Inter-brain coupling analysis reveals learning-related attention of primary school students

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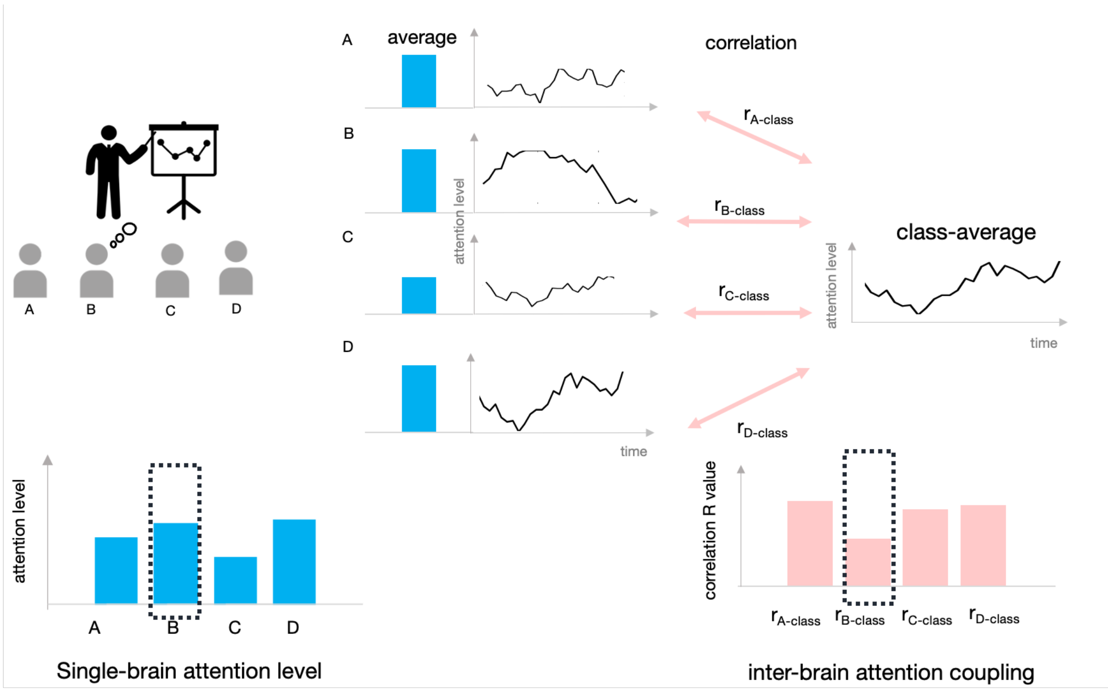
Abstract
Learning-related attention is one of the most important factors influencing learning. While technologies have enabled the automatic detection of students' attention levels, the detected states might fail to be learning-related if students did not attend learning tasks (e.g., the attention level of a student who reads comics secretly during classroom learning). This phenomenon poses challenges to the practical application, especially in the primary school stage, which is crucial for students to set up learning attitudes/strategies. Inspired by the emerging inter-person perspective in neuroscience, we proposed an inter-brain attention coupling method to detect learning-related attention. Our method is based on the premise that learning-related attention should follow the structures of course contents, which is reflected in the attention dynamics shared across students. We hypothesized that one's level of learning-related attention could be detected in the inter-brain attention coupling, which is defined as the degree to which an individual student's attention dynamics match the attention dynamics averaged across classmates. To test this idea, wearable EEG devices were used to monitor students' attention levels in a class of primary school students during classroom learning. We found that one's inter-brain attention coupling was positively correlated with academic performance: higher performances are associated with higher coupling to the class-average attention dynamics. No significant correlation was found between students' attention levels averaged within the individual and their academic performances. These results demonstrated the value of inter-brain attention coupling in assessing primary school students' learning process. We argued that inter-person coupling analysis could be useful in monitoring learning-related attention in real-world educational contexts.

Keywords:
learning-related attention, learning state monitoring, inter-brain coupling, classroom, EEG

Highlights

1. Wearable EEG devices were used to monitor students' attention levels in a class of primary school students during classroom learning.
2. A better coupling for one's attention dynamics to the class-average attention dynamics was associated with a better academic performance.
3. One's inter-brain attention coupling to class-average attention dynamics during lectures outperformed as an indicator of the learning process compared with the value of attention levels.
4. The present finding suggests that students' learning-related attention dynamics can be detected from an inter-person perspective, which will be useful for 'wild' educational applications.

Graphic Abstract



1. Introduction

Learning-related attention may be the most important factor influencing learning (Chun & Turk-Browne, 2007; Posner & Rothbart, 2014). Evidence in psychology and neuroscience suggests that attention controls what has been learned and remembered (Squire & Wixted, 2011; Weible, 2013). Nevertheless, it is difficult for teachers to spend equal time on each student to monitor their attention state in the educational practice, especially in large class sizes where teachers' time is a scarce resource (Koc & Celik, 2015; Young, 2020). For some classmates, sharing the same classroom with the same teacher does not necessarily equate to a similar guidance and feedback experience (Beaman et al., 2006).

