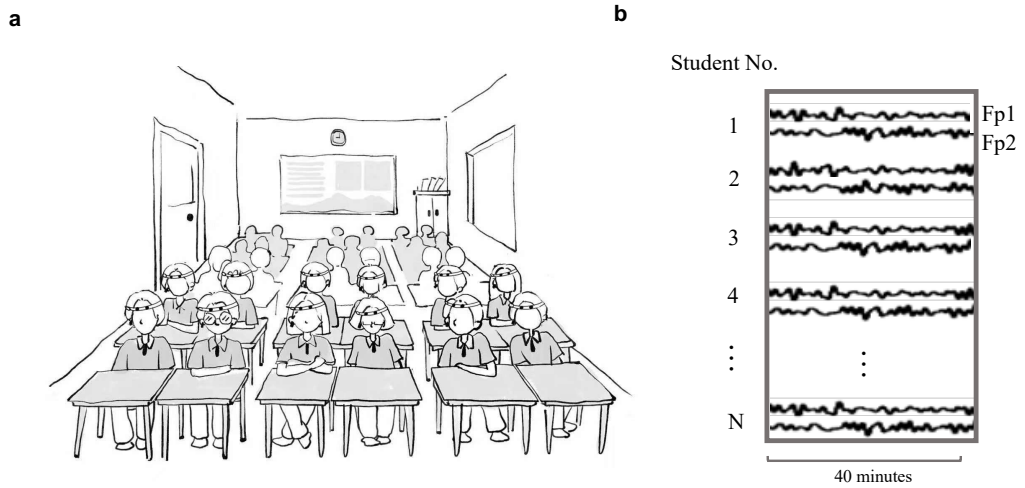

Fig.1: Experiment paradigm. **a**, An illustration of the experimental setup for students wearing an EEG headband during their regular classroom learning; **b,** An illustration of the recorded EEG signal during a session; EEGs were recorded at Fp1 and Fp2 for all the students for 40 minutes.

Real-world classroom setup and inter-brain analysis

As demonstrated in Fig.1**a**, thirty-four students from the same class (37 students in total) from grade 10 of a high school in Beijing volunteered to join the study. EEG headbands with two dry electrodes covering Fp1/2 were chosen to record students' brain signals during their regular classroom Math and Chinese sessions throughout one semester. While the EEG headbands have demonstrated their effectiveness in tracking brain states in tasks such as resting-state, sudoku games, and surgery[43–47], their signal quality was also validated with a 2-minute eye-closed/open task in the present study. Twenty-two students out of the same class participated in this task in their classroom environment. Supplementary Fig.S1 shows the signal quality validation results: compared to the eye-open condition, the eye-closed condition was associated with an expected spectral peak at the alpha range (8-13 Hz), demonstrating the reliability of the headband for classroom recording.

The data collection lasted for four months to cover the whole semester. Students' EEG signals were acquired during Chinese sessions and Math sessions for one week (one or two sessions per day) each month following the regular curriculum. The total number of sessions was 38, with 18 sessions for Chinese and 20 sessions for Math. The sessions of Math include the introduction of planar vectors, cubic geometry, plural, statistics, and probability. The sessions of Chinese include the reading of ancient and modern poems, essays and novels, and the introduction of writing. Each session lasted for 40 minutes. The students' final exam scores for Chinese and Math at the end of this semester were taken as the indicator of their learning outcomes. Compared with the specially-designed quiz, final exams are expected to boost the ecological validity as

they are derived from the highly-developed evaluation system in the daily educational practice. The final exams covered the contents of the whole semester.

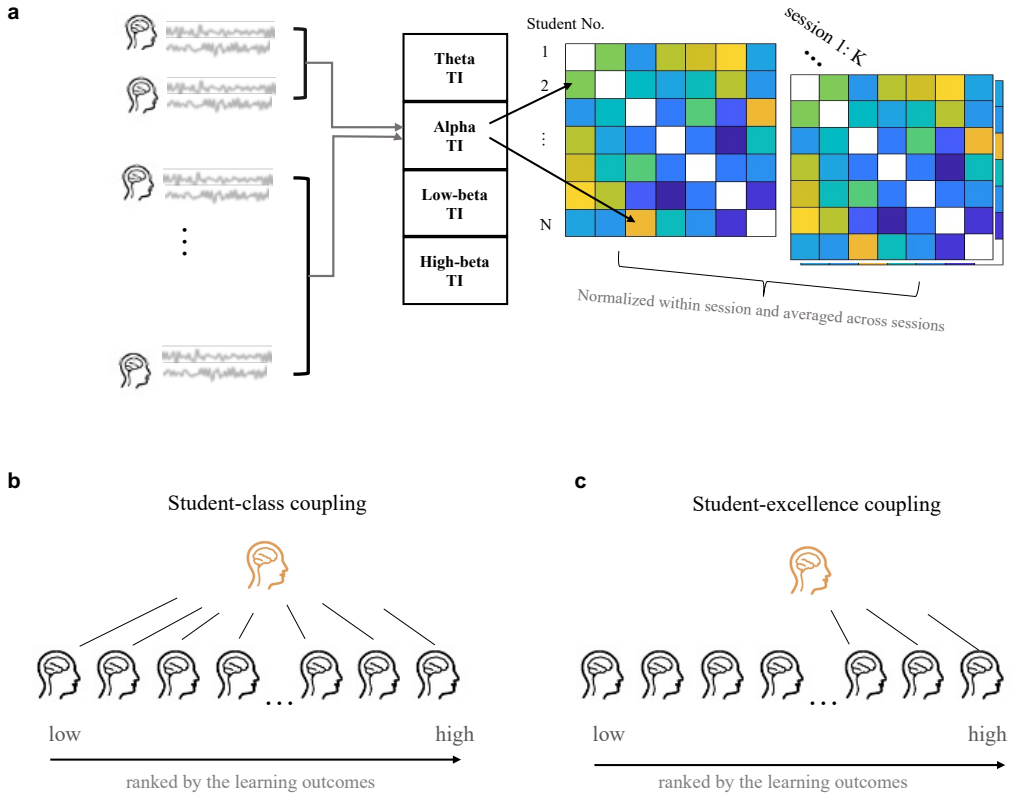

Fig 2: Schematic of the inter-brain coupling analysis. **a,** The computations of pairwise total interdependence (TI) matrix for each pair of students (i, j) for each session, at the frequency bands of theta, alpha, low-beta, and high-beta. The TI values were then normalized within each session and averaged across sessions to obtain an inter-brain coupling value for each pair of students. **b,** Student-class coupling was obtained by averaging TI values over all possible pairwise combinations between one student and the rest of the class. **c,** Student-excellence coupling was computed by averaging TI values over all possible pairwise combinations between one student and the excellences except themselves if included.

