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The Temporal Dynamics of Brain-to-Brain Synchrony Between Students and Teachers Predict Learning Outcomes

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Abstract
Much of human learning happens through interaction with other people, but little is known about how this process is reflected in the brains of students and teachers. Here, we concurrently recorded electroencephalography (EEG) data from nine groups, each of which contained four students and a teacher. All participants were young adults from the northeast United States. Alpha-band (8–12 Hz) brain-to-brain synchrony between students predicted both immediate and delayed posttest performance. Further, brain-to-brain synchrony was higher in specific lecture segments associated with questions that students answered correctly. Brain-to-brain synchrony between students and teachers predicted learning outcomes at an approximately 300-ms lag in the students' brain activity relative to the teacher's brain activity, which is consistent with the time course of spoken-language comprehension. These findings provide key new evidence for the importance of collecting brain data simultaneously from groups of learners in ecologically valid settings.

Keywords
learning, social cognition

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Social interactions play a central role in human learning. Throughout development, children acquire knowledge, skills, and attitudes by modeling other individuals (e.g., Bandura, 1986). Through interactions with peers and adults alike, children are exposed to different ideas and perspectives and develop a more sophisticated understanding of the world around them (e.g., Vygotsky, 1934/1986). Classrooms are no exception: The social dynamics among students and between students and teachers have a profound impact on students' engagement, learning, and well-being (Hamre & Pianta, 2006). Recent research suggests that the mere presence of other students in the classroom can impact students' attentiveness and learning (Forrin et al., 2021). Relatedly, synchronous learning (where students and teachers interact in real time) leads to a greater sense of belonging and better learning outcomes compared with asynchronous learning (e.g., students viewing prerecorded lectures on their own; Martin et al., 2021; Peterson et al., 2018).

Despite the central role of social dynamics in learning, little is known about the brain mechanisms that support this process (Hari et al., 2015; Pan et al., 2022; Redcay & Schilbach, 2019; Schilbach et al., 2013). This is because research on learning typically focuses on individuals measured in a controlled environment (e.g., inside a brain scanner). In the past few years, there has been growing interest in how brain activity aligns across individuals, a phenomenon we will refer to here as *brain-to-brain synchrony* (BBS; Babiloni & Astolfi,

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2014; Hamilton, 2021; Hasson et al., 2012; Shamay-Tsoory et al., 2019). There is evidence that BBS can capture cognitive, affective, and social aspects of behavior, including memory retention (Cohen & Parra, 2016; Hasson et al., 2008) and learning outcomes (Cohen et al., 2018; J. Liu et al., 2019; Meshulam et al., 2021; Pan et al., 2020; Piazza et al., 2021; Zheng et al., 2018; Zhu et al., 2021). Yet most previous research has been constrained to noninteracting individuals and/or to methods that lack temporal specificity (functional MRI [fMRI] and functional near-infrared spectroscopy [fNIRS]).

Surprisingly, a recent electroencephalography (EEG) study conducted in a real-world classroom found that BBS between students reflected student engagement but not their test performance (Bevilacqua et al., 2019). This is unexpected because BBS is hypothesized to be driven, at least partially, by shared attention (Dikker et al., 2017; Tomasello, 1995), and shared attention has been shown to affect subsequent memory and learning (Shteynberg, 2015).

Here, we used EEG to simultaneously record brain activity from groups of four students and a teacher in a simulated classroom to investigate whether BBS, both between students and between the students and the teacher, is associated with learning outcomes (Fig. 1a). We further explored how fluctuations in BBS throughout lectures predicted learning at the individual-test-question level and examined how the temporal lag between students' and teachers' brain activity moderated the relationship between BBS and learning.

Statement of Relevance

Much of human learning happens when we interact with other people, but little is known about how this process is reflected in the brain activity of students and teachers. The reason why is that learning is typically investigated in individual participants in controlled laboratory settings (e.g., inside a brain scanner). In this study, we used electroencephalography (EEG) to track the brain activity of small groups of students and their teacher during a lecture. We found that the level of brain-to-brain synchrony between students and teachers predicted student learning: Students with more similar brain responses to other students and to the teacher showed better learning outcomes. Further, brain-to-brain synchrony during specific segments of the lecture predicted how students answered individual test questions. These findings highlight the value of brain data collected simultaneously from groups of learners in real-world-like settings.

Open Practices Statement

The data and code for this study have not been made publicly available, but requests for them can be sent to the corresponding author. Sample test questions can be found in the Supplemental Material available online. Requests for the full test as well as lecture transcripts can be sent to the corresponding author. The study was not preregistered.

