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Interplay between prior knowledge and communication mode on teaching effectiveness: Interpersonal neural synchronization as a neural marker

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ABSTRACT

Teacher–student interaction allows students to combine prior knowledge with new information to develop new knowledge. It is widely understood that both communication mode and students' knowledge state contribute to the teaching effectiveness (i.e., higher students' scores), but the nature of the interplay of these factors and the underlying neural mechanism remain unknown. In the current study, we manipulated the communication modes (face-to-face [FTF] communication mode/computer-mediated communication [CMC] mode) and prior knowledge states (with vs. without) when teacher–student dyads participated in a teaching task. Using functional near-infrared spectroscopy, the brain activities of both the teacher and student in the dyads were recorded simultaneously. After teaching, perceived teacher–student interaction and teaching effectiveness were assessed. The behavioral results demonstrated that, during teaching with prior knowledge, FTF communication improved students' academic performance, as compared with CMC. Conversely, no such effect was found for teaching without prior knowledge. Accordingly, higher task-related interpersonal neural synchronization (INS) in the left prefrontal cortex (PFC) was found in the FTF teaching condition with prior knowledge. Such INS mediated the relationship between perceived interaction and students' test scores. Furthermore, the cumulative INS in the left PFC could predict the teaching effectiveness early in the teaching process (around 25–35 s into the teaching task) only in FTF teaching with prior knowledge. These findings provide insight into how the interplay between the communication mode and students' knowledge state affects teaching effectiveness. Moreover, our findings suggest that INS could be a possible neuromarker for dynamic evaluation of teacher–student interaction and teaching effectiveness.

1. Introduction

In recent years, technology has been widely integrated into education, which has led to various teaching styles. (Balakrishnan and Gan, 2016; Entwistle, 2013; McKnight et al., 2016). Convincing evidence reveals that in any teaching mode, teaching effectiveness has a great impact on students' success and motivation (Klassen and Tze, 2014). In particular, researchers strive to verify the importance of *processing fluency* (i.e., one's subjective ease or difficulty of processing information) as an internal cue that educators use to assess teaching effectiveness (Reber and Greifeneder, 2016). Previous studies have shown that both the students' prior knowledge state (Sherman and Frost, 2000) and the communication mode used in teaching (Hantula et al., 2011) could influence the processing fluency between a teacher and students, thereby affecting students' performance (Hantula et al., 2011; Koriat, 2008; Reber and Greifeneder, 2016; Sherman and Frost, 2000). Thus, educators must understand how these factors affect teaching effectiveness and then translate this understanding into practice when designing a teaching curriculum.

Teaching is a dynamic social interaction during which active communication between the teacher and students results in continuous transfer and feedback of information (Watanabe et al., 2013). Behavioral studies have revealed that face-to-face (FTF) communication and computer-mediated communication (CMC, or online course), as two different modes of communication, exert different influences on teacher–student interactions (Shalom et al., 2015; Tichavsky et al., 2015). The

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FTF mode involves immediacy (Frymier and Houser, 2000; Miller et al., 2014) and is enriched in nonverbal cues (Furnham and Chamorro-Premuzic, 2005) that ensure a good quality of teacher–student interaction (Mazer et al., 2007). In contrast, immediacy and nonverbal cues are absent or negligible in the CMC mode (Noel-Levitz., 2011). Moreover, Hantula et al. noted that FTF communication involves a higher degree of behavior synchronicity, which may allow individuals to interact with one another rapidly, facilitating the fluency of the interaction, as compared to the CMC mode (Hantula et al., 2011). It has also been reported that the fluency of the interaction between teachers and students is associated with high student grades (Rimm-Kaufman et al., 2015), growth in cognitive or intellectual skills (Kim, 2010), and gains in academic self-concept (Cole, 2011). These findings suggest that students would perform better with FTF communication mode than with CMC mode teaching.

However, processing of information with prior knowledge and experience strengthens processing fluency (Sherman and Frost, 2000), and is also positively related to students' performance (Leahy and Sweller, 2005; Yang et al., 2018) as well as problem-solving efficiency (Rittle-Johnson et al., 2009). Additionally, a previous study demonstrated that prior knowledge could enhance communication effectiveness between teachers and students in the FTF lecture task, by facilitating head nodding and mutual gaze convergence, as compared to teaching in the absence of prior knowledge (Thepsoonthorn et al., 2016). Other studies have explored the effects of prior knowledge on CMC mode; however, the conclusions are inconsistent. Kennedy et al. found that prior knowledge could improve students' performance in the CMC mode (Kennedy et al., 2015). On the other hand, another study indicated that prior knowledge had no impact on students' performance in an online course (Wells, 2000). These differences may result from distinct teaching situations, including teaching contents, organization forms, and evaluation methods. These different factors make it difficult to directly compare the exact role of prior knowledge in different communication modes. To clarify this issue, our study aimed to explore the influence of prior knowledge on teaching effectiveness via different communication modes as well as to elucidate the phydiological basis of this infuence.

Thus, in this study, we compared teacher–student interaction and students' performance under conditions involving different prior knowledge states and communication modes by adopting a "two-person neuroscience" (2 PN) approach, also known as hyperscanning. As a suitable conceptual and methodological framework for studying the neural basis of social interactions, hyperscanning focuses on dyads rather than individuals (Hari and Kujala, 2009). By adopting this emerging technique, many studies have demonstrated that interpersonal neural synchronization (INS) can be a neuromarker of various interpersonal interactions, including simple action coordination (Cui et al., 2012; Holper et al., 2012; Hu et al., 2017) and complex social communication (Jiang et al., 2012, 2015; Stolk et al., 2014). Increased INS was consistently found in some social brain regions, especially the prefrontal cortex (PFC) and the right temporo-parietal junction (rTPJ) (Cheng et al., 2015; Hu et al., 2017; Lu et al., 2018; Zheng et al., 2018). The PFC is particularly related to attention (Adolphs, 2014), planning (Kaller et al., 2011) as well as information comparisons and integrations of self and others (Zhu et al., 2018), while the rTPJ is more closely related to theory of mind and self–other distinction processes (Carter and Huettel, 2013). In addition, several studies, by using a functional near infrared spectroscopy (fNIRS)-based hyperscanning approach, have confirmed that successful knowledge transmission and adequate teaching interactions could be accompanied by significant INS in the PFC and rTPJ (Holper et al., 2013; Pan et al., 2018; Zheng et al., 2018). Thus, based on these previous findings, PFC and rTPJ were selected as regions of interest in our current study.

In this study, we aimed to provide neurobiological evidence for the processing fluency theory in terms of INS, using the fNIRS-based hyperscanning technique. We manipulated the communication modes (FTF vs. CMC) and prior knowledge states (with vs. without) when teacher–student dyads participated in a teaching task. Neural activities were simultaneously recorded in both the PFC and rTPJ during teaching tasks, based on the previous evidence on teaching (Holper et al., 2013; Takeuchi et al., 2016; Zheng et al., 2018). We hypothesized that teaching with prior knowledge would lead to higher students' scores in FTF mode compared to CMC teaching mode. Such better performance should be associated with stronger INS in the PFC and rTPJ, and thus we hypothesized that there would be a positive correlation between INS enhancement and students' scores under the FTF teaching condition with prior knowledge.

2. Materials and methods

2.1. Participants

Forty-two dyads of right-handed, healthy college students (10 male dyads and 32 female dyads, mean age = 21.0 ± 2.3 years) participated in this study. None of the participants had any history of neurological or psychiatric disorders. Two participants were paired into a dyad, one acting as the teacher and the other as the student. Each pair was randomly assigned to the FTF mode or CMC mode, with 21 dyads being assigned to each condition. Before the experiment, each participant was informed about the purpose and signed informed consent. This study was approved by the University Committee on Human Research Protection at East China Normal University and was carried out in accordance with the approved guidelines. Approximately 40 RMB was paid as monetary compensation for participation after the experiment.

2.2. Experimental procedures

We designed a mixed 2 × 2 experiment with the communication mode (FTF/CMC) as the between-subject factor and the prior knowledge state (with/without) as the within-subject factor. During the course of teaching, by remotely controlling the student's computer through the Internet, the teacher could manipulate synchronized presentation of teaching content. Participants could see each other and the teacher was allowed to use facial expressions and gestures to facilitate the teaching outcome in the FTF mode (**Fig. 1A**). Likewise, the student was also permitted to use some nonverbal cues in response to the teacher, such as a slight nod or mutual gaze. However, in CMC mode, participants sat back-to-back and could not acquire non-verbal cues from each other, and therefore they could only communicate through two synchronized computers (**Fig. 1B**).