The total interdependence (TI) method was employed to calculate the inter-brain coupling by computing the magnitude squared coherence between brain signals simultaneously recorded from two students[4,20,48]. This method has been previously used in inter-brain studies to investigate individuals' engagement and valence levels in naturalistic scenarios such as a classroom and a concert hall[4,49]. To test our hypothesis, student-class coupling and student-excellence coupling were calculated for each student as indicators of the disciplinary learning process for the whole semester, as shown in Fig.3**b, c**. Then, Pearson's correlations between individuals' student-class coupling (or student-excellence coupling) and their corresponding final exam scores

were calculated separately for soft and hard disciplines to identify neural correlates of successful classroom learning. For student-class coupling, all students were included in the correlation analysis. For student-excellence coupling, however, the excellences themselves were excluded during the correlation analysis between student-excellence coupling and final exam scores. For example, if individuals' student-excellence coupling was computed with the top N_E students, then the top N_E students' coupling values, as well as their final exam scores, will be removed, leaving $(N - N_E)$ out of the N students for conducting the correlations. Theta (4-8 Hz), alpha (8-13 Hz), low-beta (13-18 Hz), and high-beta (18-30 Hz) bands were calculated separately in the inter-brain coupling analysis.

Theta-band student-class coupling is correlated with the learning outcomes of Math

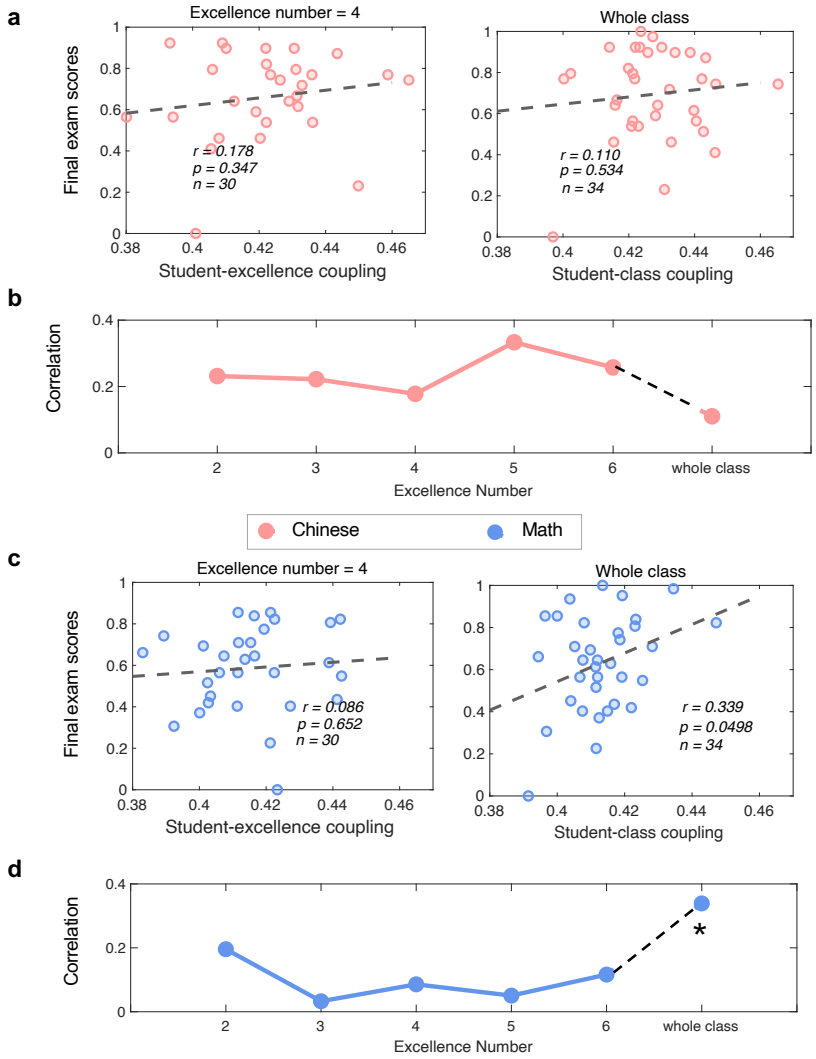

Fig.3: The correlations between theta-band student-excellence/class coupling with one's final exam score for Chinese and Math. **a**, Scatter plots between theta-band student-excellence coupling (left, excellence number = 4) and theta-band student-class coupling (right) and the final exam scores of Math. **b,** Correlation r values as a

function of the number of excellences included in the calculation of student-excellence coupling. **c,** Scatter plots between theta-band student-excellence coupling (left, excellence number = 4) and theta-band student-class coupling (right) and the final exam scores of Chinese. **d**, Correlation r values as a function of the number of excellences included in the calculation of student-excellence coupling. Note that the excellences themselves were not included in the correlation analysis. The star indicated a significant ($p < 0.05$) correlation.

Here, no significant correlations were observed between theta-band inter-brain coupling and Chinese, neither in student-excellence coupling nor in student-class coupling (Fig.3**a, b**; student-excellence coupling: $r = 0.178$, $p = 0.347$, $n = 30$, excellence number = 4; student-class coupling: $r = 0.110$, $p = 0.534$, $n = 34$). On the other hand, theta-band student-class coupling during Math sessions was found to be positively correlated with the final exam scores for Math (Fig.3**c, d**): the stronger theta-band student-class coupling, the higher final exam scores of Math ($r = 0.339$, $p = 0.0498$, $n = 34$). No significant correlations between theta-band student-excellence coupling and Math scores were found, with the number of excellences included in the calculation of student-excellence coupling varying from 2 up to 6.