Therefore, increasing interest has been drawn towards the automatic detection of students' attention levels in the field of education, learning science, and computer science (Dewan et al., 2019). For example, researchers have proposed an image analysis architecture to automatically recognize students' three attention states (engaged, boredom, and neutral) with video recordings in a classroom environment (Ashwin & Guddeti, 2020). Moreover, based on the detected attention level, teachers or online learning systems will be able to modify the learning activities or provide feedback to improve students' learning performance. For instance, Chen and Wang developed an attention monitoring and alarm system based on EEG signals to help online instructors monitor the attention states of individual learners. When the system detects a low attention level for a specific student, it will alarm the student by sending an alarm message. Significantly better learning performances were observed in the group with the proposed system than in the control group (Chen & Wang, 2018). Despite these positive findings, it should be noted that most of the previous methods were explored in colleges or high schools. The feasibility of the automatic monitoring of attention levels in primary school students needs further validation. More importantly, metacognitive skills, which are crucial for lifelong learning, develop rapidly in the stage of primary school, from kindergarten age to grade six (Dignath et al., 2008). It is suggested that it is easier to change students when setting up learning attitudes/strategies than when students have already developed disadvantageous learning behaviors (Hattie et al., 1996; Hendy & Whitebread, 2000). Therefore, the automatic monitoring of attention levels to provide personalized guidance and feedback is particularly important for primary school students.

Even if it is feasible to automatically monitor attention levels among primary school students, the detected attention levels sometimes are not necessarily learning-related if students did not attend learning tasks in the first place. Imagine this: a primary school student named Bob is attending a math class in the classroom. After the bell rang, Bob secretly takes out his comics and starts reading while the teacher's lecture is going on as background noise. Bob is not engaged in the lecture. However, we may find that the detected attention level for Bob is not lower than other students who are paying attention to the lesson. In contrast, Bob may even keep a high attention level when the comics are very interesting. Since the detected attention level is not learning-related, it will fail to characterize the learning process and even lead to wrong feedback. In previous studies, students were instructed to join in specific learning tasks (e.g., attending a lecture or reading a book) under the supervision of researchers. Under this premise, it is reasonable to assume that the detected attention level could characterize students' learning processes during the task (Sonkusare et al., 2019). However, the educational practice in the real world is usually "wilder" and more uncontrollable compared with the experimental scenarios. The detected states may not necessarily be learning-related when students like Bob fail to attend the tasks we desired. Since primary school students have generally shown lower self-control ability than adults (Eisenberg et al., 2014), it is important to capture the learning-related attention to support teachers' instructions and class management in primary schools.

The recent emerging inter-person perspective in neuroscience is expected to provide a possible solution to capture the learning-related attention among primary school students (Babiloni & Astolfi, 2014; Davidesco et al., 2019; Hasson et al., 2012; Nastase et al., 2019; Zhang, 2018). The inter-person perspective identifies the neural correlates of interest by computing the similarity across brain activity patterns of people who received the same stimuli or were involved in the same interacting scenario. Possibly the first inter-brain study reported that individual brains show a highly significant tendency to act in unison when freely viewing a popular movie. The synchronized brain activities across individuals were found in multiple brain regions, suggesting that a large extent of the human cortex is stereotypically responsive to naturalistic stimuli (Hasson et al., 2004). This finding has also been validated in typical learning scenarios such as lectures, videos, and discussions (Cohen et al., 2018; Dikker et al., 2017; Pan et al., 2018; Zheng et al., 2018). For example, similar brain activities are observed in students paying attention to the lesson during classroom learning (Dikker et al., 2017). More importantly, the shared brain responses across peers/classmates have been argued to reflect the shared attention or shared understanding of the external stimuli (i.e., the course contents) (Chen et al., 2022; Davidesco et al., 2019; Dikker et al., 2017; Meshulam et al., 2021). For students situated in the same learning task, similar brain dynamics triggered by the course contents are expected to be found across students. Note that these similar brain dynamics contain not only the low-level sensory processing that closely tracks the physical features of course contents but also the higher-level functions such as semantic and emotional processing (Hasson et al., 2004; Lerner et al., 2011). Then, averaging brain activities across classmates would enhance the consistent brain activities 'tuned' by the course contents by canceling out the idiosyncratic activities responsive to distractors. Hereby, it is plausible to consider the 'class-average' brain activity to represent a course-content-related learning process (see (Nastase et al., 2019) for a more detailed discussion).