Method

Participants

Forty-three participants (28 females) were recruited through the psychology department's research participation system and through ads posted around campus. During recruitment, participants were asked to confirm that they were (a) a native English speaker, (b) right-handed, (c) between the ages of 18 and 30, (d) a non-science major (for college students), and (e) that they had no known history of neurological conditions. Participants were tested in groups of four students each (with the exception of one group of three students that was later excluded from analysis; see below). The groups were formed on the basis of the order in which participants signed up for the study and their availability. In two groups, because of technical issues, only two participants had usable EEG data; because student-to-student BBS could not be determined for all dyads, all participants in these two sessions were excluded from analysis (n = 7). Five additional participants were omitted from analysis: three because of technical issues during EEG data collection and two because they were not native English speakers (and therefore did not meet the inclusion criteria; see Table S1 in the Supplemental Material). Thus, the final sample consisted of 31 participants (21 female) across nine groups. All participants completed high school, and the majority (76.2%) were current college undergraduates (age: M = 20.6 years, SD = 3.0).

The two teachers (one female) were professional high school science teachers. Of the nine groups included in analysis, the female teacher taught four groups, and the male teacher taught five. The students and teachers had no prior acquaintance with each other. The research was reviewed and approved by an institutional review board, and all participants provided written informed consent. All study procedures were conducted in accordance with the American Psychological Association guidelines for human subjects research.

