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

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Abstract

While it is widely acknowledged that different disciplines are associated with distinct characteristics that would require different learning strategies and approaches, how the disciplinary differences are manifested in students' daily learning process remain largely underexplored. The present study investigated the disciplinary differences from the framework of hard and soft disciplines, by recording thirty-four high-school students' EEGs simultaneously in real-classroom settings during their regular Chinese (a soft discipline) and Math (a hard discipline) courses across a whole semester. Inter-brain coupling analysis was conducted to identify the neural correlates of successful learning for different disciplines. One's theta-band inter-brain coupling to all their classmates during both the Chinese and the Math sessions was found to be positively correlated with their final exam scores of Math, while one's alpha-band inter-brain coupling to their excellent peers was positively correlated with their final exam scores of Chinese. These results demonstrated the value of inter-brain coupling for reflecting students' learning outcomes for both hard and soft disciplines and highlighted excellent peers as a good candidate to represent a successful learning process for soft disciplines. Our findings provided a piece of neuroscience evidence towards the understanding of disciplinary differences during real-world classroom learning.

Keywords:

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

Introduction

Learning knowledge from multiple disciplines is of great importance for students to prepare for a challenging world[1]. Although it is widely acknowledged that different disciplines are associated with distinct characteristics that would require different learning strategies and approaches, the investigation on the disciplinary differences of learning has been largely overlooked until the late last century[2–9].

The distinction between hard and soft disciplines is possibly one of the most influential research directions regarding disciplinary differences[3]. Whereas 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 activities (e.g., history, philosophy, language courses)[3,6,10]. The differences between hard and soft disciplines have been proven to influence teachers' teaching goals in educational practices and accordingly shape students' learning strategies and approaches[11,12]. For instance, it has been proposed that students prioritize more on knowledge from authority and expertise when learning hard disciplines than their soft counterparts[4]. Nevertheless, the disciplinary differences of learning have mainly been studied indirectly by inferring the learning process using data from expert evaluation, retrospective self-reports, learning outcomes, etc.[4,6,13]. There is a dearth of empirical studies directly addressing the learning process itself[14].

The rapidly-developing neuroscience methods have demonstrated their potential as a powerful tool to directly capture the learning process by recording the corresponding neural activities in an objective and non-intrusive way[15,16], thus supporting a direct investigation of the disciplinary differences of learning. Indeed, there are several neuroscience studies on discipline differences, and researchers have found commonalities and differences across disciplines, such as reading, mathematics, science, etc[17–19]. For instance, while shared neural activations at the bilateral inferior frontal gyrus and left middle temporal gyrus were found for the mathematics/science tasks and the sentence comprehension task, the middle frontal gyrus and inferior parietal lobule were found to activate only in tasks related to mathematics/science[19]. However, these studies have analyzed the brain as a 'learned' state. The findings mainly reflect the neural mechanisms of knowledge representation and use across disciplines, without a direct investigation on the dynamic learning process *per se*.

A few neuroscience studies have started to focus on the learning process itself, although they have not addressed disciplinary differences. Possibly the earliest study recorded the brain activities of teachers and students during a stimulated Socratic dialog task with functional near-infrared spectroscopy (fNIRS). The cortical hemodynamic response pattern was connected to the successful learning process in the teacher-student interactions[20]. While the fNIRS technique continues to serve as an important tool for researching the learning process[21–23] on disciplines such as math, music, and psychology, electroencephalograph (EEG) is gaining increasing attention in recent

years[15,24]. Especially, the popularity of portable EEG devices has made it possible to record students' brain activities during their daily learning process in real-classroom settings. Students' sustained attention, situational interests, engagement, and their relationship with teachers have been successfully assessed during their classroom learning process for disciplines such as math or biology in recent studies[25–28]. Compared to the laboratory-based studies, the real-classroom studies are advantageous for their high ecological validity, as it is difficult to simulate real disciplinary learning in the laboratory fully. Nevertheless, it should be further emphasized that these studies (both the laboratory-based and real-classroom studies) have only included one single discipline per study, and it is very difficult to conduct between-study comparisons due to the highly diverse recording devices, student populations, analysis methods, etc. Therefore, it is important to include courses from multiple disciplines in the same study in order to achieve an appropriate comparison across disciplines.

Another challenging issue for investigating the disciplinary differences of the daily learning process comes from the neural data analysis methods. The majority of the neural data analysis methods have taken an event-related perspective, in which the neural correlates of disciplinary learning were identified by extracting the neural activities related to a certain learning event as compared to a baseline[29]. Performing such an event-related analysis is challenging for real-classroom data, in which the definition of one event is difficult or even impossible. The emerging inter-brain analysis approach may be a promising candidate to resolve this issue[30–33]. Instead of defining events, 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[34–36] or are involved in the same interacting scenarios[37–39]. Hereby, the inter-brain approach is well suited for analyzing real-classroom data, as the 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[27,40–42]. Moreover, one student's neural coupling to other students was reported as an efficient neural indicator to evaluate individuals' learning process. 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[27] and their memory retention performance during a biology and chemistry course[41].

Despite these positive findings, it is worthwhile to note that the disciplines being learned in the most of available student-student neural coupling studies happened to be hard disciplines[27,28,40,41,43], and no 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. A higher coupling strength was associated with a better learning state and outcome[27,40–42]. 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)[44], it is plausible to assume that the students are expected to exhibit consistent neural activities across students. Hereby, averaging might facilitate the extraction of the neural activities 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[45], the successful learning of soft disciplines might follow a different routine, in which more scope for creativity and cultural interest are cherished compared with the hard disciplines[6]. Accordingly, the possibly different learning routines towards success might undermine the importance of 'class average' in the context of soft disciplines.

The excellent peers could serve as an alternative candidate reference to represent a successful learning process. The excellent peers (termed as 'excellence' in the following) refer to the students with a top learning outcome. As a good learning outcome has long been associated with an effective learning routine[46], it is reasonable to take excellence as a good representative for successful learning. Compared to the 'class average', the excellence could be a better candidate for a successful learning process of soft disciplines, given the possibly different learning routines. While it could be challenging to compare the two representatives (i.e., 'class average' vs. excellence) for successful learning with the conventional single-brain-based methods, the inter-brain approach enables us to have a direct comparison of them. Specifically, it is quite straightforward to compute student-class coupling and student-excellence coupling in a similar way. Comparing student-class coupling and student-excellence coupling during the learning of soft and hard disciplines would give us insights into disciplinary differences of learning.

The present study aimed to investigate the disciplinary differences in the successful learning process 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 the representative courses for the hard and soft discipline, 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[27,40,41], we hypothesized that the 'class average' might effectively represent the successful learning process during the Math courses (a hard discipline). In contrast, excellent peers could be the effective representation for the successful learning process of Chinese (a soft discipline). Correspondingly, 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 more precisely describe the neural activities for learning, the inter-brain couplings were calculated separately for EEGs at different frequency bands. No clear hypothesis regarding the difference in the involved EEG frequency band was formulated due to the 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

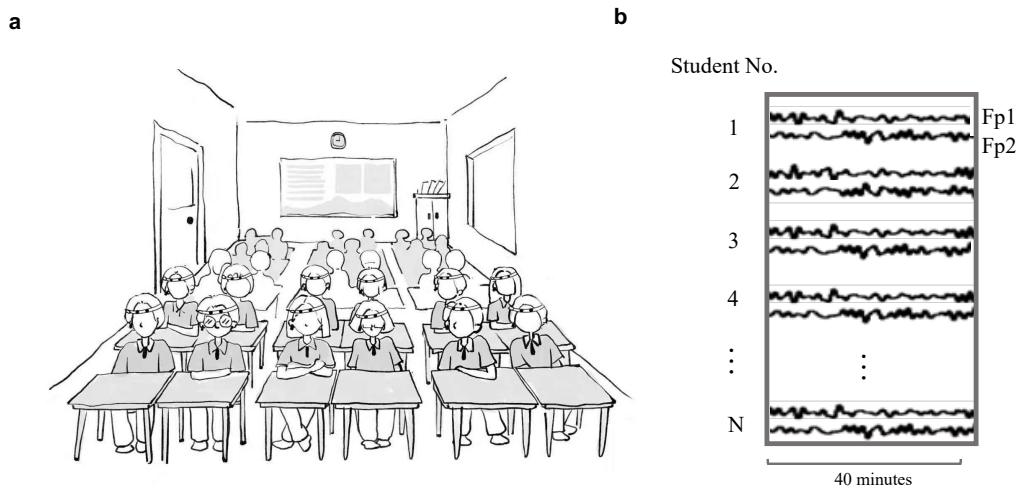

Fig.1: Experiment paradigm. **a**, An illustration of the experimental setup for students wearing an EEG headband during their regular classroom learning; **b,** An illustration of the recorded EEG signal during a session; EEGs were recorded at Fp1 and Fp2 for all the students for 40 minutes.

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 to track brain states in tasks such as resting-state, sudoku games, and surgery[47–51], 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) in 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.