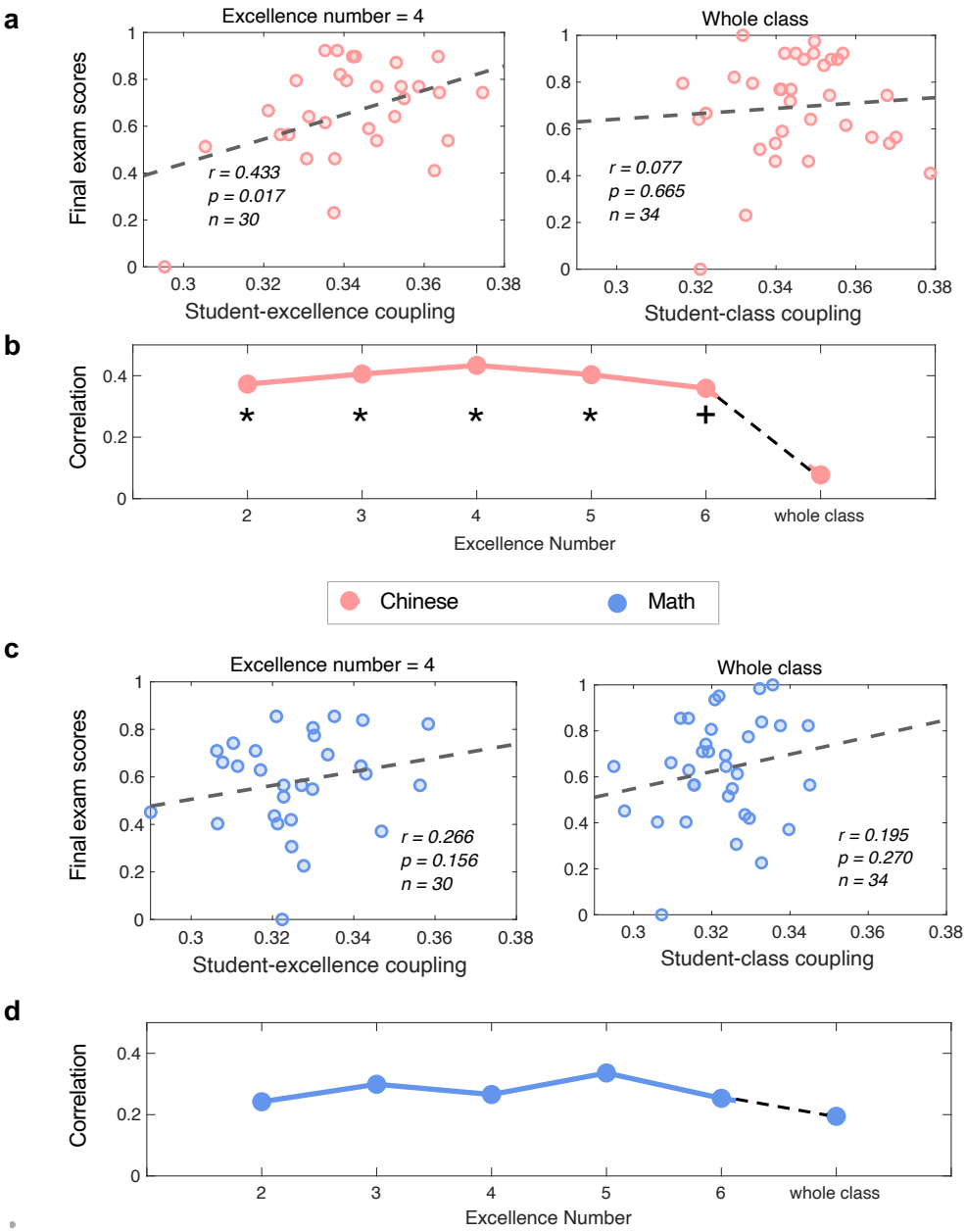

Fig.4: The correlations between alpha-band student-excellence/class coupling with one's final exam score of Chinese and Math. **a**, Scatter plots between alpha-band student-excellence coupling (left, excellence number = 4) and alpha-band student-class coupling (right) and the final exam score of Chinese. **b**, Correlation r values as a function of the number of excellences included in the calculation of student-excellence coupling. **c,** Scatter plots between alpha-band student-excellence coupling (left, excellence number = 4) and alpha-band student-class coupling (right) and the final exam scores of Math. **d,** Correlation r values as a function of the number of excellences

included in the calculation of student-excellence coupling. Note that the excellences themselves were not included in the correlation analysis. The star and the cross indicated a significant ($p < 0.05$) and a marginal significant ($p < 0.10$) correlation.

Alpha-band student-excellence coupling is correlated with the learning outcomes of Chinese

Alpha-band student-excellence coupling during Chinese sessions was significantly correlated with the final exam scores for Chinese (Fig.4**a**): the stronger the student-excellence coupling, the higher the final exam scores (r = 0.433, p = 0.017, n = 30, excellence number = 4). The correlation remained significant or marginally significant when the number of excellences included in the calculation of student-excellence coupling varied from 2 to 6 (Fig.4**b**). No significant correlations between alpha-band student-class coupling and final exam scores of Chinese were found (r = 0.077, p = 0.665, n = 34). Moreover, no significant correlations were observed between alpha-band inter-brain coupling and the final exam scores of Math, neither in student-excellence coupling nor in student-class coupling (Fig.4**c, d**; student-excellence coupling: r = 0.266, p = 0.156, n = 30, excellence number =4; student-class coupling: r = 0.195, p = 0.270, n = 34).

Frequency-specificity for outcome-related inter-brain coupling

Fig.5 further showed the overall inter-brain coupling results at all the four frequency bands (theta, alpha, low-beta, and high-beta). Inter-brain coupling at the theta and alpha bands was found to correlate with the final exam scores (as shown above) significantly. In contrast, the inter-brain coupling at the low-beta and high-beta bands failed to reach significance. We also conducted a similar inter-brain coupling analysis but focused on 1-20 Hz as several previous studies[4,20]. The results are shown in Supplementary Fig.S2: No significant correlations were found between 1-20 Hz inter-brain coupling and the final exam scores, demonstrating the value of separating different frequency bands.

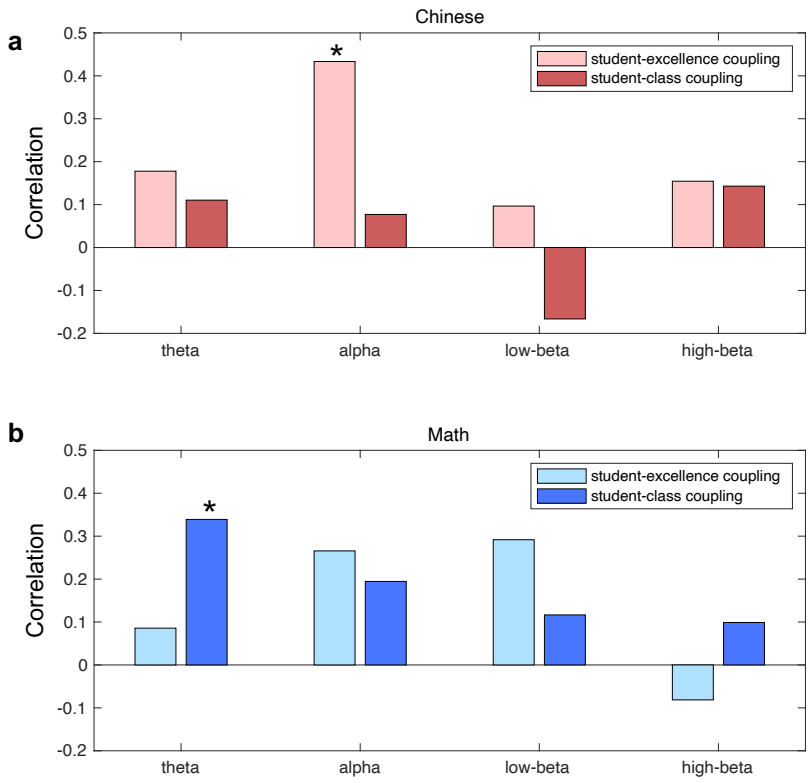

Fig.5: The correlation r values between inter-brain coupling and final exam scores at the theta, alpha, low-beta and high-beta band for **a**, Chinese and **b,** Math. The bars with a lighter color indicated student-excellence-coupling-based correlations (excellence number = 4), and the bars with a darker color indicated student-class-coupling-based correlations. The stars indicated a significant ($p < 0.05$) correlation.