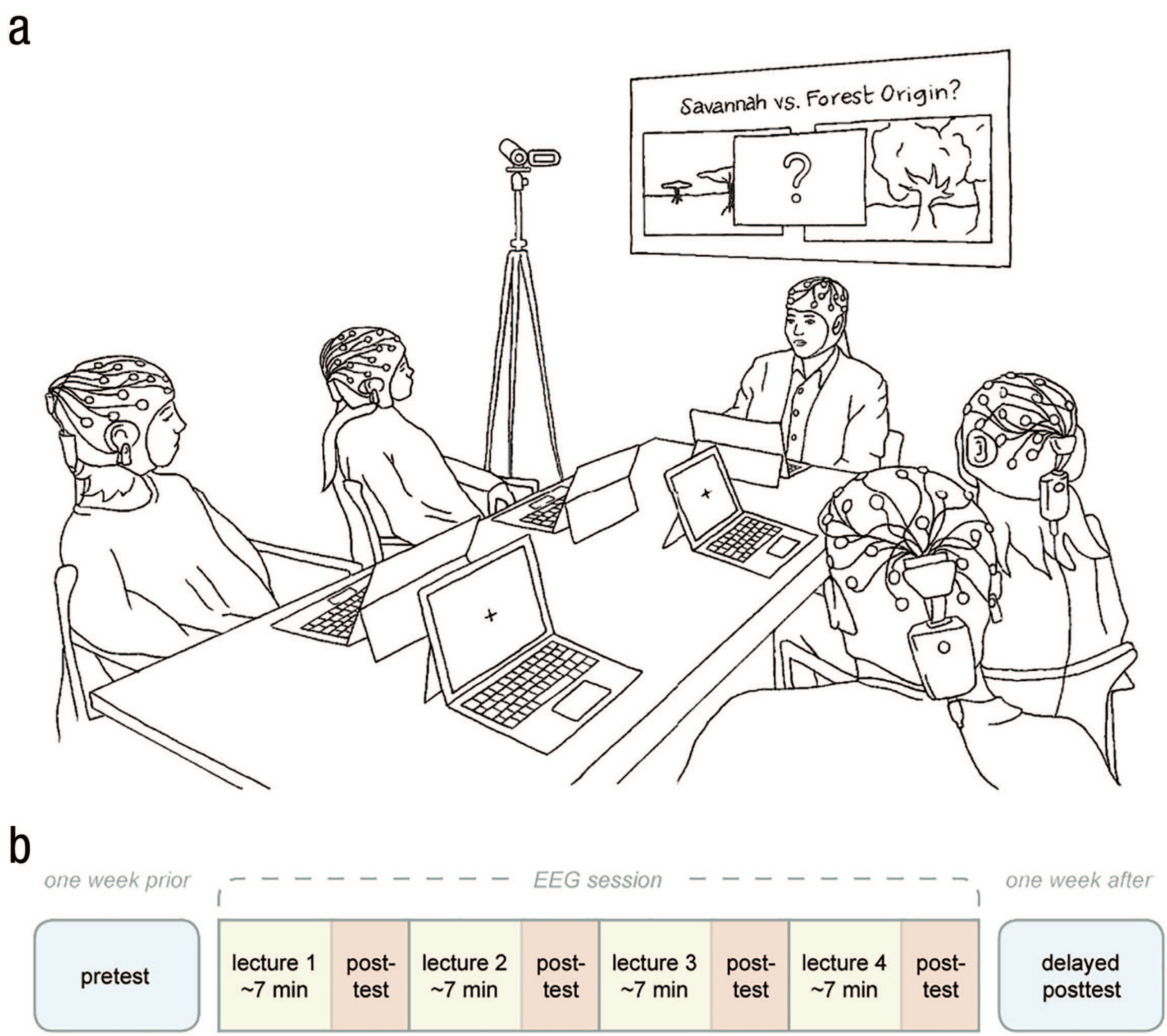

Fig. 1. Experimental setup and timeline. (a) Four students and a teacher were concurrently measured with electroencephalography (EEG) during a science lesson. (b) The lesson comprised four minilectures. A pretest was administered 1 week prior to the EEG session, and posttests were administered immediately after each lecture and 1 week after the EEG session.

Procedure

Students were seated evenly and randomly around a table, and the teacher was seated at the head of the table (Fig. 1). The experiment took place in a laboratory classroom equipped with a projector and three video cameras. Following EEG set up, baseline EEG recordings (eyes open and eyes closed) were taken to test data quality. The lesson comprised four approximately 7-min teacher-led lectures (M = 6:43 min, SD = 0:45) on discrete topics in biology and chemistry: bipedalism, insulin, habitats and niches, and lipids. Slides were projected onto a screen behind the teacher and controlled by the teacher via a tablet computer (see Fig. 1). Students were instructed to sit still, minimize head motion, and refrain from asking questions during the lectures in order to minimize speaking- and movement-related artifacts. Each lecture was preceded by brief activities, in which students could interact more freely with one another and with the teacher (not included in the current analysis). Each lecture was immediately followed by a brief topic-specific assessment to gauge lecture engagement and content knowledge (see below). Assessments were administered via a tablet computer that was placed next to each student. The lesson concluded with one final 3-min eyes-open baseline recording.

EEG hardware and data collection

Participants' EEG was recorded using a 32-channel Enobio 32 5G gel sensor system (Neuroelectrics, Barcelona, Spain; sampling rate = 500 Hz). An ear clip with two electrodes (common mode sense [CMS] and driven right leg [DRL]) served as a dual reference. Electrode placement followed the standard 10-10 EEG system. The Neuroelectrics Instrument Controller (NIC2) software application was used to record data and assess signal quality. Data were aligned between students and the teacher after recording at the millisecond level using wireless triggers that were sent every second by a tablet computer via *LabStreamingLayer* (Kothe, 2014).

Quantifying learning outcomes

For each lecture, student learning was assessed using 10 multiple-choice recognition and comprehension questions, which were developed by the two participating teachers (see Table S2 in the Supplemental Material). In order to measure learning at the individual question level, we used the same questions in the pretest, immediate posttest, and delayed posttest. To minimize priming effects, we administered the pretest a week before rather than immediately before the EEG session (Fig. 1b). Additionally, the participants were instructed not to discuss the material with each other or read about the topics covered in the lectures between the pretest and posttests. Two measures of learning were computed: (a) pretest-to-immediate-posttest change and (b) pretest-to-delayed-posttest change.

EEG preprocessing

All preprocessing was carried out using *MATLAB* (Version R2018b; The MathWorks, Natick, MA) in conjunction with *EEGLAB* (Version 14.1.1b; Delorme & Makeig, 2004). After a combination of a high-pass (> 0.5 Hz) and a low-pass (< 35 Hz) finite impulse response filter, noisy channels were identified and removed using a combination of automatic channel rejection (kurtosis, z score = 3) and inspection of channel power spectra. Continuous EEG data were then separated into 1-s epochs and visually inspected for nonneural artifacts. Independent components analysis was then conducted to identify and remove components that were associated with eyeblinks and eye movements (Jung et al., 1997). Finally, abnormal residual epochs with signals outside of the −100-μV to 100-μV range were automatically tagged and visually inspected. Because of the nature of this experiment, teacher data were inherently noisier than those of students. As a result, a more stringent data removal approach was required to obtain high-quality teacher data (see Table S3 in the Supplemental Material).