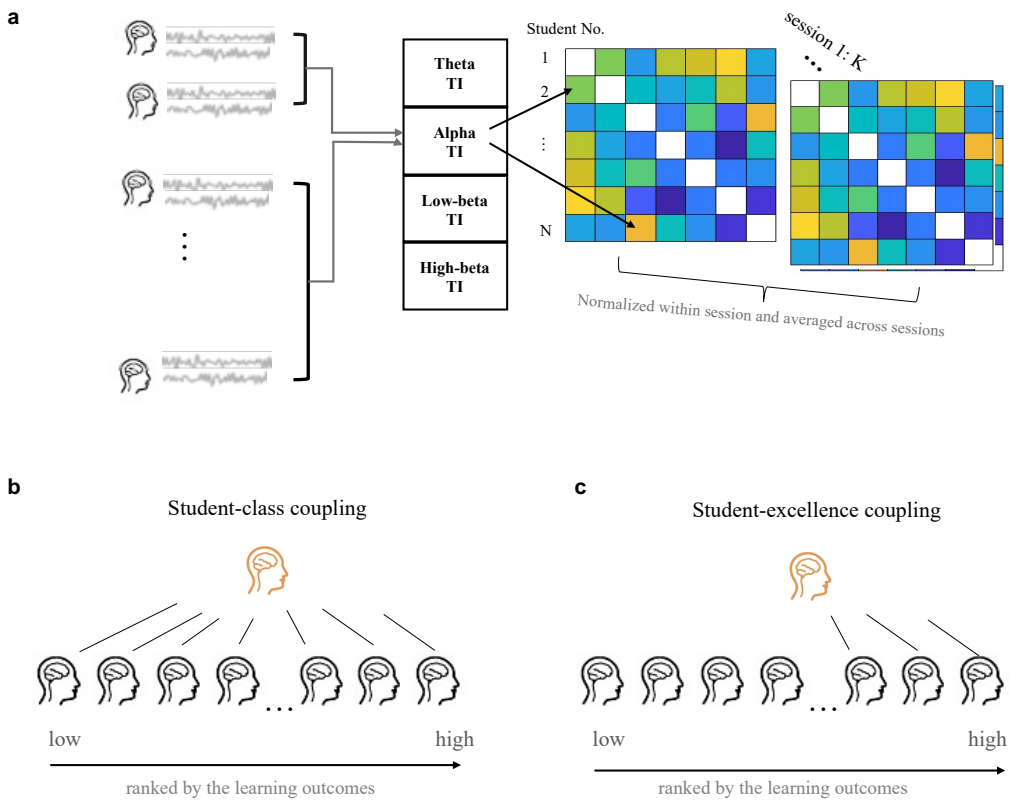

Fig 2: Schematic of the inter-brain coupling analysis. **a,** The computations of pairwise total interdependence (TI) matrix for each pair of students (i, j) for each session, at the frequency bands of theta, alpha, low-beta, and high-beta. The TI values were then normalized within each session and averaged 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[27,28,52]. This method has been previously used in inter-brain studies to investigate individuals' engagement and valence level in naturalistic scenarios such as a classroom and a concert hall[27,53]. 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 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 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.

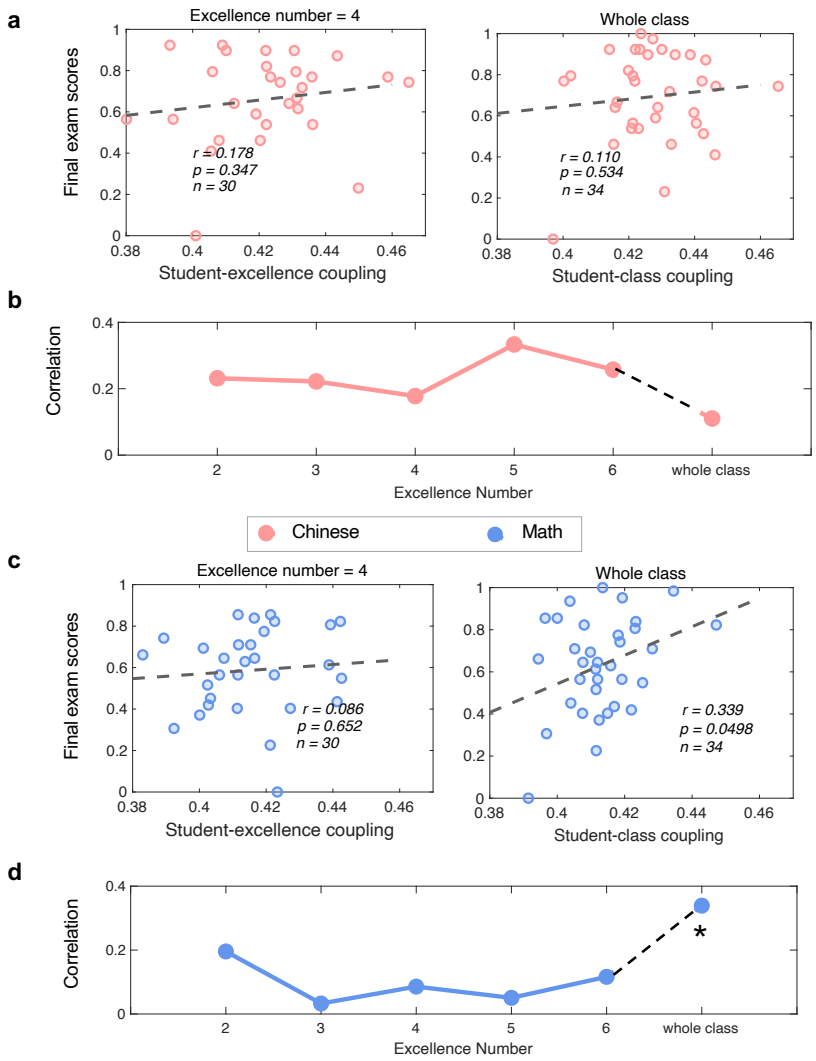

Fig.3: The correlations between theta-band student-excellence/class coupling with one's final exam score for Chinese and Math. **a**, Scatter plots between theta-band student-excellence coupling (left, excellence number = 4) and theta-band student-

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 .

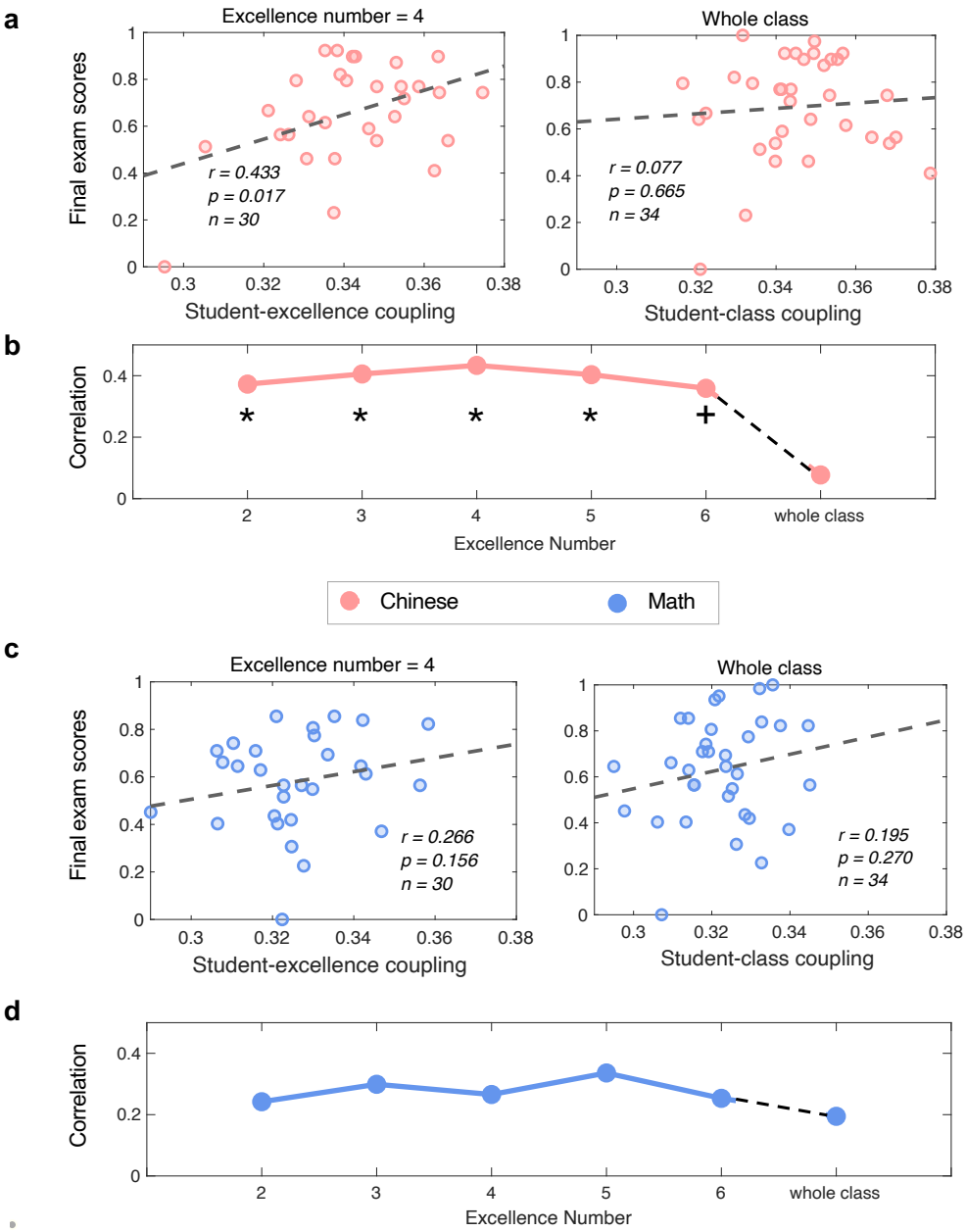

Fig.4: The correlations between alpha-band student-excellence/class coupling with one's final exam score of Chinese and Math. **a**, Scatter plots between alpha-band student-excellence coupling (left, excellence number = 4) and alpha-band student-class coupling (right) and the final exam score of Chinese. **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 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: $r = 0.195$, $p = 0.270$, $n = 34$).