Inspired by these positive findings in neuroscience, it seemed promising to consider the 'class-average' attention dynamics for representing the learning-related attention dynamics for primary school students. For students who are focused on the course, a high similarity is expected to be observed between their dynamics of attention levels and the class-average dynamics. For students like Bob who do not engage, we expected to observe a low similarity between his dynamics of attention levels and the class-average dynamics even if he might show a high value of attention levels. In order to test this hypothesis, we monitor the attention levels in a class of primary school students during their classroom learning based on a wearable EEG device. The wearable EEG device was used since it is able to monitor attention level continuously and non-intrusively (Chen & Wang, 2018; Davidesco, 2020; Xu & Zhong, 2018). Then, we calculated the degree of similarity between the attention dynamics of each student and the class-average attention dynamics (termed as 'inter-brain attention coupling') and compared its effectiveness in predicting academic performances with the widely-used attention level for each student (termed as 'single-brain attention level). We hypothesized that the inter-person perspective could capture the learning-related attention level, thus outperforming as an indicator of the academic performance compared with the widely used values of attention levels averaged on a single-person level.

2. Method

2.1 Participants

Twenty-eight students (16 females; age: 8-9 years old) from the same class (35 students in total) from grade 3 of a primary school in Shandong Province, China, volunteered to wear a headband EEG device during their regular sessions. 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.

2.2 Procedure and Data Recording

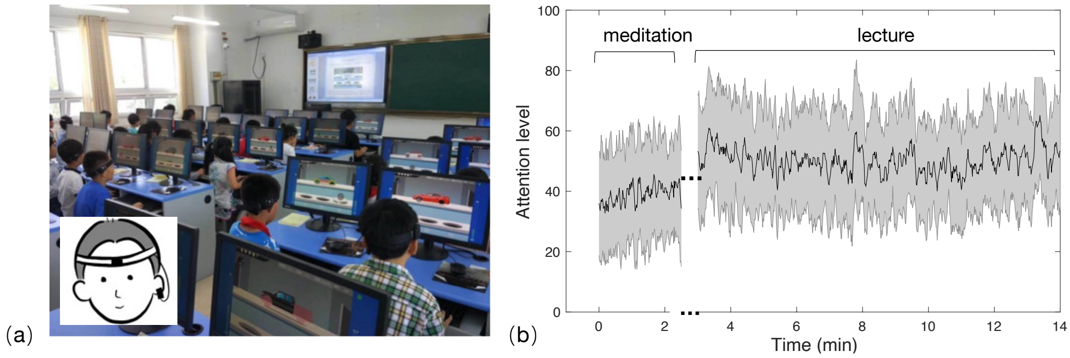


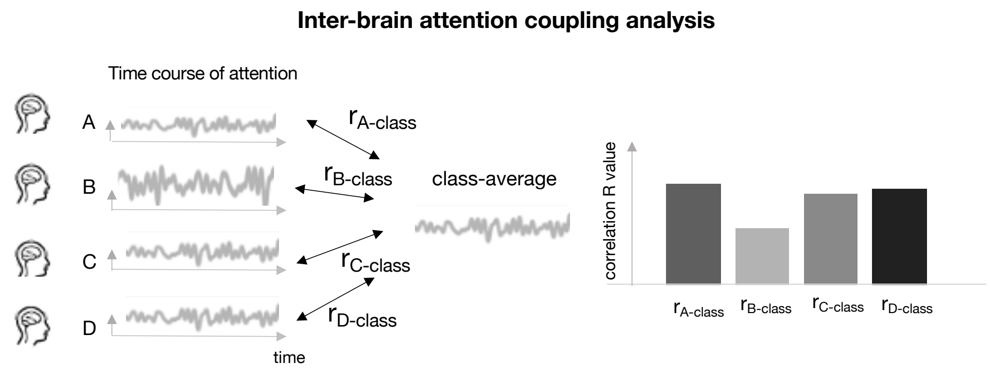
Fig.1. Experiment paradigm. (a) An illustration of the experimental setup for students wearing an EEG headband in their regular classroom. (b) The time course of the class-average attention level during the meditation and lecture tasks in a representative session. The grey shadow indicated standard deviation across students at each time point.

A single-channel headband (Cusoft, China) with dry electrodes and a NeuroSky EEG biosensor (NeuroSky, USA) was used to record EEG at Fpz over the forehead at a sampling rate of 512 Hz (Fig.1a). The reference electrode was placed on the left ear lobe with a ground at Fp1. The NeuroSky EEG biosensor can calculate every second's attention level based on their patented algorithm from EEG signals (http://neurosky.com/biosensors/eeg-sensor/algorithms/). The value for the attention level ranges from 1 to 100, indicating "very distracted" to "very focused." The detected attention level has been previously validated and used to monitor brain state in educational scenarios (Chen & Huang, 2014; Chen & Wang, 2018; Kuo et al., 2017). The quality of the detected attention level was also tested in the present study with a meditation task as a control (see details below). Fig.1b demonstrated the class-average time course for the attention level in a representative session. As shown, the class-average attention level during the meditation is lower than that during the lecture. Four students were omitted from the meditation data analysis as they failed to understand the meditation tasks.