To manipulate students' knowledge state, two different learning materials were selected. In the teaching with prior knowledge condition, teachers taught students about conditional probability of the ***probability theory***. Given that Probability Theory and Mathematical Statistics were compulsory courses for the participants as students, they could create a link between prior knowledge and the new information. To calculate conditional probability correctly, teachers would teach students how to use the formula $P(A|B) = P(A \cap B)/P(B)$ and its variants ($P(A|B)$: the probability of event A under the condition B; $P(A \cap B)$: the probability that A and B occurred at the same time; $P(B)$: the probability of event B). Under the teaching without prior knowledge condition, the teaching material was ***Option Theory*** that students were naïve to it. Teachers were required to make students comprehend the concept of Call Option and utilize the formula $FV = Ae^{n \times r}$ to compute the price of the call option accurately (FV: continuous compound interest; A: initial investment; n: the number of years; r: annual interest rate).

Before the formal experiment, teachers underwent standardized training to ensure that they fully understood the two types of teaching materials. They also had to rehearse the teaching process, based on a syllabus, within 5–6 min for each type of teaching material. Their teaching performance was assessed in three respects: the length of teaching, the speed of speech, and consistency with the syllabus. Teachers were not allowed to take part in the formal experiment until their performance met the established standard requirements.

After teaching, perceived teacher–student interaction was assessed on a 5-point Likert-type scale (1 = not at all, 5 = completely) (Kuo et al., 2014).

2.3. Tasks and procedures

Each teacher–student dyad had to perform two sessions of the teaching task (**I and II**) successively, where the sequence of teaching with prior knowledge (Probability theory) or teaching without prior knowledge (Option theory) was counterbalanced across dyads (Fig. 1C). These two teaching sessions involved the same procedures, including rest (60 s), teaching session (about 300 s), test (within 600 s), and questionnaire (about 300 s) (Fig. 1C). More specifically, the teaching session consisted of four phases: definition introduction, formula interpretation, example resolution, and knowledge summary, in that order. Immediately after each teaching session, students completed a post-experiment test, containing five questions, within 10 min. Thereafter, participants were asked to assess the perceived teacher–student interaction and familiarity with teaching materials. There was a 60-s interval between the two teaching sessions. Finally, the whole teaching task ended with a 60-s rest. In total, the whole experiment lasted around 40 min.

2.4. fNIRS data acquisition

The changes in oxygenated hemoglobin (Hbo) and deoxygenated hemoglobin (Hbr) concentrations were measured, during teaching tasks, using a NIRS system (ETG-7100, Hitachi Medical Corporation, Tokyo, Japan) with a sampling rate of 10 Hz. Two 3×5 probe patches (3-cm distance between the emitter and detector) were placed over the prefrontal regions of each of the two participants. The middle yellow optode of the lowest row of the patch was placed on the frontal pole midline point (FPz in the International 10–20 system, as the reference site). The middle column of the probe was aligned along the sagittal reference plane (Fig. 1D). The other two 4×4 probe patches were placed over the rTPJ of each of the two participants, with the yellow optode placed on P6, according to the International 10–20 system (Fig. 1E). The row of the probe was aligned along the sagittal reference plane. The correspondence between the NIRS channels and the measurement points on the cerebral cortex was displayed on the basis of the results of the virtual registration method, which had been confirmed by a multi-subject study of anatomical craniocerebral correlation (Singh et al., 2005; Tsuzuki et al., 2007).

2.5. Data analysis

2.5.1. Behavioral data analysis

Two-way mixed repeated measures analyses of variance (ANOVAs) were conducted on the perceived teacher–student interaction, familiarity with teaching materials, and students' test scores.

2.5.2. fNIRS data analysis

In the present study, we focused on changes in the Hbo concentration, as in our previous studies (Cheng et al., 2015; Hu et al., 2017), because the Hbo signal is more sensitive to changes in cerebral blood flow than the Hbr signal (Lindenberger et al., 2009). Wavelet transform coherence (WTC) analysis, in the MatLab package (http://noc.ac.uk/using-science/crosswavelet-wavelet-coherence), was used to assess the INS for each channel within each dyad (Murphy et al., 2009).

Before the WTC analysis, we used a "Correlation-Based Signal Improvement" (CBSI) method to remove artifacts of head motion (Cui et al., 2010). Then, principal component analysis (PCA) was applied to remove the global components (Zhang et al., 2016). After these pre-processing steps, we calculated the time-averaged coherence at each frequency from 0.02 to 1 Hz in order to identify the frequency ranges specifically associated with the teaching task, as reported in previous studies (Cui et al., 2012; Ikeda et al., 2017; Nozawa et al., 2016; Pan et al., 2017, 2018). The INS of the baseline (30-s rest before teaching) was subtracted from that of the teaching session. Finally, a series of one-sample t-tests were conducted for all channels, with false discovery rate (FDR) correction (Benjamini and Hochberg, 1995).

Next, we calculated the average INS for the task-block and baseline (the 30-s rest period immediately before each task). The task-related INS was defined as the INS difference of each task relative to its baseline (i.e.,

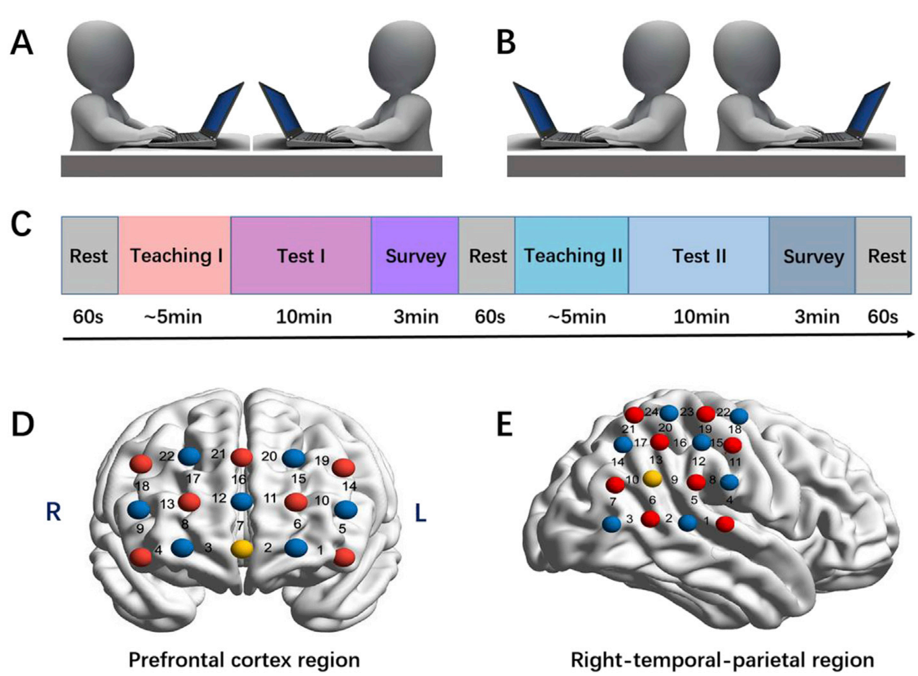

Fig. 1. Experimental design. **(A)** Face-to-face communication mode (FTF). **(B)** Computer-mediated communication mode (CMC). **(C)** Experimental procedures. **(D)** and **(E)** The optode probes were placed on the prefrontal cortex and right temporal-parietal region. FPz and P6 (yellow circles) in the International 10–20 system were used as reference sites.

task - rest). Then, the task-related INS was converted into z-scores using Fisher z-statistics before performing any statistical tests (Cui et al., 2012). Thereafter, we performed a one-sample *t*-test with FDR correction for each channel to identify the channels showing significant task-related INS ($p < 0.05$). We also generated a *t*-map of INS and smoothed it using the spline method. After obtaining the significant INS for each condition, a mixed 2×2 ANOVA on average INS was performed, followed by FDR correction, for all significant channels (CHs) at $p < 0.05$ level.

2.5.3. Relationship between behavior and INS

Pearson's correlation analysis was adopted to analyze the relationships between behavioral indicators (students' scoresand perceived teacher–student interaction) and INS, separately, under different teaching conditions.