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 were found to significantly correlate with the final exam scores (as shown above). 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 in several previous studies[27,28]. 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.

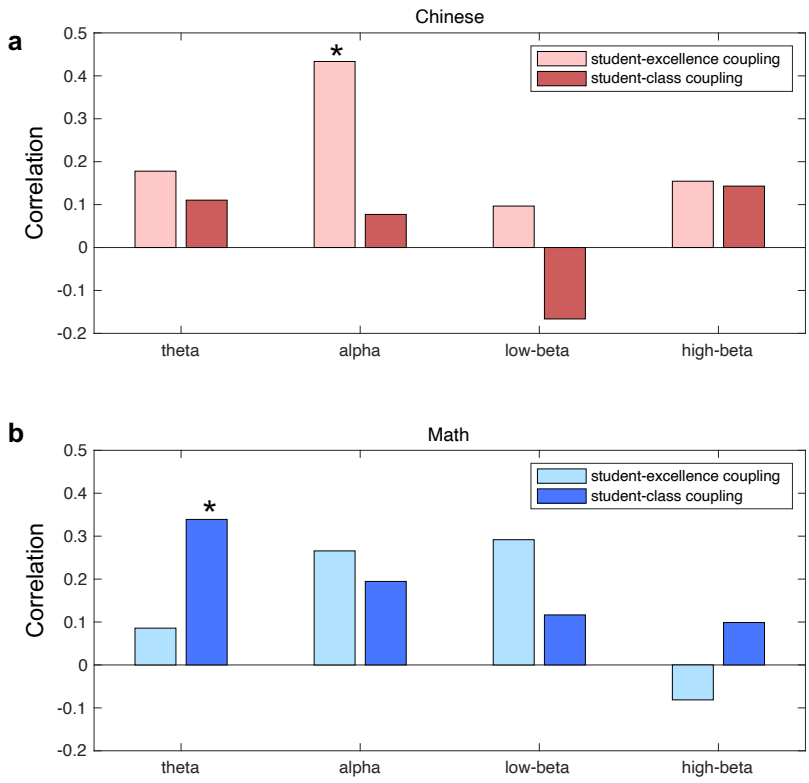

Fig.5: The correlation r values between inter-brain coupling and final exam scores at the theta, alpha, low-beta and high-beta band for **a**, Chinese and **b,** Math. The bars with a lighter color indicated student-excellence-coupling-based correlations (excellence number = 4), and the bars with a darker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

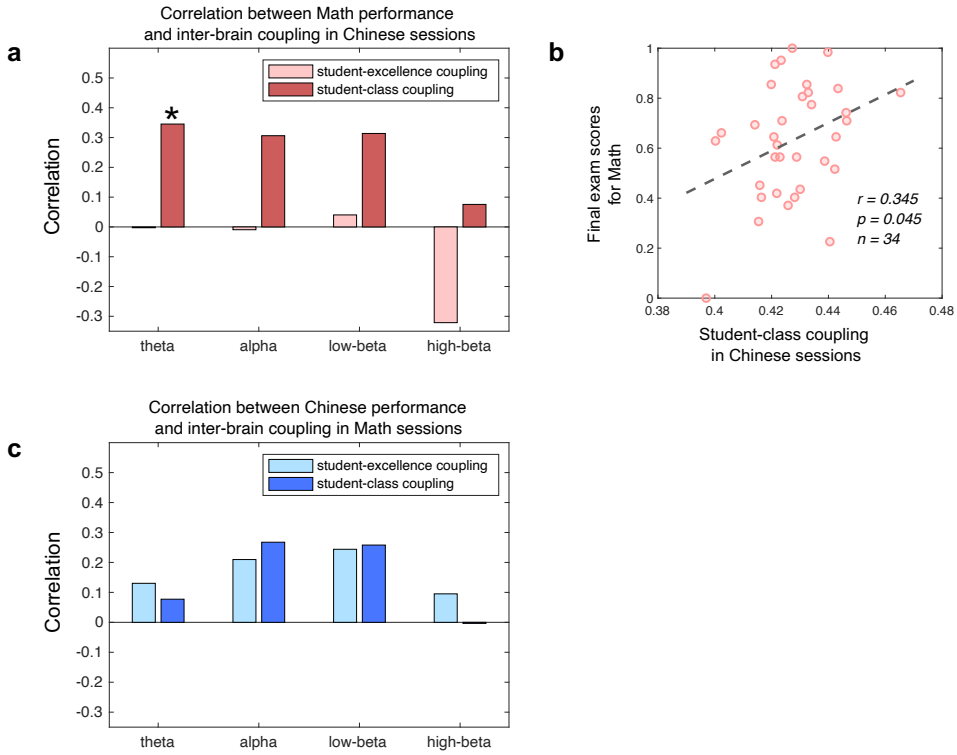

Fig.6: The correlation analysis results by switching the discipline scores, i.e., correlating inter-brain coupling in Math sessions with final exam scores of Chinese (**a**) and vice versa (**c**). **b,** Scatter plots between theta-band student-class coupling during Chinese sessions and the final exam 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.

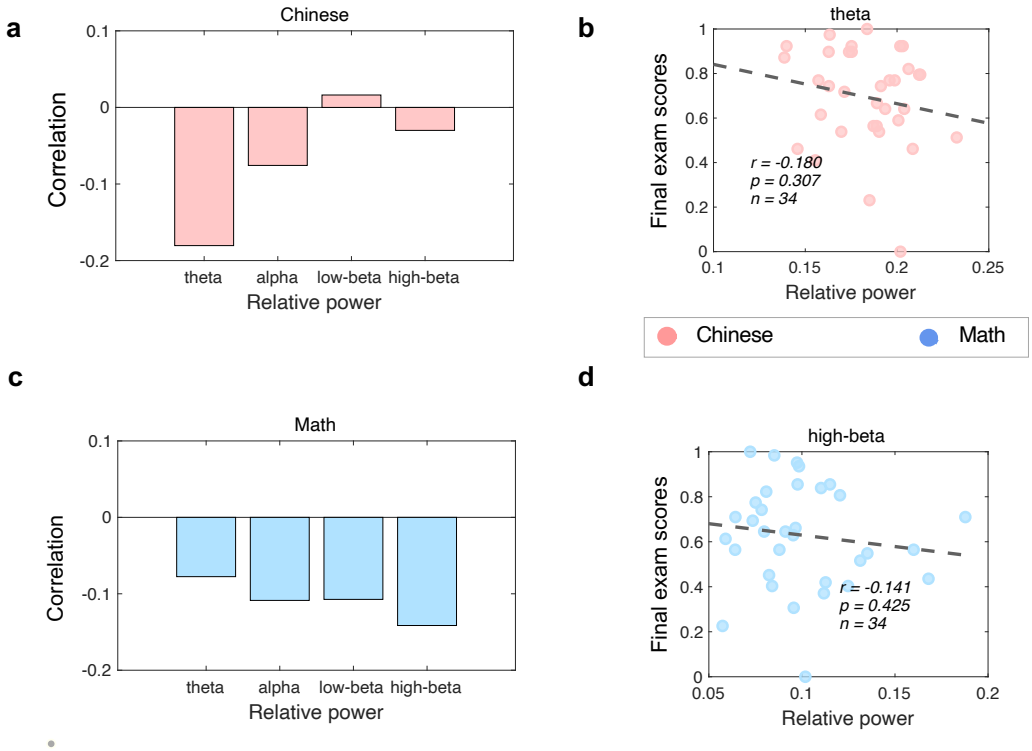

Fig.7: The correlation between the single brain's relative frequency power at the theta, alpha, low-beta and high beta band with one's final exam scores of Chinese (**a**) and Math (**c**). No significance was found in any of the frequency bands. **b,** Scatter plots between relative power at the theta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

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, differences between hard and soft disciplines in the real-world classroom learning process were investigated from a perspective of inter-brain coupling. Chinese and Math, as representative soft and hard disciplines, were compared by simultaneously recording EEG data from a class of high school students during their regular classroom learning. 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 of the Math courses, while one's alpha-band inter-brain coupling to their excellent peers was positively correlated with their final exam scores of 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 to evaluate students' learning process for both soft and hard disciplines. Moreover, these findings provide insights to understand the disciplinary differences of neural processes underlying the 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[40,41,43]. 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[54–56], sustained attention[57], and working memory[58–60], and has been found to increase in the arithmetic-related tasks[61]. 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[10]. Hereby, the theta-band brain activities could support students' continuous engagement to the hierarchical course content. Moreover, student-class coupling could imply the extent to which each student attented to the course content[27,41], or the extent to which each student interpret of the course content[40].