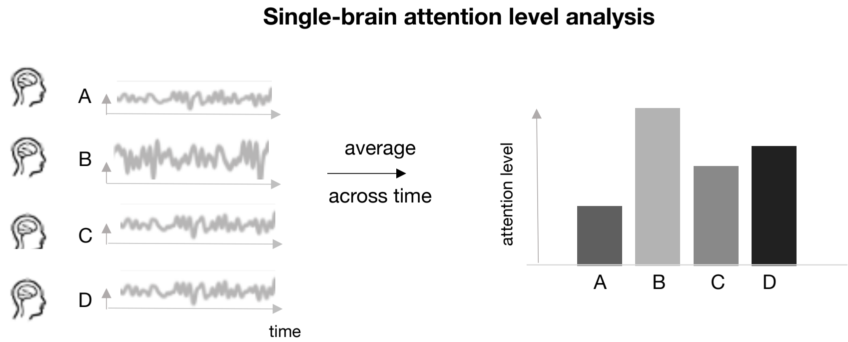
The data collection lasted for five sessions. Before each session began, students wore headbands with the help of the experimenters, and the headbands were taken off after each session. The duration of the sessions lasted around 20 minutes. During each session, students were required to meditate for around 2 minutes (i.e., closing their eyes and trying to relax). Then, their teacher gave a lecture about the introduction to neuroscience.

The exam scores were used to characterize students' academic performances. In order to exclude the possible bias in a single exam, the students' scores in Chinese and Math on their final exam in the last term, the mid-term exam, and the final exam in the present term were averaged as the indicators of their academic performances. The mean of the students' scores was 91.8, ranging from 74 to 99. The scores were sufficiently diverse to characterize the students' differences in their academic performances.

2.3 Data Processing



(a)



(b)

Fig. 2. A schematic illustration of the analysis. (a) The inter-brain attention coupling was obtained by comparing the time course of attention level for each student and the class-average pattern (average across all other students), using Pearson correlation. (b) The single-brain attention level was obtained by averaging each student's attention level dynamic across time.

To test our hypothesis, inter-brain attention coupling and single-brain attention levels were calculated for each student as indicators of the learning state during lectures, as shown in Fig.2. For the inter-brain attention coupling, we employed an inter-subject correlation framework (Nastase et al., 2019), which has been successfully used to evaluate the learning process in a computer science lesson (Meshulam et al., 2021) and the comprehension during verbal communication (Stephens et al., 2010). First, for each student, a 30-s non-overlapping time window covering 30 attention level points was used to extract the attention dynamic during the lecture. Then, for each 30-s epoch in each student, the degree to which an individual student's attention dynamics match the class-average attention dynamics (average across all other students) was computed using Pearson's correlation. The correlation value was used as the inter-brain attention coupling index for each epoch. Finally, correlation values were averaged across epochs and lectures. At the same time, the single-brain attention level was obtained by averaging the attention level dynamic within and across lectures for each student. Therefore, for each student, there would be a single-brain index and an inter-brain index as indicators of the learning process during the lectures. Then, Pearson's correlations between individuals' inter-brain attention coupling (or single-brain attention level) and their corresponding academic performances were calculated separately. Besides, a similar analysis focused on the relaxation state was conducted as a control since the NeuroSky device could also calculate the level of relaxation in each second. The value of relaxation level ranges from 1 to 100. The detected relaxation level has also been previously applied in scenarios such as learning and stress therapy (Perhakaran et al., 2016; Ülker et al., 2017).

Moreover, we also conducted the inter-brain coupling analysis and single-brain analysis based on the EEG power data outputted by the NeuroSky EEG biosensor. The EEG power at different frequency bands was calculated in each second. Here, the delta band (1-4Hz), the theta band (4-7Hz), the alpha band (8-12Hz), the beta band (13-30Hz), and the gamma band (30-40 Hz) were used in the following analysis. The power of each frequency band of interest was normalized by dividing the power in the 1-40 Hz band.