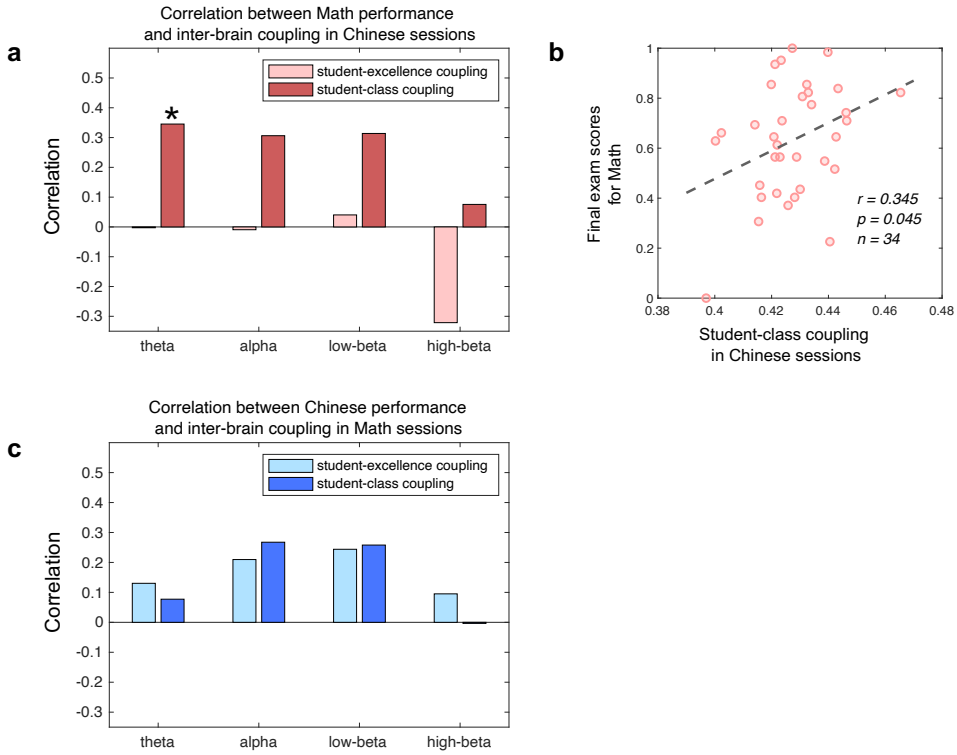

Fig.6: The correlation analysis results by switching the discipline scores, i.e., correlating inter-brain coupling in Math sessions with final exam scores of Chinese (**a**) and vice versa (**c**). **b,** Scatter plots between theta-band student-class coupling during Chinese sessions and the final exam scores of Math. The bars with a lighter color indicated student-excellence-coupling-based correlations (excellence number = 4), and the bars with a darker color indicated student-class-coupling-based correlations. The stars indicated a significant ($p < 0.05$) correlation.

To explore the discipline-specificity of the inter-brain coupling results, the correlations between final exam scores and inter-brain coupling were re-computed by switching the disciplinary scores (i.e., computing the correlation between inter-brain coupling during Math sessions and the final exam scores of Chinese, and vice versa). As shown in Fig. 6**b**, theta-band student-class coupling during Chinese sessions was significantly correlated with the final exam scores of Math (student-class coupling: $r = 0.345$, $p = 0.045$, $n = 34$). No other correlations reached significance after switching.

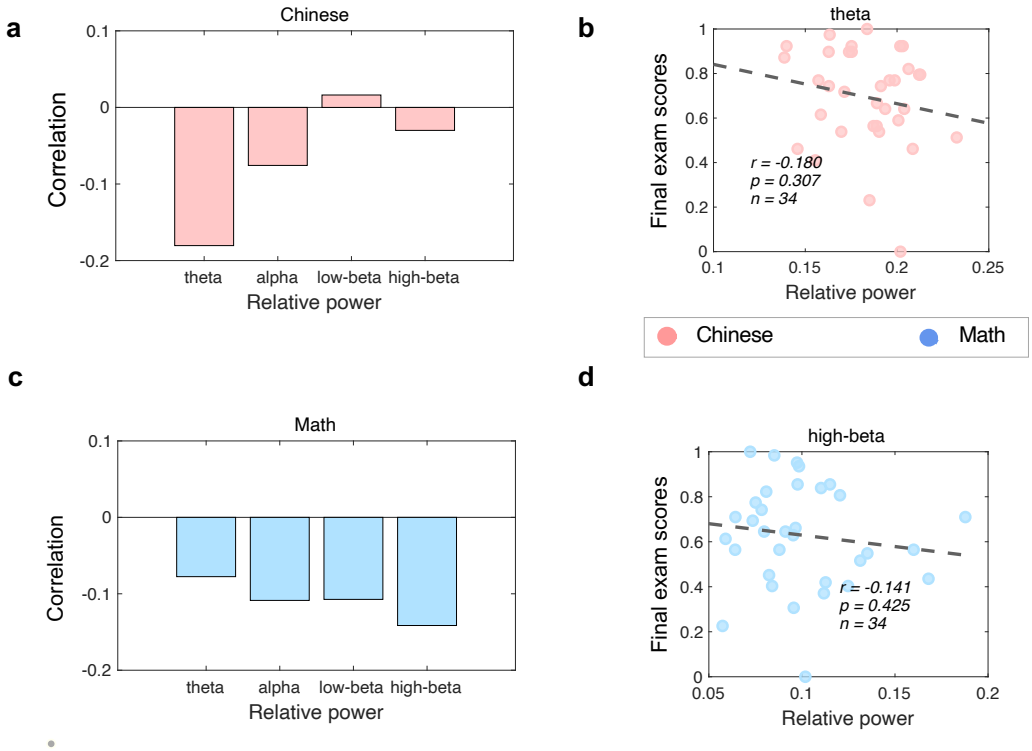

Fig.7: The correlation between the single brain's relative frequency power at the theta, alpha, low-beta, and high beta band with one's final exam scores of Chinese (**a**) and Math (**c**). No significance was found in any of the frequency bands. **b,** Scatter plots between relative power at the theta band and the final exam scores of Chinese (the highest correlation for Chinese). **d,** Scatter plots between the relative power at the high-beta band and the final exam scores of Math (the highest correlation for Math).

Single-brain features fail to be correlated with the learning outcomes

Additionally, we conducted similar correlational analyses between single-brain EEG features and the final exam scores. The relative powers at the four frequency bands from each student were taken as the single-brain EEG features. As shown in Fig.7, single-brain analysis reveals no significance correlations with disciplinary final exam scores (Fig.7**b**; the highest correlation for Chinese at the theta band: r = -0.180, p = 0.307, n = 34; Fig.7**d**; the highest correlation for Math at the high-beta band: r = -0.141, p = 0.425, n = 34).

Discussion

In the present study, the neural dynamics underlying successful classroom learning were investigated by simultaneously recording EEG data from a class of high school students during their regular classroom courses. Disciplinary differences between

Chinese (a representative soft discipline) and Math (a representative hard discipline) in the successful learning process were compared from a perspective of inter-brain coupling. Results showed that one's theta-band inter-brain coupling to all their classmates during both the Chinese and the Math sessions was positively correlated with their final exam scores in the Math courses, while one's alpha-band inter-brain coupling to their excellent peers was positively correlated with their final exam scores in the Chinese courses. No significant correlation was found between the single brain's relative power and final exam scores in either discipline. These results demonstrated the value of inter-brain coupling in evaluating students' learning process for both soft and hard disciplines. Moreover, these findings provide insights into understanding the disciplinary differences of neural processes underlying successful learning in a real-world classroom.