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 to 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, but they are more important for the learning outcomes of Math[62].

The positive correlation between alpha-band student-excellence coupling during the Chinese sessions and the students' Chinese final exam scores provides evidence on 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[57,63] and was found to involve in tasks with high internal processing demands such as creative ideation[64,65] and imagination[66]. 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 of successful learning. Although different excellence could have different internal interpretation of the course contents, they could share a similar temporal dynamics of the interpretation process. For instance, during the learning of an ancient peom, 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 is 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 activities 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[67]. 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[68]. 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[40]. 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[40], 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 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[69–71], there might be a lack of challenge for Math excellence. Consequently, the possible boredom might demotivate the excellence in following the lectures[72] and eliminate the possibly-existing correlations. By contrast, the teaching of soft disciplines such as Chinese emphasizes constructive and interpretative activities, 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 activities[19]. 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[73].

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[47–51]. 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 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 of writing.

The students' final exam scores on Chinese and Math were taken as the 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 normal 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 contained 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 [74] 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. Afterwards, 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[75]. Epochs were decomposed into neuronal and non-neuronal sources with a dictionary learning. Then, the coefficients of non-neuronal sources was 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[27,28]. 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[52]. 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.

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

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

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, 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 was 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[27,28]. 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 [27,28]. 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 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

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Supplementary Materials

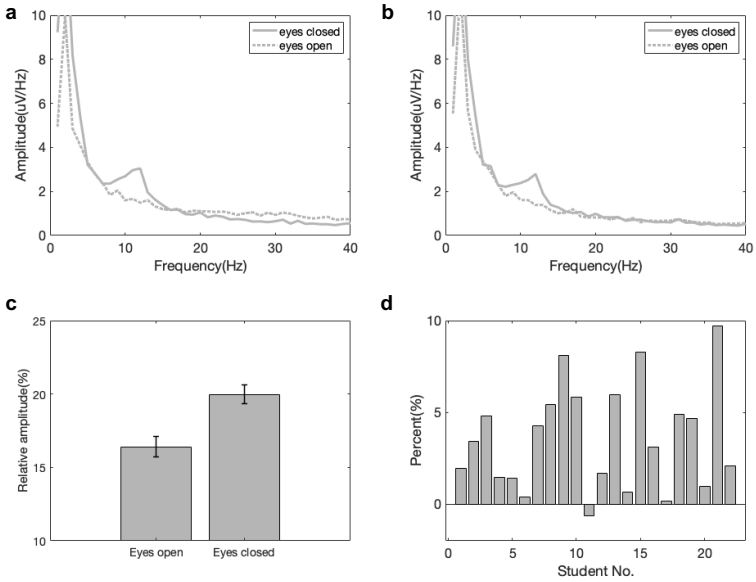


Fig.S1: The signal quality validation of EEG headbands in a 2-minute eye-closed/open task. Twenty-two students out of the same class volunteered to participate in this task. Students were required to open and close eyes for two minutes respectively when sitting in their classroom. Then, fast Fourier transform was conducted to compare the frequency spectral characteristics of EEG signals between conditions. **a,** The frequency spectra for a representative student at Fp1. The solid line represents the eye-closed condition, and the dashed lines represent the eye-open condition. **b,** The frequency spectra for the same student at Fp2. **c,** Relative amplitudes of the alpha band (8-13 Hz) in the eye-open and eye-closed conditions for all the students. Errorbar indicates standard deviation. The amplitudes were averaged across Fp1 and Fp2; **d,** Percent of relative amplitude differences (eye-closed minus eye-open) at the alpha band for each student. The amplitudes were averaged across Fp1 and Fp2.

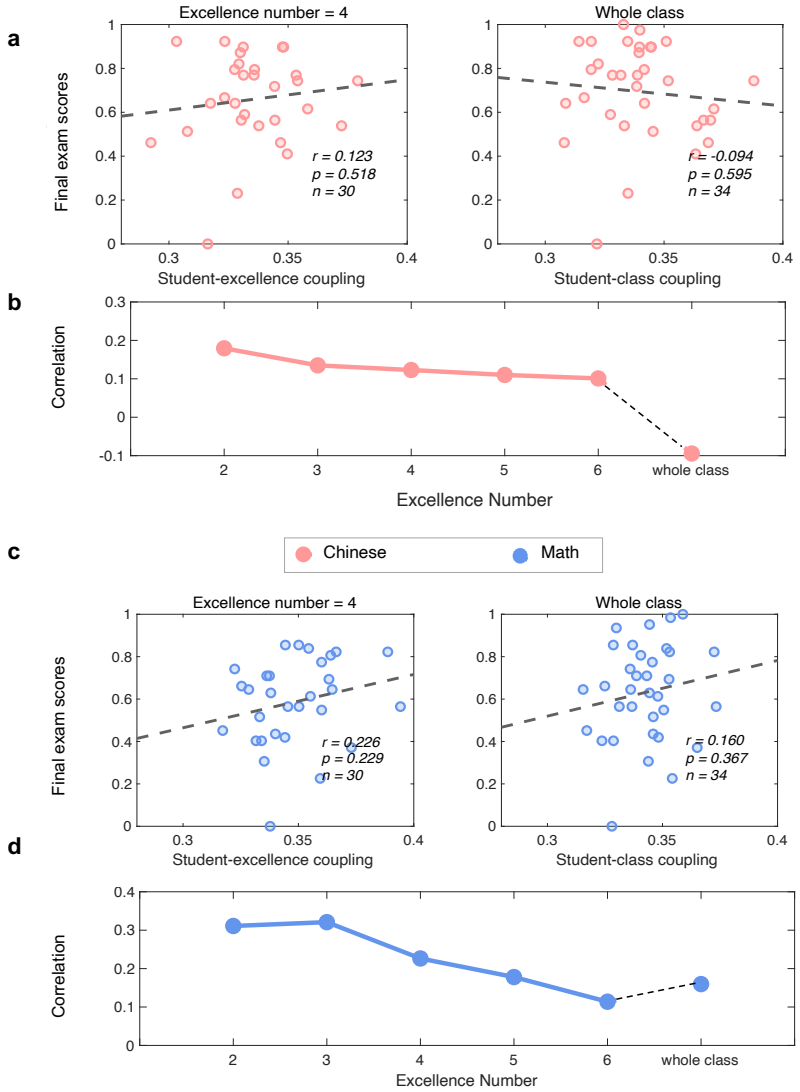


Fig.S2. The correlations between student-excellence/class coupling with one's final exam score of Chinese and Math at 1-20 Hz. **a**, Scatter plots between student-excellence coupling (left, excellence number = 4) and student-class coupling (right) and the final exam score of Chinese at 1-20 Hz. **b,** Correlation r values as a function of the number of excellences included in the calculation of student-excellence coupling. **c,** Scatter plots between student-excellence coupling (left, excellence number = 4) and student-class coupling (right) and the final exam scores of Math at 1-20 Hz. **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.

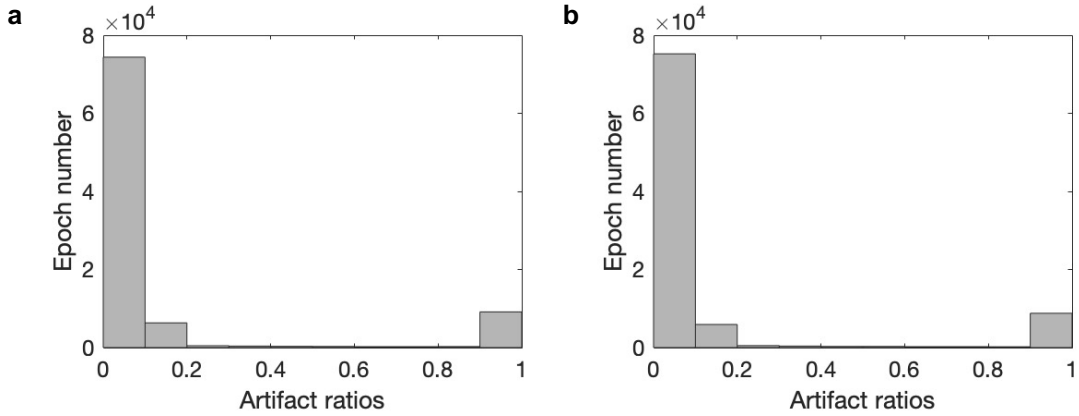


Fig.S3: The distribution of the artifacts ratios per epoch for (**a**) Fp1 and (**b**) Fp2. The ratios for saturated samples per epoch illustrated a 2-tailed distribution.