2.5.4. Mediation effect analysis

To test the mediation effect of INS on the relationship between perceived teacher–student interaction and students' scores, mediation analysis was conducted using the simple mediation model (Baron and Kenny, 1986; Hayes and Preacher, 2014) as:

$$Y = i_1 + cX + e_Y \quad [1]$$

$$M = i_2 + aX + e_M \quad [2]$$

$$Y = i_3 + c'X + bM + e_Y \quad [3]$$

This model reflects a causal sequence in which X (a predictor) is postulated to affect M (the mediator), and this effect then propagates causally to Y (the dependent variable). There are three steps to establish mediation, involving estimating regression coefficients for X and M in three regression models, as follows. (1) Regression analysis is conducted between X and Y, represented by the equation [1] with a statistically significant coefficient c. (2) X is related to M, as shown by the significant coefficient a, estimated using equation [2]. (3) When these two criteria are met, the last and the most important step is to ensure a statistically significant association between M and Y when X is statistically controlled. This is the b coefficient in equation [3].

2.5.5. Dynamics of the time-cumulative INS analysis

To examine the earliest time-point when the INS increase correlated with teaching outcome, we performed a time-cumulative INS analysis. Only those channels that showed significant task-related INS enhancement were included in this analysis. First, we normalized each teaching task into 200 epochs. For each dyad, the time-cumulative INS at epoch n was calculated as the sum of the INS ranging from the first epoch to the nth epoch. Second, two-sample *t*-tests were used to identify the earliest time-point where the time-cumulative INS increase differed among conditions. Third, correlation analyses between the time-cumulative INS and students' test scores were conducted for each epoch. For the analyses of the second and third steps, the resulting *p* values were FDR corrected.

3. Results

Eight dyads were excluded from data analysis due to their being outliers in students' scores (larger than two standard deviations of means). Therefore, data from 34 dyads (17 dyads in FTF mode and 17 dyads in CMC mode) were further analyzed in the current study.

3.1. Behavioral results

First, a two-way mixed repeated measures ANOVA analysis revealed a significant main effect of the communication mode on the perceived teacher–student interaction (TSI), $F\,(1,32) = 48.53$, $p < 0.001$, *η2 partial* $= 0.60$ (Fig. 2A). The prior knowledge state did not have a significant effect, nor did the interaction between communication mode and students' knowledge state (*Fs* < 2.04, *ps* > 0.16). The *post hoc* analysis revealed that the perceived teacher–student interaction in the FTF mode

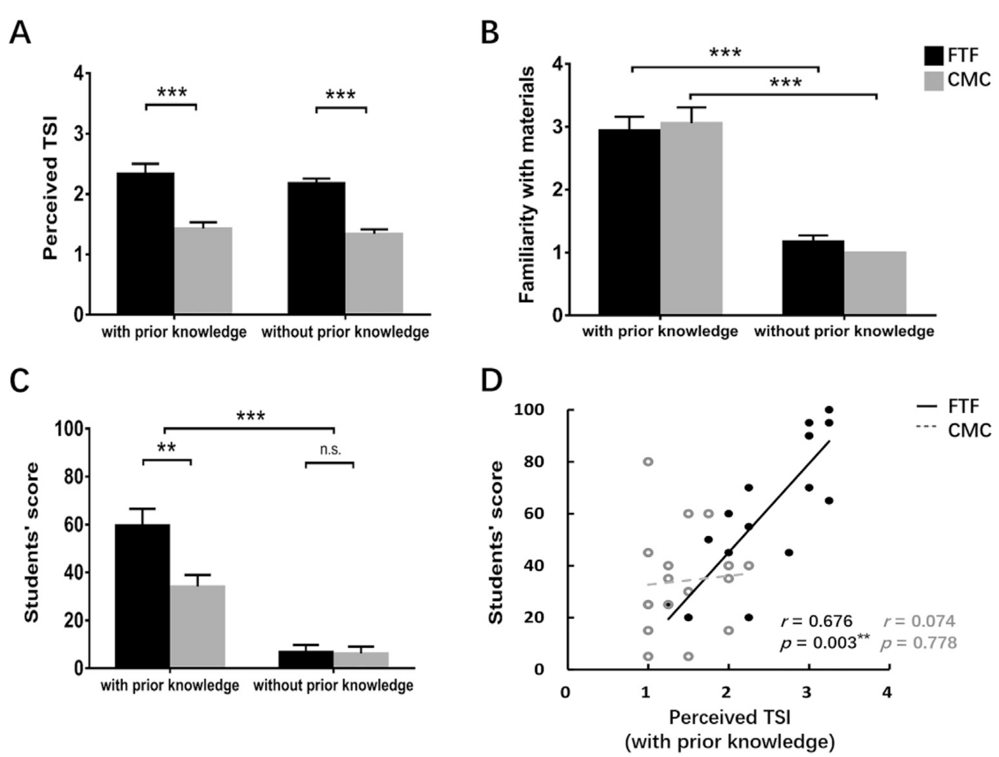

Fig. 2. Behavioral results. **(A)** Perceived teacher–student interaction (TSI). **(B)** Familiarity with materials. **(C)** Students' test scores. **(D)** Association between perceived teacher–student interaction and students' test scores in the teaching condition with prior knowledge. FTF: face-to-face communication mode; CMC: computer-mediated communication mode; TSI: teacher–student interaction. Error bars indicate standard errors. $^{**}p < 0.01$, $^{***}p < 0.001$.

(2.26±0.52) was higher than that in the CMC mode (1.41±0.42).

To assess the effect of familiarity with the teaching materials, we conducted a two-way mixedrepeated measures ANOVA analysis. A significant main effect of the knowledge state was found, $F(1,32) = 110.46$, $p < 0.001$, $\eta 2$ *partial* $= 0.78$ (Fig. 2B). No other significant effect was found (*Fs* < 0.65, *ps* > 0.43). The *post hoc* analysis confirmed that students were more familiar with the Probability theory (3±0.95) than with the Option theory(1.09±0.29). These results confirmed that the experimental manipulations were successful.

Next, similar analyses were performed on the students' test scores. We found a significant main effect of the communication mode, F (1, 32) $= 7.83$, $p < 0.01$, $\eta 2$ *partial* $= 0.20$, and the prior knowledge state, F (1, 32) $= 75.70$, $p < 0.001$, $\eta 2$ *partial* $= 0.70$, as well as a significant interaction effect between these factors, F (1, 32) $= 7.23$, $p = 0.01$, $\eta 2$ *partial* $= 0.18$. The simple effect analysis revealed that the students' test scores in the FTF mode were significantly higher than those in the CMC mode in the teaching condition with prior knowledge, t (32) $= 3.06$, $p < 0.01$, Cohen's $d = 1.05$, but not in the teaching condition without prior knowledge, t (32) $= 0.14$, $p = 0.89$, Cohen's $d = 0.05$ (Fig. 2C).

Pearson's correlation analysis showed a significantly positive correlation between perceived teacher–student interaction and the students' test scores in the FTF mode, $r = 0.68$, $p < 0.01$, but not in the CMC mode, $r = 0.07$, $p = 0.78$, in the teaching condition with prior knowledge (Fig. 2D). Silver's z procedure confirmed the significant difference between these two correlations (Silver et al., 2004), $z = 1.98$ $p = 0.047$. However, for the condition without prior knowledge, a similar analysis did not reveal a significant correlation either in the FTF mode or in the CMC mode (Fig. S2).

3.2. Interpersonal neural synchronization (INS) results

First, we found that INS was significantly higher during the teaching process than during baseline in the frequency band ranging from 0.15 to 0.31 Hz (i.e., period 3.2–6.4 s, see Fig. S1).

In the FTF teaching mode with prior knowledge, task-related INS was found in CH11, $t(16) = 3.71$, $p = 0.04$, CH12, $t(16) = 3.49$, $p = 0.05$, and CH19, $t(16) = 4.64$, $p = 0.01$, in the prefrontal area, after FDR correction (Fig. 3A). In the CMC teaching mode with prior knowledge, only CH13 in the prefrontal area, t (16) $= 5.03$, $p < 0.01$, showed significant INS enhancement after FDR correction (Fig. 3B). There was no significant INS increase for teaching without prior knowledge in the FTF or CMC modes.

To verify that INS enhancement was not obtained by chance, we permutated a time series of each participant 1000 times for each dyad. Reanalysis of the INS on the obtained randomized time series revealed no significant INS in the prefrontal area, either in the FTF or CMC teaching condition with prior knowledge (Fig. 3C).