3. Results

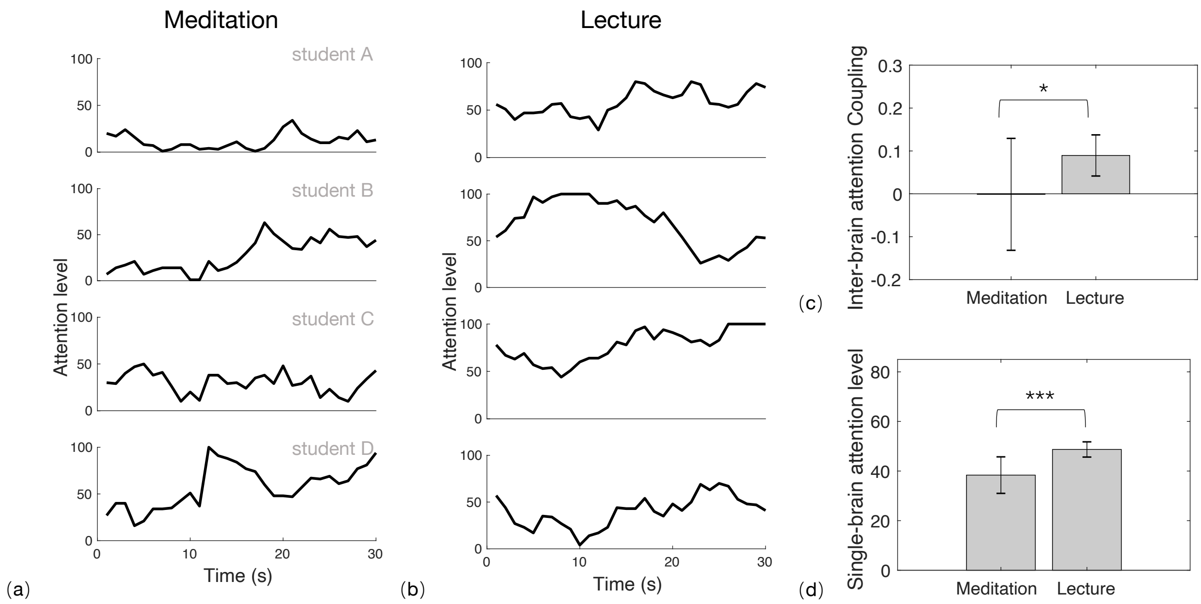


Fig.3 (a) The temporal dynamic of attention level for four representative students during meditation; (b) The temporal dynamic of attention level for four representative students during the lecture. (c)The comparison between the meditation task and the lecture for (c) inter-brain attention coupling and (d) single-brain attention level

Fig.3a and b demonstrated the temporal dynamic of the attention level for representative students during meditation and lectures. As shown in Fig.3a, similar attention dynamics were exhibited in most students when attending lectures, while distinct attention dynamics were observed in the meditation. Indeed, the average inter-brain attention coupling across students was around zero in the meditation task. In contrast, significantly higher inter-brain attention coupling was found across students during the lecture (Fig.3c, $t(23) = 3.15$, $p = .018$, paired t-test with Bonferroni correction). We also compared the average attention level between the meditation task and the lecture. As demonstrated in Fig.3d, the single-brain attention levels were significantly higher during the lecture compared with the meditation task ($t(23) = 5.56$, $p < .001$).

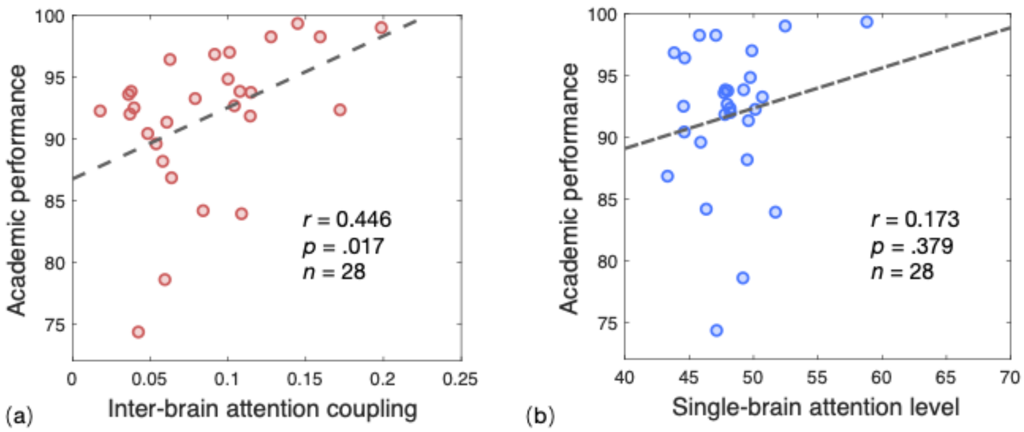


Fig.4. Correlations between the index for attention during lectures and academic performance. (**a**) Scatter plots between inter-brain attention coupling and academic performance. (**b**) Scatter plots between single-brain attention level and academic performance.

Here, individual's inter-brain attention coupling during lectures was found to be positively correlated with their academic performance (Fig.4a, $r = 0.446$, $p = .017$, $n = 28$): more similar a student's attention dynamic is to the class-average, better their academic performances are. At the same time, no significant correlations were observed between single-brain attention level and their academic performance (Fig.4b, $r = 0.173$, $p = .379$, $n = 28$). Nevertheless, the correlations in both cases increase (inter-brain attention coupling: $r = 0.589$, $p = .002$, $n = 24$; single-brain attention level: $r = 0.384$, $p = .064$, $n = 24$), respectively, when the four outliers at the left-down corner (students with academic performances < 85) were removed.