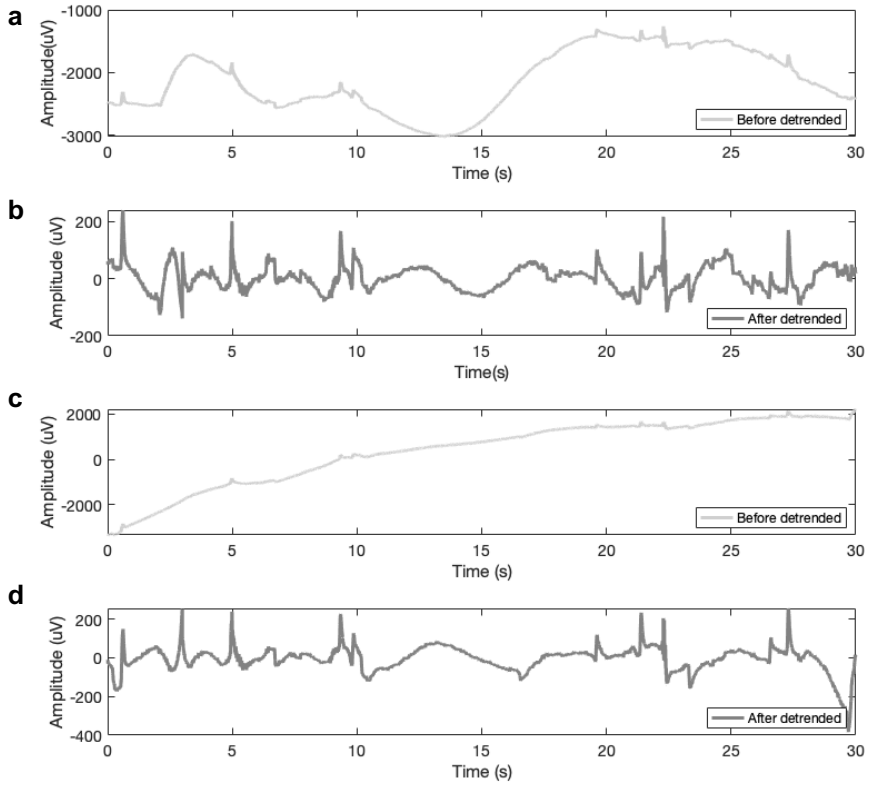


Fig.S4: An illustration of a representative EEG epoch before and after the detrending procedure with the Noisetool toolbox (**a, b**) at Fp1; (**c, d**) at Fp2. The lines with a lighter color indicated the condition before detrending. The lines with a darker color indicated the condition after detrending. The slow drift was removed after the detrending procedure.

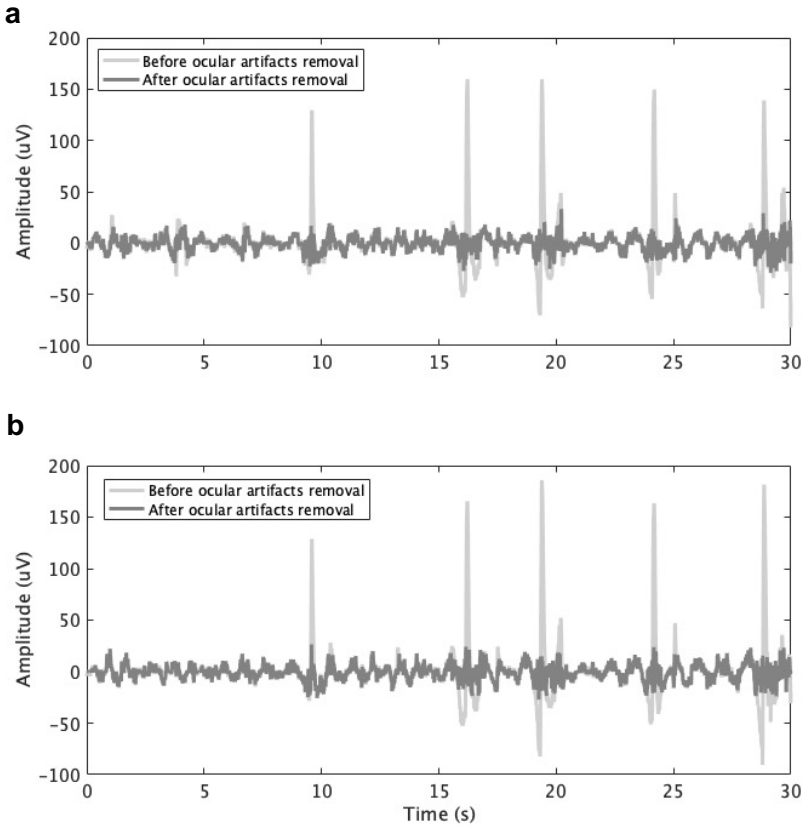


Fig.S5: An illustration of a representative EEG epoch before and after the ocular artifact removal procedure with the MSDL toolbox (**a**) at Fp1; (**b**) at Fp2. The lines with a lighter color indicated the condition before ocular artifact removal. The lines with a darker color indicated the condition after ocular artifact removal. The ocular artifact was removed after the procedure.

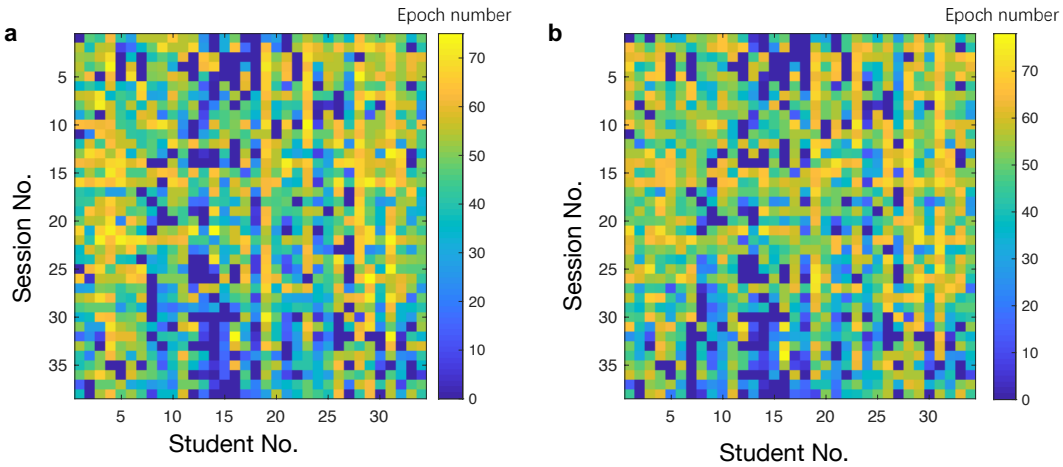
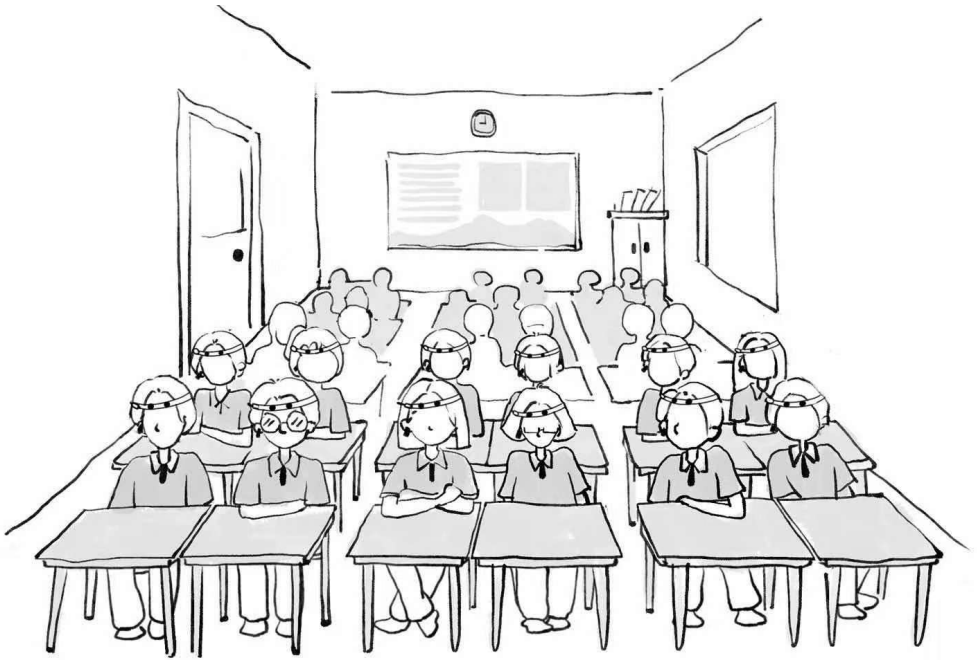
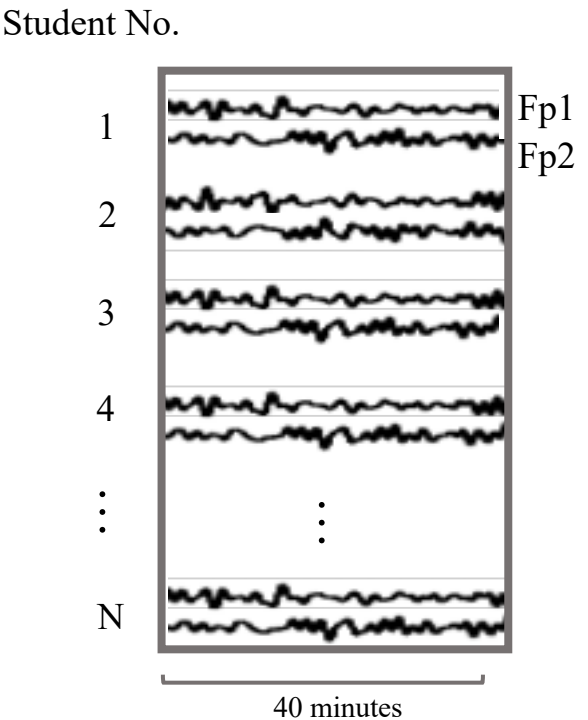