Two-way ANOVAs were performed on the task-related INS of CH11, CH12, CH13, and CH19. There was a main effect of knowledge state, F (1,32) $= 11.35$, $p = 0.02$, $\eta 2$ *partial* $= 0.26$, and a significant interaction effect at CH19, which was located in the left PFC, F (1,32) $= 8.27$, $p = 0.03$, $\eta 2$ *partial* $= 0.21$, FDR corrected. Simple effect analysis confirmed that, during teaching with prior knowledge, INS in the FTF mode was higher than that in the CMC mode (Fig. 3D, t (32) $= 3.93$, p 0.001, Cohen's $d = 1.35$). In contrast, comparison of the two communication modes showed no such difference in the teaching condition without prior knowledge (t (32) $= -0.26$, $p = 0.79$, Cohen's $d = 0.09$). No significant main effect or interaction effect was found in other channels (*ps* > 0.05, FDR corrected).

3.3. Correlations between behavioral results and INS

The INS at CH19 was significantly correlated with perceived teacher–student interaction in the FTF mode, $r = 0.61$, $p < 0.01$, but not in the CMC mode, $r = -0.08$, $p = 0.77$, during teaching with prior knowledge (Fig. 4A). Silver's z test also revealed a significant difference between these two correlations, $z = 2.08$, $p = 0.04$. Moreover, INS at CH19 was also positively correlated with students' scores in the FTF mode, $r = 0.73$, $p = 0.001$, but not in the CMC mode, $r = -0.004$, $p = 0.99$ (Fig. 4B). Moreover, Silver's z test revealed a significant difference between these two correlations, $z = 2.47$, $p = 0.01$. However, INS at CH19 was not significantly correlated with either perceived teacher–student interaction (Fig. S3A) or students' scores in the teaching condition without prior knowledge (Fig. S3B).

3.4. Mediation effect of INS at CH19

In order to investigate the role of INS in teacher–student interaction during teaching, a mediation analysis was conducted to examine the

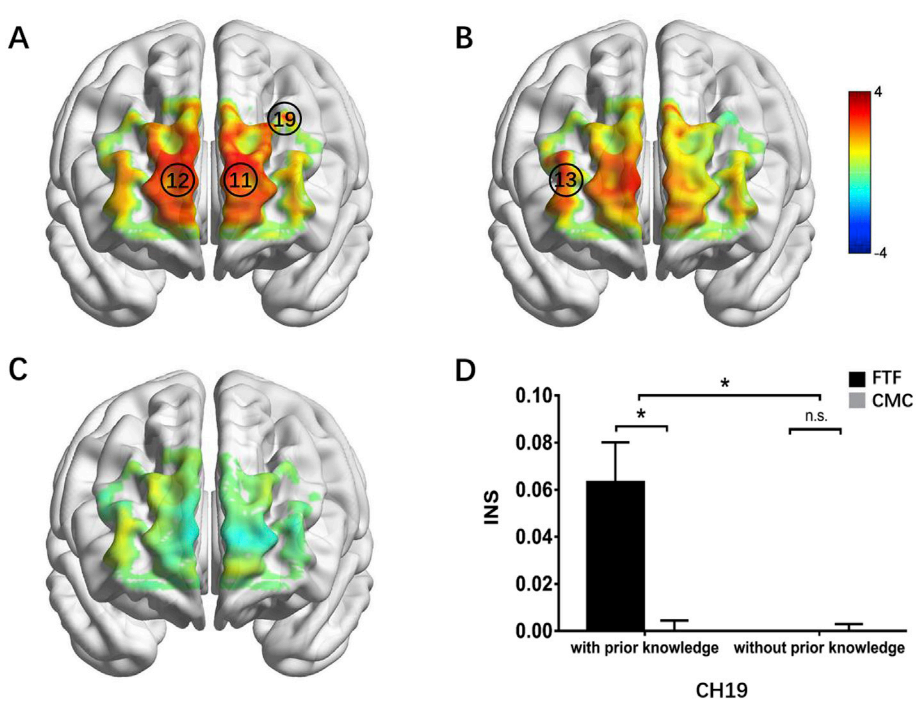

Fig. 3. Interpersonal neural synchronization during teaching task. **(A)** One-sample *t*-test map of INS in the prefrontal area under the FTF teaching condition with prior knowledge (FDR corrected). **(B)** One sample *t*-test map of INS in the prefrontal area in the CMC teaching condition with prior knowledge (FDR corrected). **(C)** One sample *t*-test map of INS for the permutated time series, based on original data, in the prefrontal area in the FTF teaching condition with prior knowledge. **(D)** Comparisons of INS in CH19 under different conditions. FTF: face-to-face communication mode; CMC: computer-mediated communication mode; INS: interpersonal neural synchronization. Error bars indicate standard errors. *$p < 0.05$.

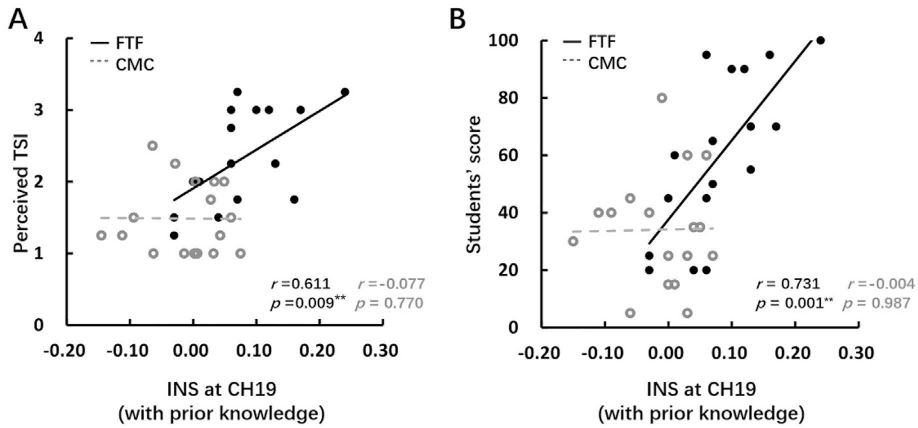

Fig. 4. Correlations between behavioral results and interpersonal neural synchronization at CH19 in the teaching condition with prior knowledge. **(A)** Pearson's correlation between INS and perceived teacher–student interaction. **(B)** Pearson's correlation between INS and students' scores. FTF: face-to-face communication mode; CMC: computer-mediated communication mode; INS: interpersonal neural synchronization; TSI: teacher–student interaction. $^{**}p < 0.01$.

mediation effect of INS at CH19 on the relationship between the perceived teacher–student interaction and the students' test scores. A step-wise regression analysis, excluding the factor of perceived teacher–student interaction, was no longer significant when INS at CH19 was introduced, $\beta = 0.37$, $p = 0.10$, as compared with the initial coefficient, $\beta = 0.68$, p 0.001 (Fig. 5). This suggested that INS at CH19 fully mediated the effect of the perceived teacher–student interaction on the students' test scores in the FTF teaching condition with prior knowledge.

3.5. Dynamic INS during teaching

To investigate how interpersonal neural synchronization at CH19 changed over the course of teaching, we first normalized the whole teaching task period under each condition into a time-series of 200 epochs and then calculated the time-cumulative INS along with the time-course of the teaching task. From the 56th epoch (about 65–90 s after the start of teaching), INS significantly increased in the FTF mode compared to that in the CMC mode in the teaching condition with prior knowledge, p 0.05, FDR corrected (Fig. 6A). However, no significant time-cumulative INS increase was found in the FTF mode or CMC mode during teaching without prior knowledge, after FDR correction (Fig. 6B). Moreover, correlation analyses revealed that, in the FTF condition with prior knowledge, the time-cumulative INS was significantly correlated with students' test scores from the 21st epoch (about 25–35 s after the start of teaching). In contrast, no such correlation was found in other three conditions, $ps > 0.05$, FDR corrected (Fig. 6C and D).