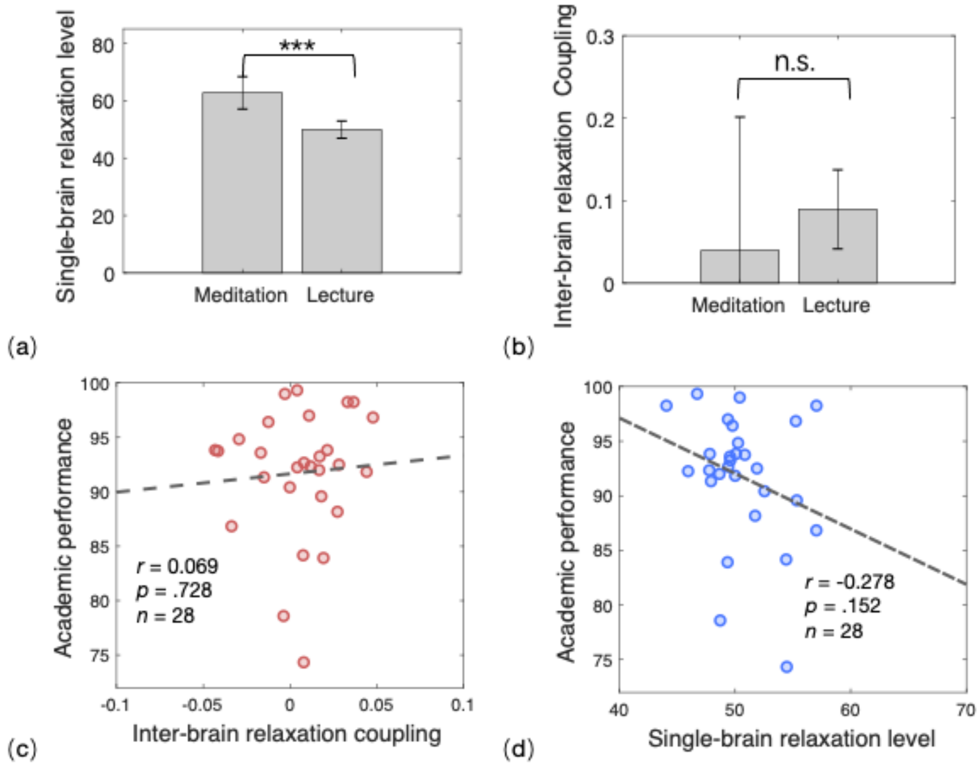


Fig.5. Results for the relaxation index. The comparison between the meditation task and the lecture for (a) single-brain attention level and (b) inter-brain attention coupling. *** indicated $p < .001$. n.s. indicated no significance.

Fig.5 further showed the results based on the relaxation index. Single-brain relaxation levels were significantly higher in the meditation task when compared with attending the lectures (Fig. 5a, $t(23) = 8.92$, $p < .001$). As the meditation task required students to relax and decrease external attention (Rubia, 2009), the higher relaxation level (see Fig. 3d) and lower attention levels during the meditation suggested the effectiveness of these cognitive indexes. No significant difference was observed in the inter-brain relaxation couplings during the meditation task compared with the lectures (Fig. 5b, $t(23) = 1.17$, $p > .05$). Moreover, the correlations between individual's relaxation index and academic performances also failed to reach significance (Fig. 5c-d, inter-brain relaxation level: $r = -0.278$, $p = .152$, $n = 28$; single-brain relaxation coupling: $r = 0.069$, $p = .728$, $n = 28$).

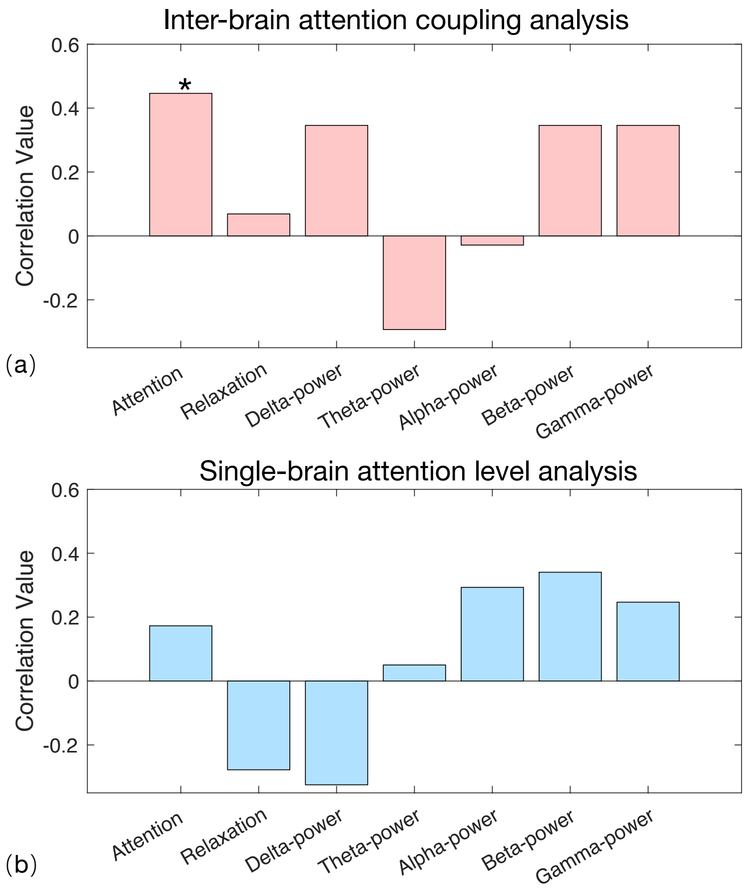


Fig.6. Correlation values between students' learning state (or EEG power) during lectures and their academic performances. Bars with a pink color indicated inter-brain-based correlations, and bars with a blue color indicated single-brain-based correlations. Stars indicated a significant ($p < .05$) correlation.