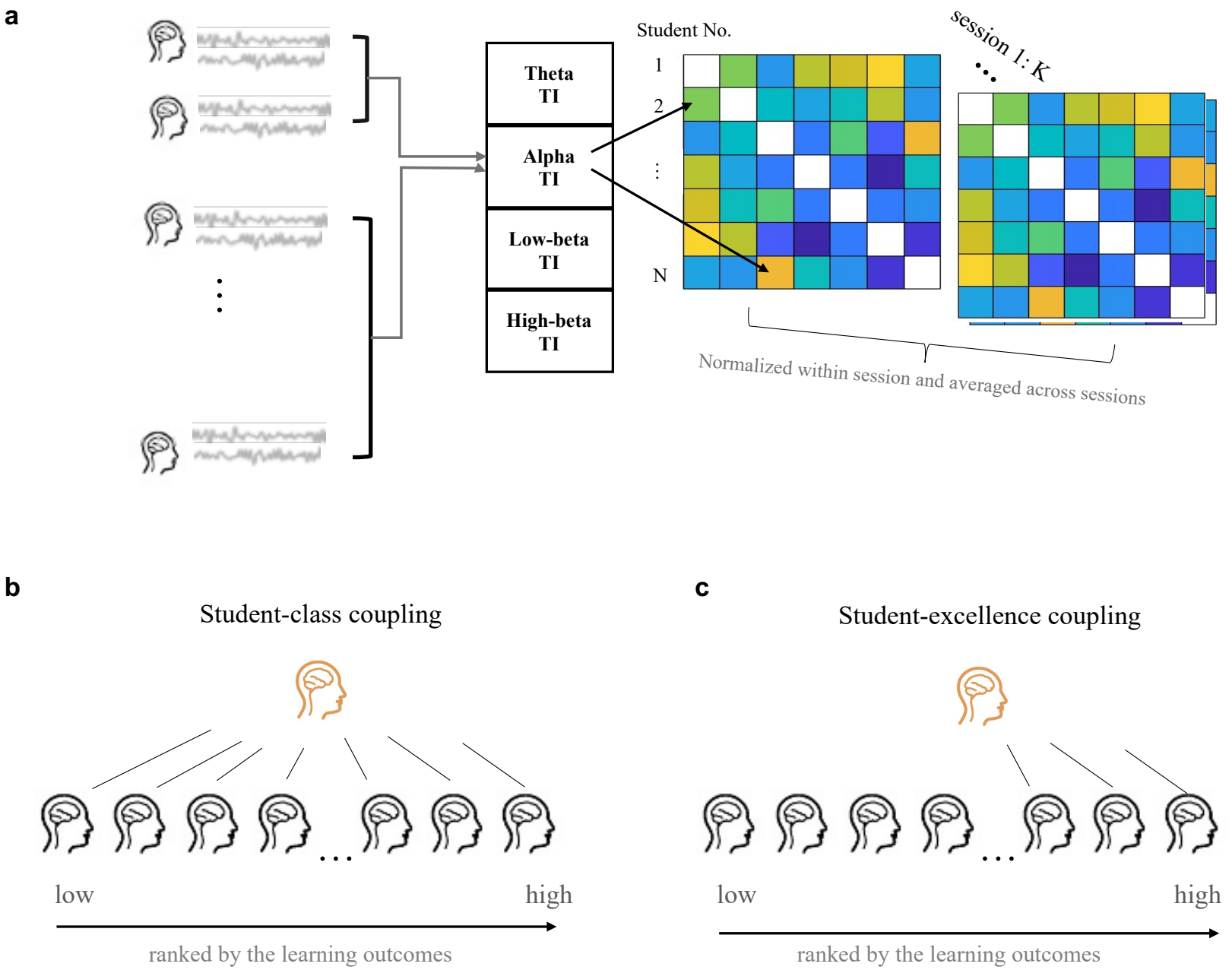
Fig.S6: The number of retained epochs per session per student (**a**) at Fp1; (**b**) at Fp2 after the preprocessing procedure. The colorbar indicated the number of retained epochs.