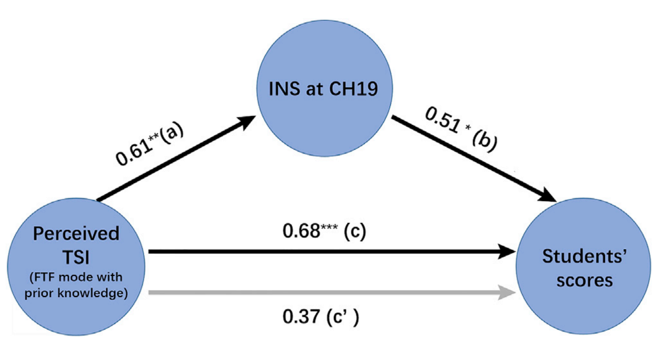

Fig. 5. The mediation effect of interpersonal neural synchronization at CH19 on the relationship between the perceived teacher–student interaction and the students' test scores. The effect of perceived teacher–student interaction on students' scores was fully mediated by INS in the FTF teaching condition with prior knowledge. FTF: face-to-face mode; CMC: computer-mediated communication mode; INS: interpersonal neural synchronization. $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

4. Discussion

By combining the real-time teaching paradigm and the fNIRS-based hyperscanning technique, we investigated how communication mode and knowledge state impacted teaching effectiveness. The behavioral results demonstrated that, during teaching with students' having prior knowledge, FTF communication improved students' academic performance, as compared to the CMC mode. Conversely, no such effect was found in the teaching condition where students lacked prior knowledge. Accordingly, higher task-related INS was found in the left PFC under the FTF teaching condition with prior knowledge. Such INS mediated the relationship between perceived interaction and the students' test scores. Furthermore, correlation analyses based on the time-cumulative INS showed that, at the early stage of teaching, the task-related INS could predict students' performance. These findings provide insight into the interplay between the communication mode and students' knowledge state on the outcome of teacher–student interaction. The aforementioned results are discussed in detail as follows.

4.1. Left prefrontal INS as a neural signature of teacher–student interaction

We observed significant INS in the left PFC under the FTF teaching condition with the prior knowledge. In addition, such task-related INS was correlated with perceived interaction and the students' test performance. These findings reinforced the association between INS and the outcomes of the teacher–student interaction reported in previous studies (Holper et al., 2013; Pan et al., 2018; Zheng et al., 2018). Therefore, taken together, our findings provide further support for INS as a neural marker of dynamic social interactions in a teaching context (Dikker et al., 2017).

In our study, INS enhancement was detected in the left PFC, which has been proven to be the crucial neural region for mentalizing (Dixon et al., 2018; Nguyen et al., 2018) and integrating information about oneself and others (Decety and Sommerville, 2003; Raposo et al., 2011; Takeuchi et al., 2016). Thus, the observed INS in the left PFC might reflect the common representation of information between the teacher and students in an integrated way. The teaching–learning process is not a simple one-way process, from the teacher to the students, but rather involves a complex, dynamic, and interpersonal interaction comprised of mutual comprehensions, evaluations, and predictions (Rodriguez, 2013). When teaching, the teachers do not transfer knowledge blindly to the students. Instead, they need not only to monitor their own teaching process, but also to estimate how well students understand the imparted knowledge. Consequently, they can make appropriate and timely adjustments and complements (Kline, 2015; Strauss et al., 2014). In the

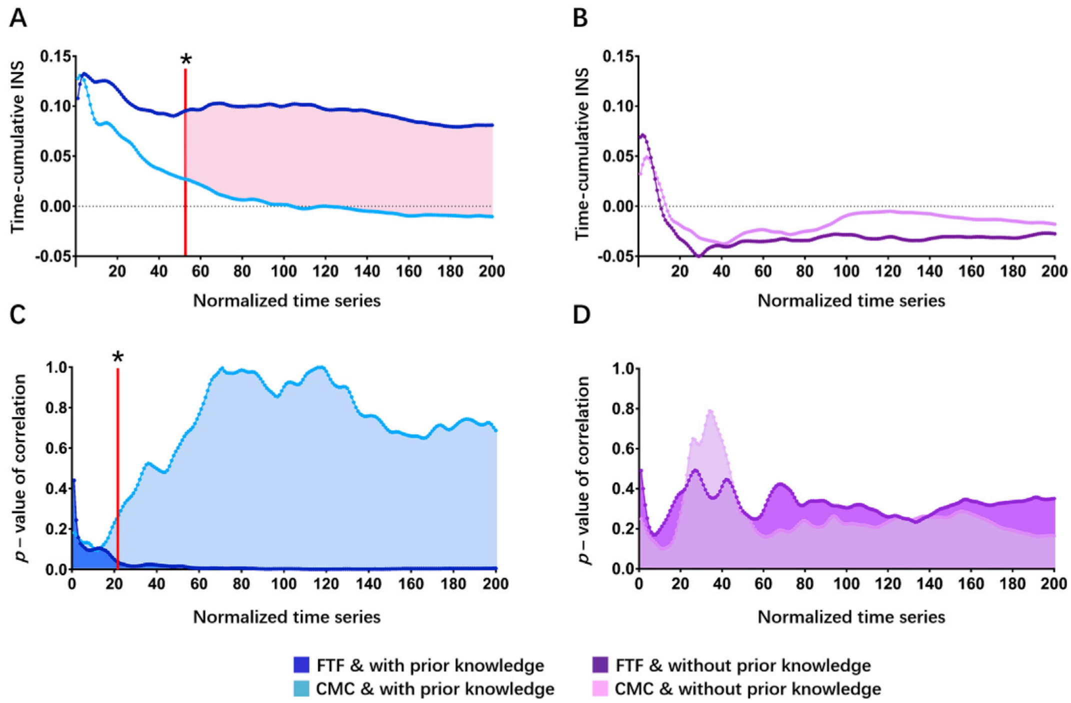

Fig. 6. The dynamics of the time-cumulative interpersonal neural synchronization as well as the relationship between time-cumulative interpersonal neural synchronization and the students' performance. **(A)** The time-cumulative INS increase of 200 normalized epochs in the FTF and CMC teaching condition with prior knowledge. The red vertical line with one asterisk indicates the earliest time-point when a significant difference in the task-related INS was found, and pink color indicates the INS significant difference between these two conditions, $^*p < 0.05$, FDR corrected. **(B)** The time-cumulative INS increase of 200 normalized epochs in the FTF and CMC teaching condition without prior knowledge. **(C)** Dynamic correlations between the time-cumulative INS and students' scores in the FTF and CMC teaching condition with prior knowledge. The red vertical line with one asterisk indicates the earliest time-point (21st epoch, 25–35 s after the start of teaching) when the correlation between INS and the students' scores reached statistical significance at $p < 0.05$, with FDR correction, in the FTF teaching condition with prior knowledge. **(D)** Dynamic correlations between the time-cumulative INS and the students' scores in the FTF and CMC teaching condition without prior knowledge.

same way, students are not simply passive listeners or recipients of knowledge. They should comprehend and internalize information transferred to them by teachers (Strauss et al., 2014). Hence, both teachers and students require representations of the others' minds and integration of information regarding oneself and the other. Correspondingly, the increased INS in the PFC may reflect the neural basis of such synchronous teacher–student experience, as well as the "flow" of teaching to a certain extent (Kent, 2013; Rodriguez, 2013).

However, no significant INS was found in the rTPJ, a region widely accepted as being a crucial component of the "social brain" that subserves social cognitions (Carter and Huettel, 2013). Previous studies have demonstrated that the rTPJ is selective to socially relevant stimulus (Bilek et al., 2017; Corbetta et al., 2008), is closely related to theory of mind (Koster-Hale and Saxe, 2013; Van Overwalle and Baetens, 2009) and is regarded as the crucial neural substrate for empathy (Mai et al., 2016; Singer and Lamm, 2009). Furthermore, INS enhancement in the rTPJ has been detected in many social interactions, including joint attention (Bilek et al., 2015) and cooperative group creation (Lu et al., 2018) and economic exchange (Tang et al., 2016). However, as also reported in a similar hyperscanning study on teaching (Pan et al., 2018), we did not detect this neural phenomenon in this region either. In the study by Pan et al., brain activity in the IFC, rather than the TPJ which was also the region of interest, synchronized across teachers and students during part learning. The researchers believed that TPJ and PFC might work in a network during social interactive learning. Indeed, as a supramodal association area, TPJ is functionally connected with many brain regions and integrates information from different inputs (Bilek et al., 2015, 2017; Bzdok et al., 2013; Van Overwalle and Baetens, 2009). Given above-mentioned findings, both the PFC and rTPJ play important roles in dynamic social interactions. Further studies will be needed to explore their respective functions and brain network functions.