The correlation between individuals' student-class coupling and their learning outcomes for Math verified and extended previous inter-brain findings. By investigating hard disciplines such as physics, biology, and computer science, recent studies have demonstrated student-class coupling as a useful tool to evaluate the learning process[36,37,39]. Our results about Math, another representative hard discipline, are in line with these studies, where student-class coupling was also found to be correlated with students' learning outcomes. Moreover, after decomposing data into different frequency bands, our results extended previous findings by showing the functional importance of the frontal theta-band activity during real-classroom learning. Frontal theta activity has been reported to reflect cognitive processes such as cognitive control[50–52], sustained attention[53], and working memory[54–56], and has been found to increase in the arithmetic-related tasks[57]. During the learning of hard disciplines, the emphasis on developing a capacity to master and apply the accepted scientific viewpoints would require the students to align with the course material[6]. Hereby, the theta-band brain activity could support students' continuous engagement with the hierarchical course content. Moreover, student-class coupling could imply the extent to which each student attented to the course content[4,37], or the extent to which each student interpreted the course content[36].

The positive correlation between theta-band student-class coupling during the Chinese sessions and the learning outcomes of Math further suggested that the class-level frontal theta-band activity could reflect the required cognitive processes shared across the two disciplines. The learning of Chinese would also rely on cognitive control, sustained attention, and working memory that allows students to attend the courses. Nevertheless, the non-significant correlation between theta-band student-class coupling and the Chinese final exam scores in the present study might also suggest the relatively loose link between these cognitive processes and the learning outcomes of Chinese. This finding was similar to a previous study where students' studiousness and continuous engagement have been suggested to be beneficial for both the learning of Math and German. However, they are more important for the learning outcomes of Math[58].

The positive correlation between alpha-band student-excellence coupling during the Chinese sessions and the students' Chinese final exam scores provides evidence of the critical neural correlates for soft-discipline learning. The distinct frequency band (alpha) compared to Math (theta) suggests that successful learning of Chinese and Math could rely on substantially different cognitive processes. Despite the lack of neuroscience evidence on soft-discipline learning, the frontal alpha-band activity could be related to the inhibition of stimulus-driven attention[53,59] and was found to involve in tasks with high internal processing demands such as creative ideation[60,61] and imagination[62]. More importantly, student-excellence coupling rather than student-class coupling was informative about the Chinese learning outcomes, highlighting the excellent peers as a good reference for successful learning. Although different excellence could have different internal interpretations of the course contents, they could share similar temporal dynamics of the interpretation process. For instance, during the learning of an ancient poem, two top students could immerse in the aesthetic experience simultaneously while constructing different scenarios in their minds. Note that EEG recordings used in our study are advantageous in capturing the temporal dynamics of the learning process rather than the fine-grained representation of the content. Taken together, it is plausible to assume that the temporal dynamics of the frontal alpha activity of the excellences might represent an internal processing state for interpretation construction, which is critical for the learning of Chinese. Moreover, unlike the entrainment to external stimuli (course contents), this internal state might not necessarily share across classmates, which results in the observed positive results of student-excellence coupling rather than student-class coupling.

It is necessary to distinguish between the excellent peers found in this study and the experts that have been often referred to in the field of education. In educational practice, the expert-like mastery of knowledge has been regarded as the target of students' development and has been linked to good learning outcomes[63]. For example, when the cognitive processes of emergency medicine trainees were found to become more expert-like, their performance improved as well in the crisis resource management tasks[64]. A recent fMRI study also reported that one's neural alignment (coupling) to the experts could positively predict the final exam score of their computer science course[36]. While experts have been regarded as a well-established reference for successful learning, our results suggested that excellences could also serve as an alternative reference, as a higher inter-brain coupling towards excellences led to a better learning outcome for Chinese. Moreover, compared with experts who might learn in a way qualitatively different from that of students due to their broader understanding of the field[36], excellences with similar prior knowledge about the to-be-learned content might be particularly efficient as a reference for the successful learning process starting as a novice.

It should also be noted that the non-significant student-excellence-coupling-based correlation results for the learning outcomes of Math did not necessarily undermine the potential importance of excellence for effective Math learning. On the one hand, the

correlation coefficients between the Math-session student-excellence coupling and the Math final exam scores still reached a positive value of >0.2 at the alpha band (Fig. 4**d**). On the other hand, the Math excellence might not adequately express their optimal learning process during the Math sessions. Specifically, since the classroom teaching was designed to meet the need of the majority of the class[65–67], there might be a lack of challenge for Math excellence. Consequently, the possible boredom might demotivate the excellence in following the lectures[68] and eliminate the possibly-existing correlations. By contrast, the teaching of soft disciplines such as Chinese emphasizes constructive and interpretative activity, which is expected to be similarly challenging for students at different proficiency levels.

As the first study to investigate the disciplinary differences of students' successful learning process in real-classroom settings, there are several limitations to be noted. First, further validation with a larger group of students from different educational stages will be needed as the present number of samples is limited and focused in grade 10. The two-channel portable EEG devices used in the present study are expected to support larger-sample research in a real-world classroom in the near future. Second, while Chinese and Math were chosen to represent soft and hard disciplines here, more disciplines were needed to be investigated to fully verify the framework of hard/soft disciplines. Specifically, as our findings indicated some cognitive processes might share across the learning of different disciplines, the involvement of more disciplines would facilitate a deeper understanding of the domain-specific process and domain-general process across disciplines during real-world learning activity [69]. Third, we used the scores of final exams to describe the learning outcomes. Although this method has been consistently and widely used in educational practices, more diverse indexes adopted in future studies are expected to provide a more comprehensive picture of students' learning outcomes from cognitive, behavioral, and affective dimensions[70].

Methods

Participants

Thirty-six students (16 females; age: 15-16 years old) from the same class (37 students in total) from grade 10 of a high school in Beijing volunteered to wear a headband EEG device during their regular Math and Chinese sessions throughout one semester. The study was conducted in accordance with the Declaration of Helsinki, and the protocol (THU201708) was approved by the ethics committee of the Department of Psychology, Tsinghua University. All the participants and their legal guardians gave their written informed consent.

Procedure and Data Recording

A two-channel headband with dry electrodes (Brainno, SOSO H&C, Korea) was used to record EEG at Fp1 and Fp2 over the forehead at a sampling rate of 250 Hz. The reference electrode was placed on the right ear lobe with a ground at Fpz. The EEG device has been used previously in monitoring brain state during resting state, sudoku

games, and surgery[43–47]. The signal quality of the headband was also tested in the present study by using an eye-closed/open task with 22 out of the same 36 students in their classroom environment.

The data collection lasted for four months to cover the whole semester. Students' EEG signals during Chinese sessions and Math sessions were recorded for one week (one or two sessions per day) in each month following the regular curriculum. The total number of sessions was 39, with 19 sessions for Chinese and 20 sessions for Math. Before Chinese or Math sessions began, students wore headbands with the help of the experimenters, and the headbands were taken off after each session. Each session lasted for 40 minutes. There was one Chinese session when EEG devices failed to record any data due to technical issues. Two students were omitted from the analysis due to consistent poor quality EEG data across sessions. This left 34 students in 18 sessions for Chinese and 20 sessions for Math in the following analysis.