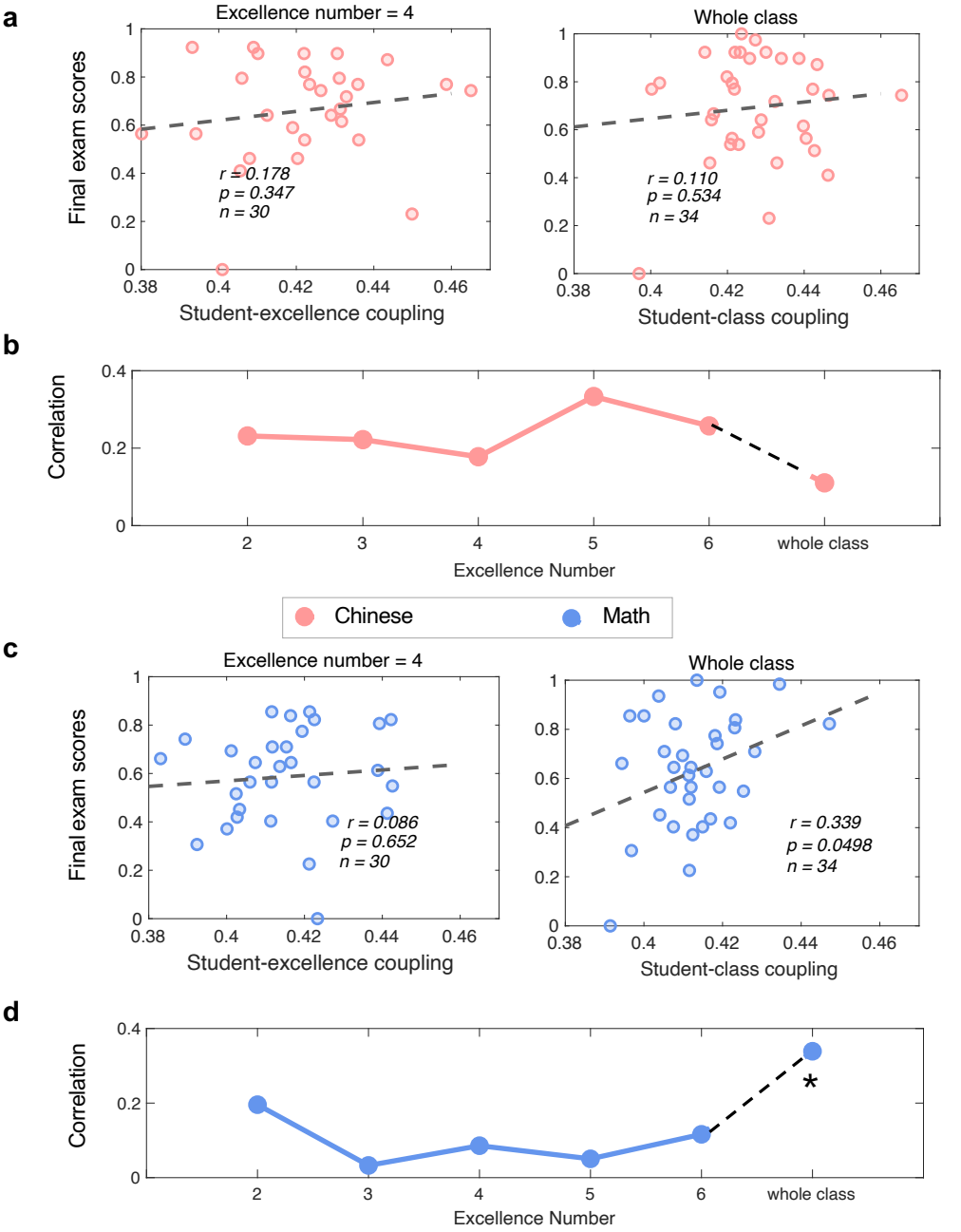
a

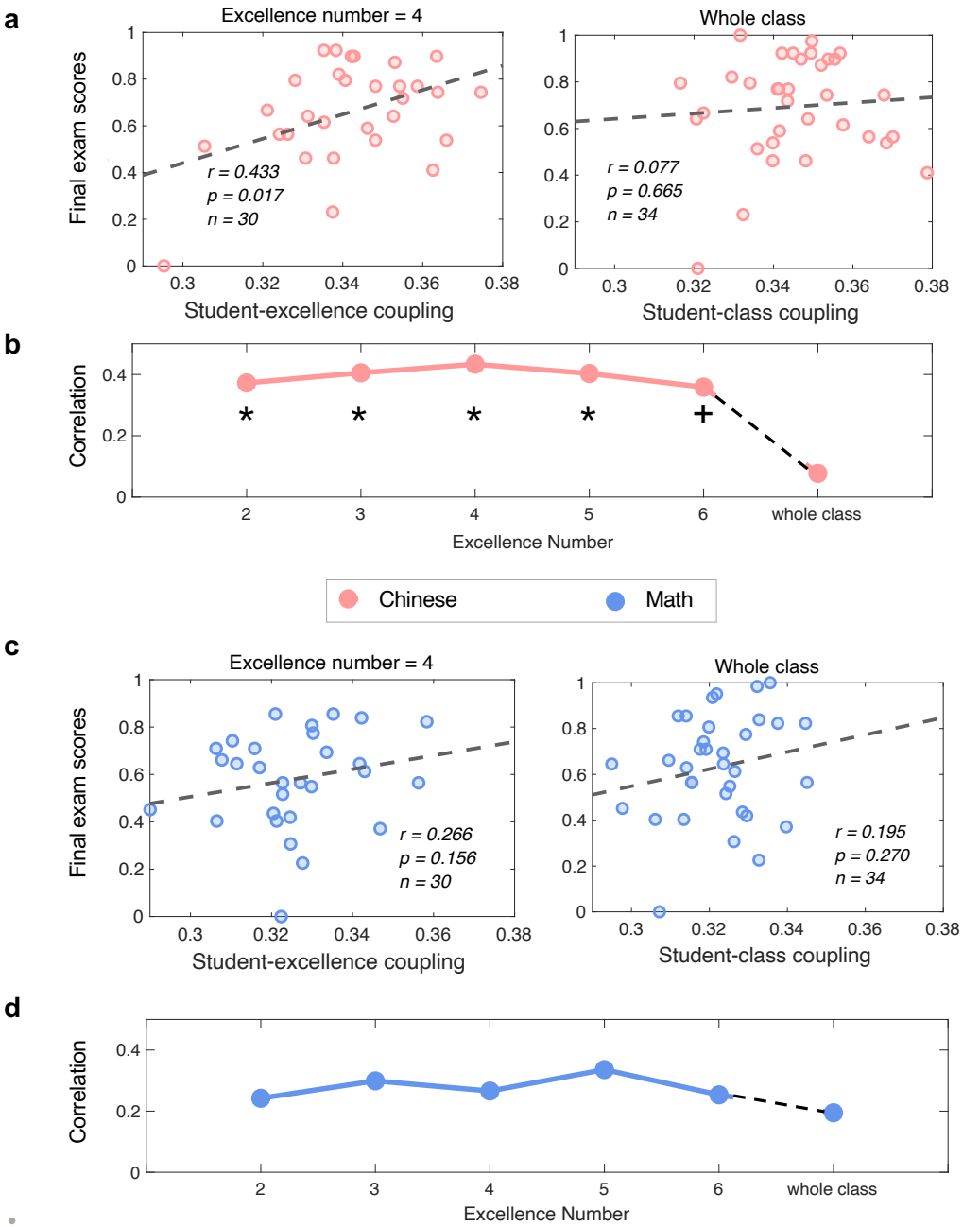


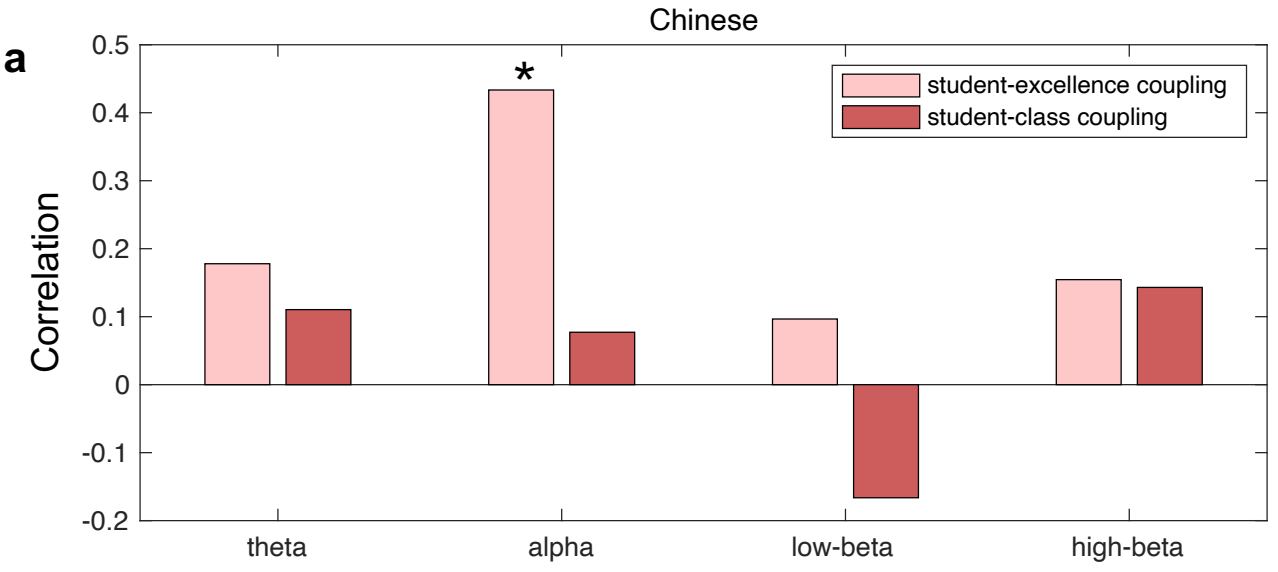
b

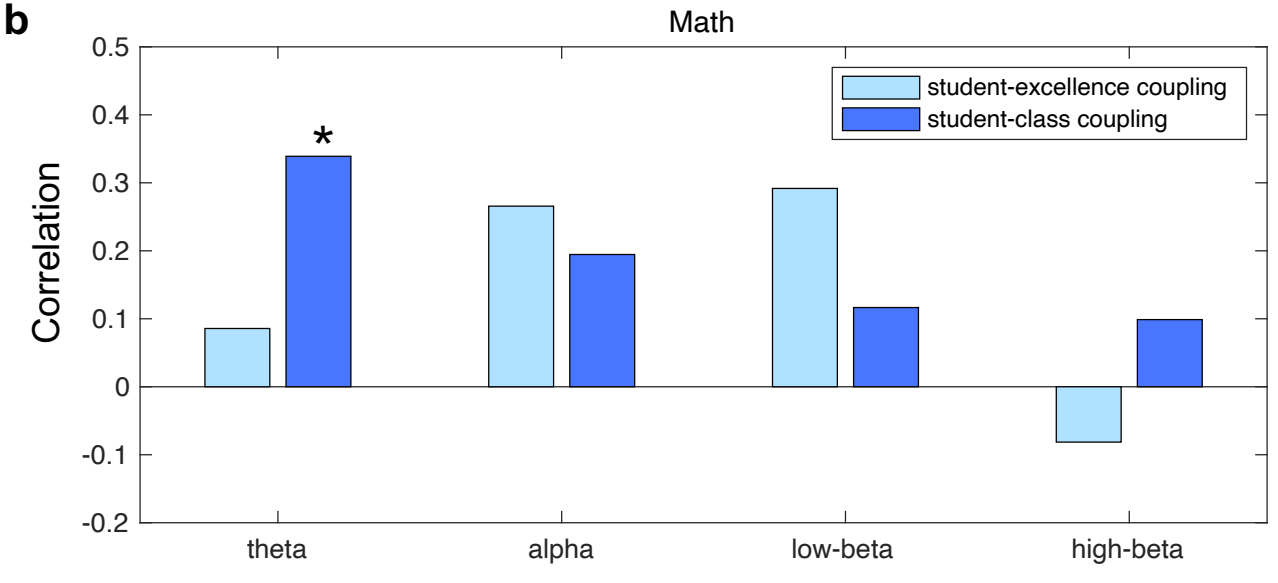


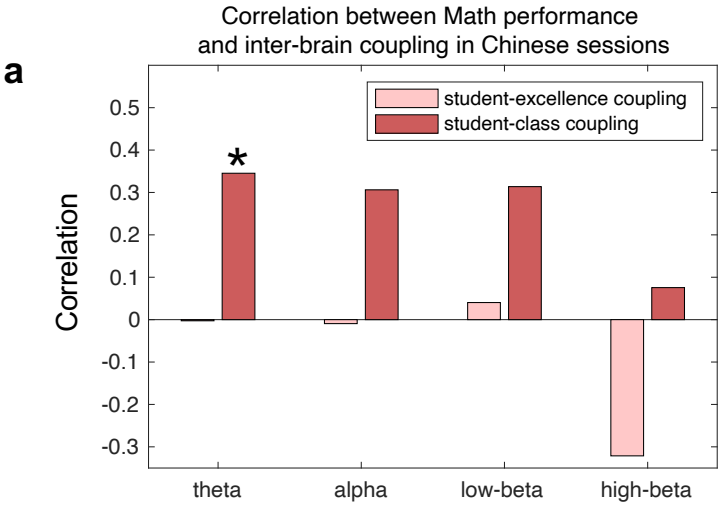

a
Theta TI
Alpha TI
Low-beta TI
High-beta TI
Student No.
1
2
N
session 1: K
Normalized within session and averaged across sessions
b
Student-class coupling
low
high
ranked by the learning outcomes
c
Student-excellence coupling
low
high
ranked by the learning outcomes