4.2. Effect of the interplay between knowledge state and communication mode on INS

We found an effect of an interplay between knowledge states and communication modes on students' performance and task-related INS. Behaviorally, during teaching with prior knowledge, students' scores were higher in the FTF mode than in the CMC mode. Correspondingly, at a neural level, the FTF mode also induced stronger INS in teacher–student dyads than did the CMC mode. Nevertheless, no difference was observed between these two communication modes during teaching without prior knowledge.

The impacts of prior knowledge in education have been widely investigated and its relationship to communication effectiveness during teaching and learning has been described (Thepsoonthorn et al., 2016). On one hand, by having prior knowledge related to new content, students are in a "ready state", which can accelerate their learning and consolidate their mastery of knowledge by creating links between new and old knowledge. Additionally, nonverbal behaviors, such as mutual gaze and head nodding, can be observed, which form a good basis for mutual understanding in teacher–student dyads (Lira et al., 2008). On the other hand, FTF communication provides teachers with opportunities to evaluate students' learning states through facial expressions and other nonverbal cues. By integrating such information with their syllabus, teachers can adjust their teaching pace to facilitate a fluid learning process. Therefore, during the teaching and learning processes, teachers and students are not independent individuals, but are a closely related unit. To promote communication effectiveness, they need to integrate information about themselves and others. Such a synchronous experience may be the cause for the stronger INS in the left PFC in the FTF teaching condition with prior knowledge.

Furthermore, the present study also makes an important contribution to the processing fluency theory. So far, previous studies have examined either the effect of prior knowledge (Sherman and Frost, 2000) or communication mode (Hantula et al., 2011) on teaching outcomes, which highlights their independent effects and portrays distinct patterns in each. Although it is complementary to previous studies, our findings suggest a "cooperative" interplay rather than parallel relationship between prior knowledge states and communication modes. Both our behavioral and neural results confirmed this interaction effect, which resulted in higher students' scores and stronger INS, in the FTF teaching condition with prior knowledge. Future research will be needed to translate the findings from laboratory studies to applications in school settings.

4.3. Early INS could differentiate and predict the outcome of teaching

Since teaching is a dynamic interpersonal interaction, it is far from enough to understand the teaching process just through its consequence (Watanabe et al., 2013). To take a much closer look at the teaching process on the neural level, we did time-course analyses. The results showed that about 65–90 s after the beginning of the teaching process, the difference in time-cumulative INS between the two communication modes became significant and persisted until the end of the teaching process. This finding was partly consistent with that in Zheng et al. (2018). In their study, three different styles were included: lecturing, interactive teaching, and video-based teaching. Teaching style-related INS at the TPJ reached significance after about 76 s of teaching, representing good communication between the teachers and students at the beginning of the teaching process. However, in our study, the early boundary to discriminate different teaching conditions was the INS in the left PFC. Given that the left PFC is involved in mentalizing and integrating information from self and others, INS in the left PFC may suggest the shared representation of information, which contributes to optimal teaching and learning experiences. However, the above-mentioned variations can also be explained by the difference in teaching content, teaching time, or teaching style, which remains to be further studied.

Moreover, during teaching with prior knowledge, the time-cumulative INS in the FTF mode was positively correlated with students' performance from as early as about 25–35 s after teaching task. It should be noted that the earliest time point for predicting the students' scores based on INS in our study is sooner than that shown by Zheng et al. (2018). One possible explanation of this difference is the teaching content in the task. In the aforementioned study, numerical reasoning was selected as the teaching content due to its novelty to most participants. However, in the present study, under the FTF teaching condition with prior knowledge, students were familiar with probability theory. Consequently, at the early stage of the task, they had shared understanding of the content, which led to shared neural responses.

4.4. Limitations

Several limitations of this study need to be noted. First, the data were collected in a short teaching period (i.e., about 5 min) in a laboratory setting. Therefore, it remains unclear whether the results can be generalized to a longer teaching period (i.e., 45 min) in a real-world setting. Future studies should investigate the dynamic nature of teacher–student interaction in real classrooms. Second, fNIRS allows detection of brain signals only from the cerebral cortex; therefore, signals from deep brain areas cannot be detected. Entire brain measurement is needed to advance our understanding of teacher–student interactions. Third, due to the lack of eye-tracking and video materials, we could not quantify the magnitude of teacher–student interactions. Since prior knowledge can facilitate mutual gaze and head nodding synchrony in FTF teaching (Thepsoonthorn et al., 2016), measurement and analysis of nonverbal communication behaviors are necessary and worthwhile, as this could bring to light the interaction between communication modes and students' knowledge reserve.

5. Conclusions

In this study, we demonstrated that the interplay between the communication mode and prior knowledge contributed to teaching effectiveness. Using the fNIRS-based hyperscanning approach, we observed that brain activities in the PFC synchronized across teachers and students, particularly in the FTF teaching mode, when the students had prior knowledge. INS enhancements mediated the relationship between perceived interaction and students' test scores. Moreover, the early prefrontal INS was correlated with teaching effectiveness. Taken together, these results indicate that prefrontal INS may be a good neural signature of teacher–student interaction. Our results provide interpersonal neural evidence for the processing fluency theory of teaching, and increase our understanding of the nature of dynamic teacher–student interactions.

Contribution

B. G., and X. L. designed the experiment. J. L., R. Z., and B. G. performed the study. J. L., D. Y analyzed the data. J. L., S.O., and X. L. wrote the manuscript.

Competing financial interests

The authors declare no competing financial interests.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.neuroimage.2019.03.004.

References

Adolphs, R., 2014. Social attention and the ventromedial prefrontal cortex. Brain 137, 1572–1574. https://doi.org/10.1093/brain/awu108.

Balakrishnan, V., Gan, C.L., 2016. Students' learning styles and their effects on the use of social media technology for learning. Telematics Inf. 33, 808–821. https://doi.org/10.1016/j.tele.2015.12.004.

Baron, R.M., Kenny, D.A., 1986. The moderator–mediator variable distinction in social psychological research: conceptual, strategic, and statistical considerations. J. Personal. Soc. Psychol. 51, 1173. https://doi.org/10.1037/0022-3514.51.6.1173.

Benjamini, Y., Hochberg, Y., 1995. Controlling the false discovery rate: a practical and powerful approach to multiple testing. J. R. Stat. Soc. Ser. B-Stat. 289–300. https://doi.org/10.2307/2346101.

Bilek, E., Ruf, M., Schäfer, A., Akdeniz, C., Calhoun, V.D., Schmahl, C., Demanuele, C., Tost, H., Meyer-Lindenberg, A., 2015. Information flow between interacting human brains: identification, validation, and relationship to social expertise. P. Natl. Acad. Sci. 112, 5207–5212. https://doi.org/10.1073/pnas.1421831112.

Bilek, E., Stößel, G., Schäfer, A., Clement, L., Ruf, M., Robnik, L., Neukel, C., Tost, H., Kirsch, P., Meyer-Lindenberg, A., 2017. State-dependent cross-brain information flow in borderline personality disorder. JAMA psychiatry 74, 949–957. https://doi.org/10.1001/jamapsychiatry.2017.1682.

Bzdok, D., Langner, R., Schilbach, L., Jakobs, O., Roski, C., Caspers, S., Laird, A.R., Fox, P.T., Zilles, K., Eickhoff, S.B., 2013. Characterization of the temporo-parietal junction by combining data-driven parcellation, complementary connectivity analyses, and functional decoding. Neuroimage 81, 381–392. https://doi.org/10.1016/j.neuroimage.2013.05.046.

Carter, R.M., Huettel, S.A., 2013. A nexus model of the temporal-parietal junction. Trends Cognit. Sci. 17, 328–336. https://doi.org/10.1016/j.tics.2013.05.007.

Cheng, X., Li, X., Hu, Y., 2015. Synchronous brain activity during cooperative exchange depends on gender of partner: a fNIRS-based hyperscanning study. Hum. Brain Mapp. 36, 2039–2048. https://doi.org/10.1002/hbm.22754.

Cole, D., 2011. Debunking anti-intellectualism: an examination of African American college students' intellectual self-concepts. Rev. High. Educ. 34, 259–282. https://doi.org/10.1353/rhe.2010.0025.

Corbetta, M., Patel, G., Shulman, G.L., 2008. The reorienting system of the human brain: from environment to theory of mind. Neuron 58, 306–324. https://doi.org/10.1016/j.neuron.2008.04.017.