Fig.6 demonstrated the summarized correlation results between students' learning state (or EEG power) during lectures and their academic performances. As mentioned above, a significant correlation was only found between students' inter-brain attention coupling (the similarity between a student's attention dynamics and the average across all the other classmates) and their academic performances. When using the EEG power data for analysis, all the correlations failed to reach significance.

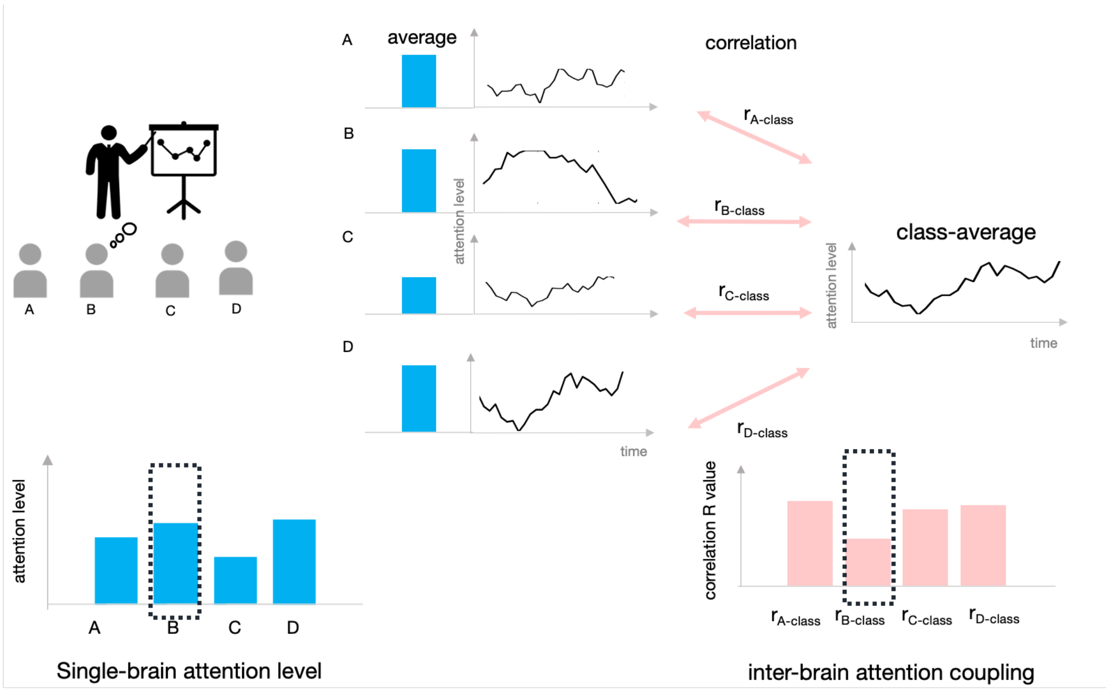


Fig. 7. An illustration to show the idea of inter-brain attention coupling analysis. When students attend the lecture (for example, A, C, and D), their time course of attention level is expected to be similar. However, for student B, who engaged in the comics, his attention dynamics are expected to align with his distractors (e.g., the comic books). Therefore, while the average attention level for student B may not necessarily be lower than other students, the inter-brain coupling analysis is expected to distinguish him from other students by comparing the time course of attention level for each student and the class-average pattern with correlation analysis.

4. Discussion

The present study proposed an inter-brain attention coupling analysis framework to monitor students' learning-related attention. We recorded the attention levels of a class of primary school students with wearable EEG devices during their classroom learning. Results showed that one's inter-brain attention coupling to class-average dynamics during lectures was positively correlated with their academic performance. At the same time, no significant correlation was found between the single-brain attention level and the academic performance. A similar analysis based on the relaxation index failed to reach significant correlations. Our results verify the feasibility of the automatic monitoring of attention levels in primary school students. Then, we extend applications of detected states from an inter-person perspective and suggest its potential as a useful tool to evaluate the learning process. More importantly, compared with the widely-used attention level for individual students, we argue that inter-brain coupling analysis is expected to be particularly useful in monitoring learning states in 'wild' educational practical scenarios by providing learning-related information.