During the Chinese and Math sessions, the learning content was taught according to the arrangement of the school. The Math sessions include the introduction of planar vectors, cubic geometry, plural, statistics, and probability; the Chinese sessions include the reading of ancient and modern poems, essays, and novels and the introduction to writing.

The students' final exam scores in Chinese and Math were taken as indicators of their learning outcomes. The final exams covered the contents of the whole semester. Both exams were scored out of 100. The median of the students' Math scores was 73, ranging from 33 to 95, and the median of the students' Chinese scores was 69, ranging from 40 to 79. The scores were sufficiently diverse to characterize the students' individual differences in their learning outcomes. These scores were normalized to [0, 1] using a min-max transformation for the following analysis.

Data Preprocessing

As the EEG data were recorded during a regular classroom environment and the students were instructed to attend the Chinese and Math sessions, as usual, more artifacts were expected as compared to the conventional, highly-controlled laboratory settings. In the present study, there were three types of prominent artifacts: 1) a high value indicating signal saturation possibly due to losing contacts of the headband; 2) slow drifts related to extensive head or body movements; 3) ocular artifacts related to eye movements.

The recorded EEG data were segmented into non-overlapping 30-sec epochs for preprocessing. As shown in Supplementary Fig. S3, the ratios for saturated samples per epoch illustrated a 2-tailed distribution that most epochs containing saturated samples for less than 10% or more than 90%. Therefore, 50% was chosen as a threshold empirically. One epoch would be rejected if it contained saturated samples for more than 50%. The remaining epochs were then processed to remove the slow drifts with the NoiseTools toolbox [71] under Matlab (MathWorks, USA). The removal of the slow drifts was achieved by using the nt_detrending() function. By estimating the position

of the glitch, this function could perform a weighted polynomial fit and achieve a better fit to the non-glitch parts. The processed epochs were further band-pass filtered between 0.1 Hz and 40 Hz with 1-s zero-padding at both ends. Afterward, the ocular artifacts were attenuated with the MSDL (multi-scale dictionary learning) toolbox, which was efficient in ocular artifacts removal for single-channel EEG signals[72]. Epochs were decomposed into neuronal and non-neuronal sources with dictionary learning. Then, the coefficients of non-neuronal sources were set to zero to achieve artifact reduction with the seq_MSDL() function. Supplementary Fig.S4 and S5 illustrated representative examples before and after the abovementioned artifact rejection procedure. Finally, epochs were rejected automatically if any samples at any channels exceeded a ± 150 μV threshold. With the above preprocessing procedure, 57.2±1.85 % epochs were retained per student, ranging from 31.2% to 76.7%. The data retention rate was comparable with previous EEG studies in classroom settings[4,20]. The number of retained epochs per session per student is shown in Supplementary Fig.S6.

Data Processing

The inter-brain coupling between all possible student pairs was computed using the total interdependence (TI) method as its efficacy in capturing the temporal relationship between two time series[48]. TI was estimated by computing the magnitude squared coherence using the Welch method when clean 30-s epochs were available at the same moments from both students. For X_i, a 30-s epoch from a certain student i and X_j, an overlapping epoch from another student j, TI value was calculated as follows.

$$TI_{X_i,X_j} = -\frac{2}{f_s}\sum_{m=1}^{M} ln(1 - C^2_{X_i,X_j}(m\Delta f))\Delta f \quad (1)$$

$$\Delta f = \frac{f_s}{2(M-1)} \quad (2)$$

Here, $C_{X_i,X_j}()$ is the magnitude squared coherence calculation, f_s is the sampling rate, M is the number of desired frequency points in the interval between 0 and the Nyquist frequency $\frac{f_s}{2}$. The Δf is the frequency resolution. Theta, alpha, and low-beta and high-beta TI were computed by summing the coherence values within 4-8 Hz, 8-13 Hz, 13-18 Hz, and 18-30 Hz, respectively.

TI for one pair of students for each session was obtained by averaging TI values across all epochs and the two recording electrodes. A minimum of 6 artifact-free common epochs for paired students were included for further analysis. The lower limit was empirically chosen to get a comparable minimum data amount for each pair of students with previous studies[4,20]. 96.6% of TI values for each pair and each epoch remained for the following analysis. A $N * N$ pairwise TI matrix (N is the number

of students) could be obtained for each session. TI values within the matrix were then normalized to [0,1] for each session following the practice in previous studies [4,20]. Then, the matrixes were averaged across K sessions to obtain an averaged inter-brain coupling for each pair of students for a specific discipline ($K = 18$ for Chinese and $K = 20$ for Math).

Then, student-class coupling for student i was obtained by averaging TI values over all possible pairwise combinations between the student i and the rest of the class. Student-excellence coupling for student i was computed by averaging TI values over all possible pairwise combinations between the student i and the excellences except themselves if included. Therefore, for each student, there would be a student-class coupling value and a student-excellence coupling value as indicators of a disciplinary learning process for the whole semester for each frequency band.

Furthermore, Pearson's correlations between individuals' student-class coupling (or student-excellence coupling) and their corresponding learning outcomes were calculated for soft and hard disciplines separately. For student-class coupling, all students were included in the correlation analysis. For student-excellence coupling, however, the excellences themselves were not included during the correlation analysis between student-excellence coupling and learning outcomes. For example, if individuals' student-excellence coupling was computed with the top N_E students, then, the top N_E students' coupling values, as well as their learning outcomes, will be removed, leaving $(N - N_E)$ out of the N students for conducting the correlations. The effect of excellence number on the relationship between student-excellence coupling and learning outcomes was analyzed.

Additionally, we conducted similar correlational analyses between single-brain EEG features and the final exam scores for comparison. The relative power of each frequency band of interest (theta, alpha, and low-beta and high-beta) was obtained by dividing the power in the 1-40 Hz band after a fast Fourier transform for each 30-second epoch. Then, the relative powers of each frequency band of interest were averaged across all epochs and all sessions within each discipline for each student as the single-brain EEG features. Finally, Pearson's correlations between individuals' single-brain EEG features and their corresponding learning outcomes were calculated for soft and hard disciplines separately.

Acknowledgement

We would like to thank Professor Yongdi Zhou and Zhuoran Li for their comments on the manuscript. This work was supported by the National Natural Science Foundation of China (61977041, 6210020370 and 62177030), and Tsinghua University Spring Breeze Fund (2021Z99CFY037).

Data availability

The raw data will be available upon reasonable request to the corresponding author due to underage privacy protection. The minimum de-identified dataset used to generate the

findings of this study are available at : https://cloud.tsinghua.edu.cn/d/83a776b5db1349c29fd7/.

Code availability

The Matlab code for analysis and figures generation are available at: https://cloud.tsinghua.edu.cn/d/83a776b5db1349c29fd7/.