Cui, X., Bray, S., Reiss, A.L., 2010. Functional near infrared spectroscopy (NIRS) signal improvement based on negative correlation between oxygenated and deoxygenated hemoglobin dynamics. Neuroimage 49, 3039–3046. https://doi.org/10.1016/j.neuroimage.2009.11.050.

Cui, X., Bryant, D.M., Reiss, A.L., 2012. NIRS-based hyperscanning reveals increased interpersonal coherence in superior frontal cortex during cooperation. Neuroimage 59, 2430–2437. https://doi.org/10.1016/j.neuroimage.2011.09.003.

Decety, J., Sommerville, J.A., 2003. Shared representations between self and other: a social cognitive neuroscience view. Trends Cognit. Sci. 7, 527–533. https://doi.org/10.1016/j.tics.2003.10.004.

Dikker, S., Wan, L., Davidesco, I., Kaggen, L., Oostrik, M., McClintock, J., Rowland, J., Michalareas, G., Van Bavel, J.J., Ding, M., Poeppel, D., 2017. Brain-to-Brain synchrony tracks real-world dynamic group interactions in the classroom. Curr. Biol. 27, 1375–1380. https://doi.org/10.1016/j.cub.2017.04.00.

Dixon, M.L., De La Vega, A., Mills, C., Andrews-Hanna, J., Spreng, R.N., Cole, M.W., Christoff, K., 2018. Heterogeneity within the frontoparietal control network and its relationship to the default and dorsal attention networks. P. Natl. Acad. Sci. 115, E1598–E1607. https://doi.org/10.1073/pnas.1715766115.

Entwistle, N.J., 2013. Styles of Learning and Teaching: an Integrated Outline of Educational Psychology for Students, Teachers and Lecturers. David Fulton Publishers, London.

Frymier, A.B., Houser, M.L., 2000. The teacher-student relationship as an interpersonal relationship. CEd 49, 207–219. https://doi.org/10.1080/03634520009379209.

Furnham, A., Chamorro-Premuzic, T., 2005. Individual differences in students' preferences for lecturers' personalities. J. Individ. Differ. 26, 176–184. https://doi.org/10.1027/1614-0001.26.4.176.

Hantula, D.A., Kock, N., D'Arcy, J.P., DeRosa, D.M., 2011. Media compensation theory: a Darwinian perspective on adaptation to electronic communication and collaboration. In: Evolutionary Psychology in the Business Sciences. Springer Berlin Heidelberg, Berlin, pp. 339–363. https://doi.org/310.1007/1978-1003-1540-92784-92786_92713.

Hari, R., Kujala, M.V., 2009. Brain basis of human social interaction: from concepts to brain imaging. Physiol. Rev. 89, 453–479. https://doi.org/10.1152/physrev.00041.2007.

Hayes, A.F., Preacher, K.J., 2014. Statistical mediation analysis with a multicategorical independent variable. Br. J. Math. Stat. Psychol. 67, 451–470. https://doi.org/10.1111/bmsp.12028.

Holper, L., Goldin, A.P., Shalóm, D.E., Battro, A.M., Wolf, M., Sigman, M., 2013. The teaching and the learning brain: a cortical hemodynamic marker of teacher–student interactions in the Socratic dialog. Int. J. Educ. Res. 59, 1–10. https://doi.org/10.1016/j.ijer.2013.02.002.

Holper, L., Scholkmann, F., Wolf, M., 2012. Between-brain connectivity during imitation measured by fNIRS. Neuroimage 63, 212–222. https://doi.org/10.1016/j.neuroimage.2012.06.028.

Hu, Y., Hu, Y., Li, X., Pan, Y., Cheng, X., 2017. Brain-to-brain synchronization across two persons predicts mutual prosociality. Soc. Cognit. Affect Neurosci. 12, 1835–1844. https://doi.org/10.1093/scan/nsx118.

Ikeda, S., Nozawa, T., Yokoyama, R., Miyazaki, A., Sasaki, Y., Sakaki, K., Kawashima, R., 2017. Steady beat sound facilitates both coordinated group walking and inter-subject neural synchrony. Front. Hum. Neurosci. 11, 147. https://doi.org/10.3389/fnhum.2017.00147.

Jiang, J., Chen, C., Dai, B., Shi, G., Ding, G., Liu, L., Lu, C., 2015. Leader emergence through interpersonal neural synchronization. P. Natl. Acad. Sci. 112, 4274–4279. https://doi.org/10.1073/pnas.1422930112.

Jiang, J., Dai, B., Peng, D., Zhu, C., Liu, L., Lu, C., 2012. Neural synchronization during face-to-face communication. J. Neurosci. 32, 16064–16069. https://doi.org/10.1523/JNEUROSCI.2926-12.2012.

Kaller, C.P., Rahm, B., Spreer, J., Weiller, C., Unterrainer, J.M., 2011. Dissociable contributions of left and right dorsolateral prefrontal cortex in planning. Cerebr. Cortex 21, 307–317. https://doi.org/10.1093/cercor/bhq096.

Kennedy, G., Coffrin, C., De Barba, P., Corrin, L., 2015. Predicting success: how learners' prior knowledge, skills and activities predict MOOC performance. International Conference on Learning Analytics and Knowledge 136–140. https://doi.org/10.1145/2723576.2723593.

Kent, A., 2013. Synchronization as a classroom dynamic: a practitioner's perspective. Mind Brain Educ 7, 13–18. https://doi.org/10.1111/mbe.12002.

Kim, Y.K., 2010. Racially different patterns of student-faculty interaction in college: a focus on levels, effects, and causal directions. Journal of the Professoriate 3, 161–189.

Klassen, R.M., Tze, V.M., 2014. Teachers' self-efficacy, personality, and teaching effectiveness: a meta-analysis. Educ. Res. Rev. 12, 59–76. https://doi.org/10.1016/j.edurev.2014.06.001.

Kline, M.A., 2015. How to learn about teaching: an evolutionary framework for the study of teaching behavior in humans and other animals. Behav. Brain Sci. 38 e31. https://doi.org/10.1017/S0140525X14000090.

Koriat, A., 2008. Easy comes, easy goes? The link between learning and remembering and its exploitation in metacognition. M Comput. 36, 416–428. https://doi.org/10.3758/MC.36.2.416.

Koster-Hale, J., Saxe, R., 2013. Theory of mind: a neural prediction problem. Neuron 79, 836–848. https://doi.org/10.1016/j.neuron.2013.08.020.

Kuo, Y.-C., Walker, A.E., Schroder, K.E., Belland, B.R., 2014. Interaction, Internet self-efficacy, and self-regulated learning as predictors of student satisfaction in online education courses. Internet High Educ. 20, 35–50. https://doi.org/10.1016/j.iheduc.2013.10.001.

Leahy, W., Sweller, J., 2005. Interactions among the imagination, expertise reversal, and element interactivity effects. J. Exp. Psychol. Appl. 11, 266. https://doi.org/10.1037/1076-898X.11.4.266.

Lindenberger, U., Li, S.C., Gruber, W., Muller, V., 2009. Brains swinging in concert: cortical phase synchronization while playing guitar. BMC Neurosci. 10, 22. https://doi.org/10.1186/1471-2202-10-22.

Lira, E.M., Ripoll, P., Peiró, J.M., Orengo, V., 2008. How do different types of intragroup conflict affect group potency in virtual compared with face-to-face teams? A longitudinal study. Behav. Inf. Technol. 27, 107–114. https://doi.org/10.1080/01449290600875151.

Lu, K., Xue, H., Nozawa, T., Hao, N., 2018. Cooperation makes a group be more creative. Cerebr. Cortex. https://doi.org/10.1093/cercor/bhy215.

Mai, X., Zhang, W., Hu, X., Zhen, Z., Xu, Z., Zhang, J., Liu, C., 2016. Using tDCS to explore the role of the right temporo-parietal junction in theory of mind and cognitive empathy. Front. Psychol. 7, 380. https://doi.org/10.3389/fpsyg.2016.00380.

Mazer, J.P., Murphy, R.E., Simonds, C.J., 2007. I'll see you on "Facebook": the effects of computer-mediated teacher self-disclosure on student motivation, affective learning, and classroom climate. CEd 56, 1–17. https://doi.org/10.1080/03634520601009710.

McKnight, K., O'Malley, K., Ruzic, R., Horsley, M.K., Franey, J.J., Bassett, K., 2016. Teaching in a digital age: how educators use technology to improve student learning. JRTEd 48, 194–211. https://doi.org/10.1080/15391523.2016.1175856.