The present study highlighted the potential of class-average attention dynamics to represent learning-related attention dynamics during educational practices. As shown in Fig.3c, while the average inter-brain attention coupling across students was around zero in the meditation task when students tried to reduce focus on surroundings, similar attention dynamics emerged only in the lecture condition when shared external stimuli (i.e., the course contents) existed. Previous studies have suggested that the class-average brain dynamics could reflect the characteristics of the shared course contents (Dikker et al., 2017; Nastase et al., 2019). Then, by comparing one student's attention dynamic with the class-average dynamic, we expected to filter out idiosyncratic dynamics responsive to distractors, thus capturing the learning-related attention dynamics intended by the course contents. Indeed, students' academic performances were significantly positively correlated with the degree of similarity between their attention dynamics and the class-average attention dynamics (i.e., inter-brain attention coupling) rather than values of the attention level (i.e., single-brain attention level), suggesting the effectiveness of the inter-brain attention coupling analysis. This finding was also consistent with previous studies where one student's neural coupling to all their peers or classmates was positively correlated with their self-reported engagement, memory retention performances, and the final exam scores (Chen et al., 2022; Davidesco et al., 2019; Dikker et al., 2017; Meshulam et al., 2021). While previous inter-brain studies mainly focus on middle school students or undergraduate students, the present study provides unique evidence on the inter-brain patterns of primary school students.

The present study suggested that the inter-brain coupling analysis based on cognitive indexes calculated from brain signals could reflect the effective learning process. Compared to raw brain signals, the present results based on the attention level are expected to be more interpretable for understanding the psychological processes behind learning. By using the relaxation index as a control, we highlighted the importance of learning-related attention in successful classroom learning. Together with recent developments in cognitive state decoding based on brain signals from in the field of brain-computer interface and affective computing (Aricò et al., 2018; Ding et al., 2021; Gao et al., 2021; Hu et al., 2019), the complex mental processes during learning are expected to be further decomposed towards a deeper understanding of the real-world learning process. Besides, the present study did not observe the significant correlation between the inter-brain EEG-power coupling and academic performances, which might be explained by the different developmental stages of experiment samples, or the limited single-channel EEG recordings.

It should be noted that the non-significant single-brain-attention-level-based correlation results for the academic performances did not necessarily undermine the potential importance of the single-brain attention level. The correlation between single-brain attention level and academic performance reached marginal significance with a positive correlation coefficient of 0.384 after ruling out outliers (students with relatively low academic performances), suggesting the potential for the single-brain attention level to evaluate the learning process (Chen & Wang, 2018). Nevertheless, the correlation failed to reach significance when including all the students. One possible explanation might be that students with relatively low academic performances might focus on some distractors during class. Their single-brain attention level might not be lecture-related and eliminate the possibly-existing correlations. By contrast, the inter-brain attention coupling could be more efficient in capturing the learning-related state and reach a significant correlation with academic performances (see an illustration in Fig.7).

It should also be noted that the present finding of the inter-person perspective is not limited to classroom learning or the cognitive index decoded from EEG signals. While it is validated in a classroom learning setting-up, this analysis framework can also be applied in other scenarios such as Massive Open Online Courses and synchronized/asynchronized online courses, where other students are not coexisting in time or space (Meshulam et al., 2021). The learning-related attention levels for a new learner could be detected by comparing individuals' attention dynamics with the pre-recorded dynamics of attention from a bunch of students who were attentive to the same courses. Then, while the EEG-based attention level was used to describe the learning process in the present study, the learning states detected by other methods could also be well-suited in the inter-person perspective (Prochazkova et al., 2022). Nevertheless, future studies would be required to test this feasibility.

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 on grade 3. The single-channel portable EEG device is expected to support larger-sample research in a real-world classroom in the near future. Second, it is widely acknowledged that disciplinary differences could substantially influence learning (Neumann, 2001). More kinds of courses were needed to be investigated the possible influences of disciplinary differences since there are possibly different neurocognitive mechanisms to support successful learning in different disciplines. Third, we used the attention levels and relaxation levels to describe the learning state. Although learning-related attention level has been considered the most important factor that influences the learning process (Posner & Rothbart, 2014), more diverse indexes such as affective states (Ashwin & Guddeti, 2020) and mental efforts (Lin & Kao, 2018) are expected to provide a more comprehensive picture of students' learning.

5. Conclusions

In the present study, we argue that students' learning-related attention dynamics can be detected from an inter-person perspective, which will be useful for 'wild' educational applications. We validated this idea by monitoring the attention levels of a class of primary school students during their classroom learning with wearable EEG devices. Results showed that one's inter-brain attention coupling to class-average attention dynamics during lectures outperformed as an indicator of the learning process compared with the value of attention levels. The present study suggests the feasibility of the inter-person analysis to monitor students' learning-related attention dynamics. Moreover, since the present findings are based on a single-channel EEG device, the high portability and low cost of this commercial device allow the present finding readily to apply in educational practices.

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Credit author statement

Jingjing Chen: Conceptualization, Methodology, Visualization, Writing – original draft preparation.

Xu Bin: Data collection, Data curation. **Dan Zhang**: Conceptualization, Methodology, Validation, Writing- Reviewing and Editing.

Declaration of competing interest

B. Xu has a financial interest in Cusoft, Inc.The other authors declare no competing financial interests.

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