Author contributions

D.Z. and Y.Z. designed the experiment and revised the manuscript. J.C. analyzed the data and wrote the manuscript. Q.P pre-analzed the data. X.G. and B.L. collected the data.

Reference

1. Darling-Hammond, L., Flook, L., Cook-Harvey, C., Barron, B. & Osher, D. Implications for educational practice of the science of learning and development. *Applied Developmental Science* **24**, 97–140 (2020).
2. Valiente, C., Swanson, J., DeLay, D., Fraser, A. M. & Parker, J. H. Emotion-related socialization in the classroom: Considering the roles of teachers, peers, and the classroom context. *Developmental psychology* **56**, 578 (2020).
3. Vandenbroucke, L., Spilt, J., Verschueren, K., Piccinin, C. & Baeyens, D. The classroom as a developmental context for cognitive development: A meta-analysis on the importance of teacher–student interactions for children's executive functions. *Review of Educational Research* **88**, 125–164 (2018).
4. Dikker, S. *et al.* Brain-to-brain synchrony tracks real-world dynamic group interactions in the classroom. *Current biology* **27**, 1375–1380 (2017).
5. Biglan, A. Relationships between subject matter characteristics and the structure and output of university departments. *Journal of applied psychology* **57**, 204 (1973).
6. Lindblom-Ylänne, S., Trigwell, K., Nevgi, A. & Ashwin, P. How approaches to teaching are affected by discipline and teaching context. *Studies in Higher education* **31**, 285–298 (2006).
7. Neumann, R., Parry, S. & Becher, T. Teaching and learning in their disciplinary contexts: A conceptual analysis. *Studies in higher education* **27**, 405–417 (2002).
8. Rosman, T., Mayer, A.-K., Kerwer, M. & Krampen, G. The differential development of epistemic beliefs in psychology and computer science students: A four-wave longitudinal study. *Learning and Instruction* **49**, 166–177 (2017).
9. Smith*, S. N. & Miller, R. J. Learning approaches: Examination type, discipline of study, and gender. *Educational psychology* **25**, 43–53 (2005).
10. Hofer, B. K. Dimensionality and disciplinary differences in personal epistemology. *Contemporary educational psychology* **25**, 378–405 (2000).

11. Arbaugh, J. B. Does academic discipline moderate CoI-course outcomes relationships in online MBA courses? *The Internet and Higher Education* **17**, 16–28 (2013).
12. Foung, D. & Chen, J. Discovering disciplinary differences: blending data sources to explore the student online behaviors in a University English course. *Information Discovery and Delivery* (2019).
13. Janssen, T. W. *et al.* Opportunities and limitations of mobile neuroimaging technologies in educational neuroscience. *Mind, Brain, and Education* (2021).
14. Karuza, E. A., Emberson, L. L. & Aslin, R. N. Combining fMRI and behavioral measures to examine the process of human learning. *Neurobiology of learning and memory* **109**, 193–206 (2014).
15. De Sanctis, P. *et al.* Time to move: Brain dynamics underlying natural action and cognition. *European Journal of Neuroscience* (2021).
16. Xu, J. & Zhong, B. Review on portable EEG technology in educational research. *Computers in Human Behavior* **81**, 340–349 (2018).
17. Davidesco, I. Brain-to-brain synchrony in the STEM classroom. *CBE—Life Sciences Education* **19**, es8 (2020).
18. Ko, L.-W., Komarov, O., Hairston, W. D., Jung, T.-P. & Lin, C.-T. Sustained attention in real classroom settings: An EEG study. *Frontiers in human neuroscience* **11**, 388 (2017).
19. Babiker, A., Faye, I., Mumtaz, W., Malik, A. S. & Sato, H. EEG in classroom: EMD features to detect situational interest of students during learning. *Multimedia Tools and Applications* **78**, 16261–16281 (2019).
20. Bevilacqua, D. *et al.* Brain-to-brain synchrony and learning outcomes vary by student–teacher dynamics: Evidence from a real-world classroom electroencephalography study. *Journal of cognitive neuroscience* **31**, 401–411 (2019).
21. Babiloni, F. & Astolfi, L. Social neuroscience and hyperscanning techniques: past, present and future. *Neuroscience & Biobehavioral Reviews* **44**, 76–93 (2014).
22. Zhang, D. Computational EEG analysis for hyperscanning and social neuroscience. in *Computational EEG Analysis* 215–228 (Springer, 2018).
23. Hasson, U., Ghazanfar, A. A., Galantucci, B., Garrod, S. & Keysers, C. Brain-to-brain coupling: a mechanism for creating and sharing a social world. *Trends in cognitive sciences* **16**, 114–121 (2012).
24. Nastase, S. A., Gazzola, V., Hasson, U. & Keysers, C. Measuring shared responses across subjects using intersubject correlation. *Social Cognitive and Affective Neuroscience* vol. 14 667–685 (2019).
25. Sonkusare, S., Breakspear, M. & Guo, C. Naturalistic stimuli in neuroscience: critically acclaimed. *Trends in cognitive sciences* **23**, 699–714 (2019).
26. Hasson, U., Nir, Y., Levy, I., Fuhrmann, G. & Malach, R. Intersubject synchronization of cortical activity during natural vision. *science* **303**, 1634–1640 (2004).

27. Ding, Y., Hu, X., Xia, Z., Liu, Y.-J. & Zhang, D. Inter-brain EEG feature extraction and analysis for continuous implicit emotion tagging during video watching. *IEEE Transactions on Affective Computing* **12**, 92–102 (2018).
28. Li, Z. *et al.* Speaker–listener neural coupling reveals an adaptive mechanism for speech comprehension in a noisy environment. *Cerebral Cortex* **31**, 4719–4729 (2021).
29. Holper, L. *et al.* The teaching and the learning brain: A cortical hemodynamic marker of teacher–student interactions in the Socratic dialog. *International Journal of Educational Research* **59**, 1–10 (2013).
30. Liu, H., Zhao, C., Wang, F. & Zhang, D. Inter-brain amplitude correlation differentiates cooperation from competition in a motion-sensing sports game. *Social cognitive and affective neuroscience* **16**, 552–564 (2021).
31. Pan, Y., Cheng, X., Zhang, Z., Li, X. & Hu, Y. Cooperation in lovers: an f NIRS-based hyperscanning study. *Human brain mapping* **38**, 831–841 (2017).
32. Nozawa, T., Sasaki, Y., Sakaki, K., Yokoyama, R. & Kawashima, R. Interpersonal frontopolar neural synchronization in group communication: an exploration toward fNIRS hyperscanning of natural interactions. *Neuroimage* **133**, 484–497 (2016).
33. Zheng, L. *et al.* Enhancement of teaching outcome through neural prediction of the students' knowledge state. *Human Brain Mapping* **39**, 3046–3057 (2018).
34. Pan, Y. *et al.* Instructor-learner brain coupling discriminates between instructional approaches and predicts learning. *Neuroimage* **211**, 116657 (2020).
35. Pan, Y., Novembre, G., Song, B., Li, X. & Hu, Y. Interpersonal synchronization of inferior frontal cortices tracks social interactive learning of a song. *Neuroimage* **183**, 280–290 (2018).
36. Meshulam, M. *et al.* Neural alignment predicts learning outcomes in students taking an introduction to computer science course. *Nature communications* **12**, 1–14 (2021).
37. Davidesco, I. *et al.* Brain-to-brain synchrony predicts long-term memory retention more accurately than individual brain measures. *BioRxiv* 644047 (2019).
38. Zhu, Y., Pan, Y. & Hu, Y. Learning desire is predicted by similar neural processing of naturalistic educational materials. *ENeuro* **6**, (2019).
39. Cohen, S. S. *et al.* Neural engagement with online educational videos predicts learning performance for individual students. *Neurobiology of learning and memory* **155**, 60–64 (2018).
40. Brandt, N. D., Lechner, C. M., Tetzner, J. & Rammstedt, B. Personality, cognitive ability, and academic performance: Differential associations across school subjects and school tracks. *Journal of personality* **88**, 249–265 (2020).
41. Zhang, L. Revisiting the predictive power of thinking styles for academic performance. *the Journal of Psychology* **138**, 351–370 (2004).
42. Marton, F. & Säljö, R. On qualitative differences in learning: I—Outcome and process. *British journal of educational psychology* **46**, 4–11 (1976).