Miller, A.N., Katt, J.A., Brown, T., Sivo, S.A., 2014. The relationship of instructor self-disclosure, nonverbal immediacy, and credibility to student incivility in the college classroom. CEd 63, 1–16. https://doi.org/10.1080/03634523.2013.835054.

Murphy, K., Birn, R.M., Handwerker, D.A., Jones, T.B., Bandettini, P.A., 2009. The impact of global signal regression on resting state correlations: are anti-correlated networks introduced? Neuroimage 44, 893–905. https://doi.org/10.1016/j.neuroimage.2008.09.036.

Nguyen, T., Fan, T., George, S.R., Perreault, M.L., 2018. Disparate effects of lithium and a GSK-3 inhibitor on neuronal oscillatory activity in prefrontal cortex and Hippocampus. Front. Aging Neurosci. 9, 434. https://doi.org/10.3389/fnagi.2017.00434.

Noel-Levitz, 2011. National Online Learners Priorities Report. Retrieved from. http://www.noellevitz.com/upload/Papers_and_Research/2011/PSOL_report2011.pdf.

Nozawa, T., Sasaki, Y., Sakaki, K., Yokoyama, R., Kawashima, R., 2016. Interpersonal frontopolar neural synchronization in group communication: an exploration toward fNIRS hyperscanning of natural interactions. Neuroimage 133, 484–497. https://doi.org/10.1016/j.neuroimage.2016.03.059.

Pan, Y., Cheng, X., Zhang, Z., Li, X., Hu, Y., 2017. Cooperation in lovers: an fNIRS-based hyperscanning study. Hum. Brain Mapp. 38, 831–841. https://doi.org/10.1002/hbm.23421.

Pan, Y., Novembre, G., Song, B., Li, X., Hu, Y., 2018. Interpersonal synchronization of inferior frontal cortices tracks social interactive learning of a song. Neuroimage 183, 280–290. https://doi.org/10.1016/j.neuroimage.2018.08.005.

Raposo, A., Vicens, L., Clithero, J.A., Dobbins, I.G., Huettel, S.A., 2011. Contributions of frontopolar cortex to judgments about self, others and relations. Soc. Cognit. Affect Neurosci. 6, 260–269. https://doi.org/10.1093/scan/nsq033.

Reber, R., Greifeneder, R., 2016. Processing fluency in education: how metacognitive feelings shape learning, belief formation, and affect. Educ. Psychol. 52, 84–103. https://doi.org/10.1080/00461520.2016.1258173.

Rimm-Kaufman, S.E., Baroody, A.E., Larsen, R.A.A., Curby, T.W., Abry, T., 2015. To what extent do teacher–student interaction quality and student gender contribute to fifth graders' engagement in mathematics learning? J. Educ. Psychol. 107, 170–185. https://doi.org/10.1037/a0037252.

Rittle-Johnson, B., Star, J.R., Durkin, K., 2009. The importance of prior knowledge when comparing examples: influences on conceptual and procedural knowledge of equation solving. J. Educ. Psychol. 101, 836. https://doi.org/10.1037/a0016026.

Rodriguez, V., 2013. The human nervous system: a framework for teaching and the teaching brain. Mind Brain Educ 7, 2–12. https://doi.org/10.1111/mbe.12000.

Shalom, J.G., Israeli, H., Markovitzky, O., Lipsitz, J.D., 2015. Social anxiety and physiological arousal during computer mediated vs. face to face communication. Comput. Hum. Behav. 44, 202–208. https://doi.org/10.1016/j.chb.2014.11.056.

Sherman, J.W., Frost, L.A., 2000. On the encoding of stereotype-relevant information under cognitive load. Pers. Soc. Psychol. Bull. 26, 26–34. https://doi.org/10.1177/0146167200261003.

Silver, N.C., Hittner, J.B., May, K., 2004. Testing dependent correlations with nonoverlapping variables: a Monte Carlo simulation. J. Exp. Educ. 73, 53–69. https://doi.org/10.3200/JEXE.71.1.53-70.

Singer, T., Lamm, C., 2009. The social neuroscience of empathy. Ann. N. Y. Acad. Sci. 1156, 81–96. https://doi.org/10.1111/j.1749-6632.2009.04418.x.

Singh, A.K., Okamoto, M., Dan, H., Jurcak, V., Dan, I., 2005. Spatial registration of multichannel multi-subject fNIRS data to MNI space without MRI. Neuroimage 27, 842–851. https://doi.org/10.1016/j.neuroimage.2005.05.019.

Stolk, A., Noordzij, M.L., Verhagen, L., Volman, I., Schoffelen, J.M., Oostenveld, R., Hagoort, P., Toni, I., 2014. Cerebral coherence between communicators marks the emergence of meaning. P. Natl. Acad. Sci. 111, 18183–18188. https://doi.org/10.1073/pnas.1414886111.

Strauss, S., Calero, C.I., Sigman, M., 2014. Teaching, naturally. Trends Neurosci Educ 3, 38–43. https://doi.org/10.1016/j.tine.2014.05.001.

Takeuchi, N., Mori, T., Suzukamo, Y., Izumi, S.I., 2016. Integration of teaching processes and learning assessment in the prefrontal cortex during a video game teaching-learning task. Front. Psychol. 7, 2052. https://doi.org/10.3389/fpsyg.2016.02052.

Tang, H., Mai, X., Wang, S., Zhu, C., Krueger, F., Liu, C., 2016. Interpersonal brain synchronization in the right temporo-parietal junction during face-to-face economic exchange. Soc. Cognit. Affect Neurosci. 11, 23–32. https://doi.org/10.1093/scan/nsv092.

Thepsoonthorn, C., Yokozuka, T., Miura, S., Ogawa, K., Miyake, Y., 2016. Prior knowledge facilitates mutual gaze convergence and head nodding synchrony in face-to-face communication. Sci. Rep. 6, 38261. https://doi.org/10.1038/srep38261.

Tichavsky, L.P., Hunt, A.N., Driscoll, A., Jicha, K., 2015. "It's just nice having a real teacher": student perceptions of online versus face-to-face instruction. Int. J. Scholarsh. Teach. Learn. 9, 2. https://doi.org/10.20429/ijsotl.2015.090202.

Tsuzuki, D., Jurcak, V., Singh, A.K., Okamoto, M., Watanabe, E., Dan, I., 2007. Virtual spatial registration of stand-alone fNIRS data to MNI space. Neuroimage 34, 1506–1518. https://doi.org/10.1016/j.neuroimage.2006.10.043.

Van Overwalle, F., Baetens, K., 2009. Understanding others' actions and goals by mirror and mentalizing systems: a meta-analysis. Neuroimage 48, 564–584. https://doi.org/10.1016/j.neuroimage.2009.06.009.

Watanabe, S., Hara, K., Ohta, K., Iino, H., Miyajima, M., Matsuda, A., Hara, M., Maehara, T., Matsuura, M., Matsushima, E., 2013. Aroma helps to preserve information processing resources of the brain in healthy subjects but not in temporal lobe epilepsy. Seizure 22, 59–63.

Wells, J.G., 2000. Effects of an on-line computer-mediated communication course, prior computer experience and Internet knowledge, and learning styles on students' Internet attitudes. J. Ind. Teach. Educ. 37, 22–53.

Yang, T.-C., Chen, M.C., Chen, S.Y., 2018. The influences of self-regulated learning support and prior knowledge on improving learning performance. Comput. Educ. 126, 37–52. https://doi.org/10.1016/j.compedu.2018.06.025.

Zhang, X., Noah, J.A., Hirsch, J., 2016. Separation of the global and local components in functional near-infrared spectroscopy signals using principal component spatial filtering. Neurophotonics 3, 015004. https://doi.org/10.1117/1.NPh.3.1.015004.

Zheng, L., Chen, C., Liu, W., Long, Y., Zhao, H., Bai, X., et al., 2018. Enhancement of teaching outcome through neural prediction of the students' knowledge state. Hum. Brain Mapp. 39, 3046–3057. https://doi.org/10.1002/hbm.24059.

Zhu, R., Feng, C., Zhang, S., Mai, X., Liu, C., 2018. Differentiating guilt and shame in an interpersonal context with univariate activation and multivariate pattern analyses. Neuroimage 186, 476–486. https://doi.org/10.1016/j.neuroimage.2018.11.012.