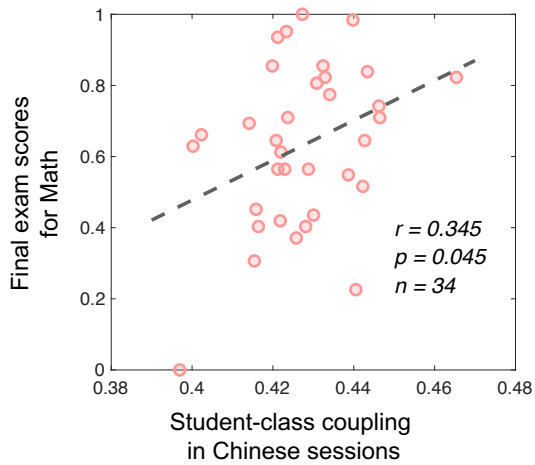

a
Excellence number = 4
Final exam scores
r = 0.178
p = 0.347
n = 30
Student-excellence coupling
Whole class
r = 0.110
p = 0.534
n = 34
Student-class coupling
b
Correlation
Excellence Number
whole class
Chinese
Math
c
Excellence number = 4
Final exam scores
r = 0.086
p = 0.652
n = 30
Student-excellence coupling
Whole class
r = 0.339
p = 0.0498
n = 34
Student-class coupling
d
Correlation
Excellence Number
whole class
*

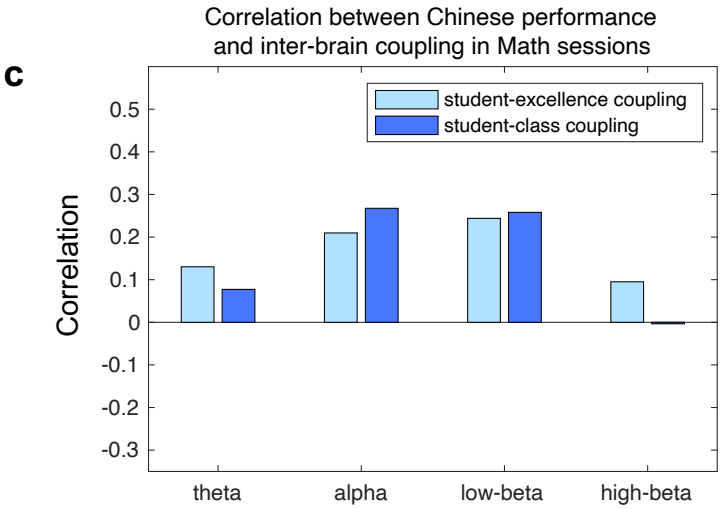

a
Excellence number = 4
Final exam scores
r = 0.433
p = 0.017
n = 30
Student-excellence coupling
Whole class
r = 0.077
p = 0.665
n = 34
Student-class coupling
b
Correlation
Excellence Number
whole class
Chinese
Math
c
Excellence number = 4
Final exam scores
r = 0.266
p = 0.156
n = 30
Student-excellence coupling
Whole class
r = 0.195
p = 0.270
n = 34
Student-class coupling
d
Correlation
Excellence Number
whole class

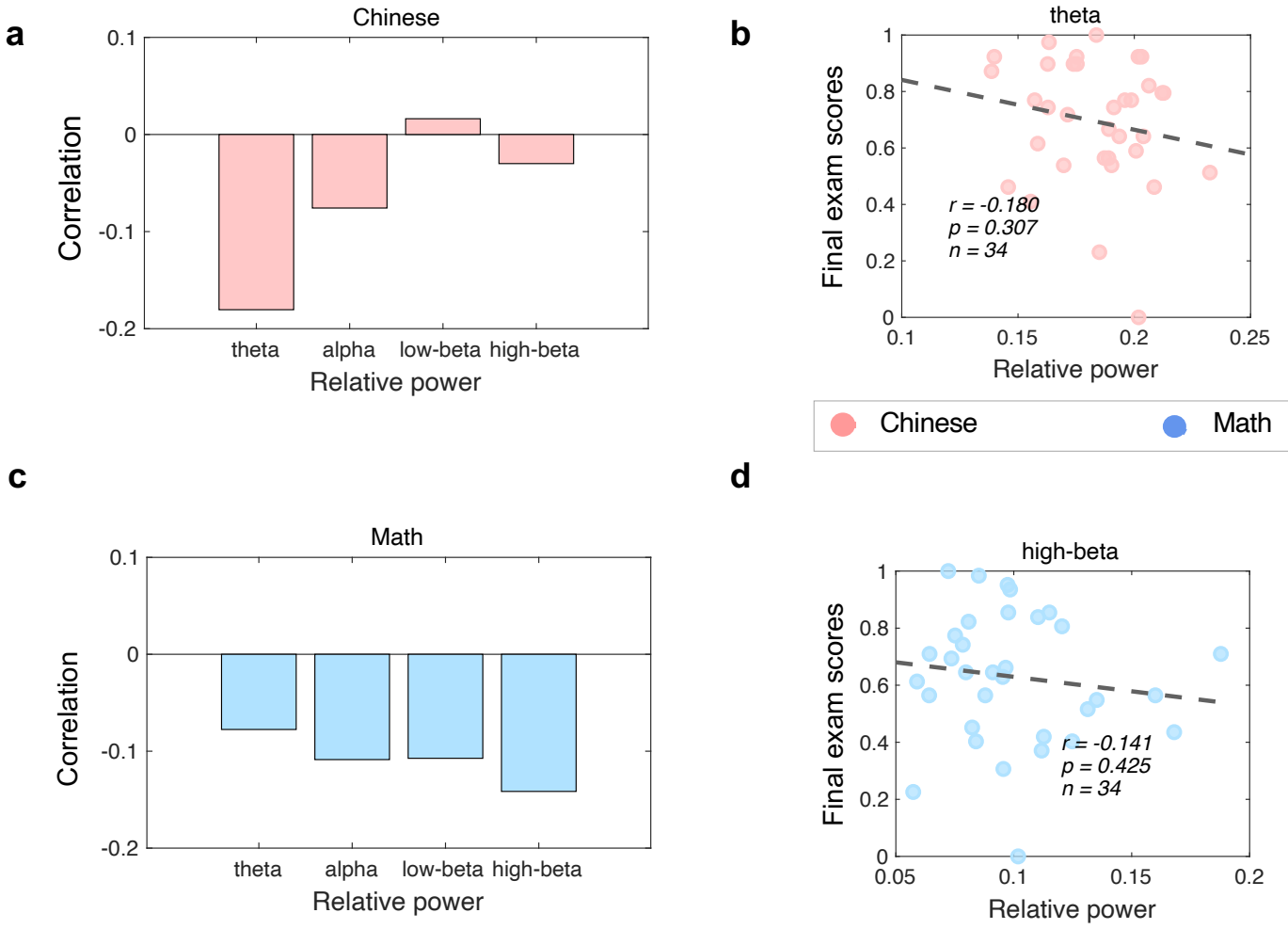

a
Chinese
Correlation
0.5
0.4
0.3
0.2
0.1
0
-0.1
-0.2
*
student-excellence coupling
student-class coupling
theta
alpha
low-beta
high-beta


b
Math
Correlation
0.5
0.4
0.3
0.2
0.1
0
-0.1
-0.2
*
student-excellence coupling
student-class coupling
theta
alpha
low-beta
high-beta


a
Correlation between Math performance
and inter-brain coupling in Chinese sessions
student-excellence coupling
student-class coupling
Correlation
0.5
0.4
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
*
theta
alpha
low-beta
high-beta


b
Final exam scores
for Math
1
0.8
0.6
0.4
0.2
0
0.38
0.4
0.42
0.44
0.46
0.48
r = 0.345
p = 0.045
n = 34
Student-class coupling
in Chinese sessions


c
Correlation between Chinese performance
and inter-brain coupling in Math sessions
student-excellence coupling
student-class coupling
Correlation
0.5
0.4
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
theta
alpha
low-beta
high-beta


a
Chinese
Correlation
0.1
0
-0.1
-0.2
theta
alpha
low-beta
high-beta
Relative power
b
theta
Final exam scores
1
0.8
0.6
0.4
0.2
0
0.1
0.15
0.2
0.25
Relative power
r = -0.180
p = 0.307
n = 34
Chinese
Math
c
Math
Correlation
0.1
0
-0.1
-0.2
theta
alpha
low-beta
high-beta
Relative power
d
high-beta
Final exam scores
1
0.8
0.6
0.4
0.2
0
0.05
0.1
0.15
0.2
Relative power
r = -0.141
p = 0.425
n = 34