43. Jang, K.-I., Lee, S., Lee, S.-H. & Chae, J.-H. Frontal alpha asymmetry, heart rate variability, and positive resources in bereaved family members with suicidal ideation after the Sewol ferry disaster. *Psychiatry investigation* **15**, 1168 (2018).
44. Kang, J.-S., Ojha, A. & Lee, M. Development of Intelligent Learning Tool for Improving Foreign Language Skills Based on EEG and Eye Tracker. in *Proceedings of the 3rd international conference on human-agent interaction* 121–126 (2015).
45. Kang, J.-S., Ojha, A. & Lee, M. Concentration monitoring with high accuracy but low cost EEG device. in *International Conference on Neural Information Processing* 54–60 (Springer, 2015).
46. Kwon, J.-W. *et al.* Intraoperative real-time stress in degenerative lumbar spine surgery: simultaneous analysis of electroencephalography signals and heart rate variability: a pilot study. *The Spine Journal* **20**, 1203–1210 (2020).
47. Kwon, J.-W. *et al.* Which Factors Affect the Stress of Intraoperative Orthopedic Surgeons by Using Electroencephalography Signals and Heart Rate Variability? *Sensors* **21**, 4016 (2021).
48. Wen, X., Mo, J. & Ding, M. Exploring resting-state functional connectivity with total interdependence. *Neuroimage* **60**, 1587–1595 (2012).
49. Chabin, T. *et al.* Interbrain emotional connection during music performances is driven by physical proximity and individual traits. *Annals of the New York Academy of Sciences* (2021).
50. Cavanagh, J. F. & Frank, M. J. Frontal theta as a mechanism for cognitive control. *Trends in cognitive sciences* **18**, 414–421 (2014).
51. Cavanagh, J. F. & Shackman, A. J. Frontal midline theta reflects anxiety and cognitive control: meta-analytic evidence. *Journal of physiology-Paris* **109**, 3–15 (2015).
52. Eschmann, K. C., Bader, R. & Mecklinger, A. Topographical differences of frontal-midline theta activity reflect functional differences in cognitive control abilities. *Brain and cognition* **123**, 57–64 (2018).
53. Clayton, M. S., Yeung, N. & Kadosh, R. C. The roles of cortical oscillations in sustained attention. *Trends in cognitive sciences* **19**, 188–195 (2015).
54. Jensen, O. & Tesche, C. D. Frontal theta activity in humans increases with memory load in a working memory task. *European journal of Neuroscience* **15**, 1395–1399 (2002).
55. Maurer, U. *et al.* Frontal midline theta reflects individual task performance in a working memory task. *Brain topography* **28**, 127–134 (2015).
56. Sauseng, P., Griesmayr, B., Freunberger, R. & Klimesch, W. Control mechanisms in working memory: a possible function of EEG theta oscillations. *Neuroscience & Biobehavioral Reviews* **34**, 1015–1022 (2010).
57. Williams, C. C., Kappen, M., Hassall, C. D., Wright, B. & Krigolson, O. E. Thinking theta and alpha: Mechanisms of intuitive and analytical reasoning. *NeuroImage* **189**, 574–580 (2019).

58. Haag, L. & Götz, T. Mathe ist schwierig und Deutsch aktuell: Vergleichende Studie zur Charakterisierung von Schulfächern aus Schülersicht. *Psychologie in Erziehung und Unterricht* **59**, 32–46 (2012).
59. Sauseng, P. *et al.* EEG alpha synchronization and functional coupling during top-down processing in a working memory task. *Human brain mapping* **26**, 148–155 (2005).
60. Fink, A. & Benedek, M. EEG alpha power and creative ideation. *Neuroscience & Biobehavioral Reviews* **44**, 111–123 (2014).
61. Lustenberger, C., Boyle, M. R., Foulser, A. A., Mellin, J. M. & Fröhlich, F. Functional role of frontal alpha oscillations in creativity. *Cortex* **67**, 74–82 (2015).
62. Cooper, N. R., Burgess, A. P., Croft, R. J. & Gruzelier, J. H. Investigating evoked and induced electroencephalogram activity in task-related alpha power increases during an internally directed attention task. *Neuroreport* **17**, 205–208 (2006).
63. Adams, W. K. & Wieman, C. E. Development and validation of instruments to measure learning of expert-like thinking. *International Journal of Science Education* **33**, 1289–1312 (2011).
64. Szulewski, A. *et al.* Starting to think like an expert: an analysis of resident cognitive processes during simulation-based resuscitation examinations. *Annals of Emergency Medicine* **74**, 647–659 (2019).
65. Petrilli, M. J. All together now? Education high and low achievers in the same classroom. *Education Next* **11**, 48–56 (2011).
66. VanTassel-Baska, J. & Stambaugh, T. Challenges and possibilities for serving gifted learners in the regular classroom. *Theory into practice* **44**, 211–217 (2005).
67. Westberg, K. L. & Daoust, M. E. The results of the replication of the classroom practices survey replication in two states. *The National Research Center on the Gifted and Talented Newsletter* **3**, (2003).
68. Glass, T. F. What gift?: The reality of the student who is gifted and talented in public school classrooms. *Gifted Child Today* **27**, 25–29 (2004).
69. Wang, L., Li, M., Yang, T. & Zhou, X. Mathematics Meets Science in the Brain. *Cerebral Cortex* (2021).
70. Wei, X., Saab, N. & Admiraal, W. Assessment of cognitive, behavioral, and affective learning outcomes in massive open online courses: A systematic literature review. *Computers & Education* **163**, 104097 (2021).
71. de Cheveigné, A. & Arzounian, D. Robust detrending, rereferencing, outlier detection, and inpainting for multichannel data. *NeuroImage* **172**, 903–912 (2018).
72. Kanoga, S., Kanemura, A. & Asoh, H. Multi-scale dictionary learning for ocular artifact reduction from single-channel electroencephalograms. *Neurocomputing* **347**, 240–250 (2019).