EEG analysis

The data were analyzed using custom-built MATLAB code and the *FieldTrip* toolbox (Oostenveld et al., 2011). Using Butterworth filters of order four, we filtered EEG data within three frequency bands: theta (3–7 Hz), alpha (8–12 Hz), and beta (13–20 Hz). The instantaneous phase of the filtered EEG signals was extracted using the Hilbert transform. Then, for each 1-s epoch and for each one-on-one paired combinations of electrodes (e.g., O1–O1, P3–P3), circular correlation (Jammalamadaka & Sengupta, 2001) was calculated as follows:

$$\text{circular correlation}_{x,y} = \frac{\sum_{k=1}^{N} \sin\left(x-\bar{x}\right)\sin(y-\bar{y})}{\sqrt{\sum_{k=1}^{N} \sin^2\left(x-\bar{x}\right)\sin^2(y-\bar{y})}},$$

where x corresponds to an EEG channel in Participant 1 and y corresponds to the same EEG channel in Participant 2. $\bar{x}$ and $\bar{y}$ are the mean directions of the EEG channels. N is the number of samples in each epoch ($N = 500$). In the calculation of circular correlation, only overlapping EEG channels and epochs were considered. In other words, if a specific channel or epoch was excluded for Participant 1, it was also excluded for Participant 2 (Bevilacqua et al., 2019; Dikker et al., 2017).

Circular correlation was chosen because it has been shown to be the least sensitive to spurious couplings of EEG hyperscanning data (Burgess, 2013). Circular correlations were calculated for each pair of students within a group and between each student and the teacher (see Fig. S1 in the Supplemental Material). Calculated circular correlations were normalized by Fisher's Z transformation and averaged across epochs, lectures, and electrode pairs to produce more stable measures. Finally, circular correlations values were averaged within three predefined regions of interest (ROIs) adopted from (Clarke et al., 2011): posterior electrodes (P3, P4, P7, P8, PO3, PO4, Pz, Oz, O1, O2), central electrodes (Cz, T7, T8, C3, C4, FC5, FC6, CP1, CP2, CP5, CP6), and frontal electrodes (F3, F4, F7, F8, Fz, Fp1, Fp2, AF3, AF4, FC1, FC2).

For power analysis, the 1-s epochs were multiplied with a Hanning taper, and power spectra (4–30 Hz) were computed using a fast Fourier transform. Power spectra were then averaged across all epochs within each lecture. To normalize the data, we divided alpha power by the averaged power in the 4 to 20 Hz band (referred to as "relative power"; Dikker et al., 2020).

In lecture segment analysis, we averaged data across question-specific epochs identified on the basis of the lecture transcript rather than averaging circular correlation values across the entire duration of each lecture. Because information needed to answer a specific question could have been mentioned more than once in the lecture, all these instances were included in the analysis. However, to obtain stable BBS estimates, we included lecture segments of only 3 s or longer (similar results were obtained with higher thresholds of 5 s and 7 s). A question was categorized as "learned" if a student answered it correctly in the posttest but not in the pretest. A question was categorized as "not learned" if a student's answer had not changed between the pretest and the posttest (i.e., the student either already knew the answer to the question before the lecture or answered it correctly before the lecture but incorrectly after the lecture). BBS values were minimum-maximum normalized before averages were computed across students.

In time-lagged cross-correlation analysis, for each student–teacher dyad, we shifted the time course of the teacher between –500 ms and 500 ms in steps of 100 ms with respect to the time course of the student (similar to the procedure of Wass et al., 2018). Alpha-band BBS was computed for each temporal lag as described above.

Statistical analysis

A within-dyad bootstrapping analysis was used to control for spurious (i.e., coincidental) BBS (Pérez et al., 2019; Zhou et al., 2021). For each student–student and student–teacher dyad, BBS was computed between all combinations of lectures given at different time points (e.g., Lecture 1–Lecture 2, Lecture 1–Lecture 3). We expected that BBS would be higher for matching versus nonmatching lectures. This hypothesis was tested using a nonparametric bootstrap-based t test, in which BBS values for nonmatching lectures were shuffled 10,000 times and compared with the real BBS values. This analysis was repeated for each combination of frequency band and region of interest, and the resulting p values were false discovery rate (FDR) corrected for multiple comparisons ($q = 0.05$; Fig. S2 in the Supplemental Material).

Because students were nested within groups, data were analyzed using multilevel modeling treating group as the unit of analysis to control for nonindependence in student responses. The MIXED procedure in SPSS was used. BBS was considered a Level 1 predictor and pretest-to-immediate/delayed-posttest changes were treated as the outcome variables.

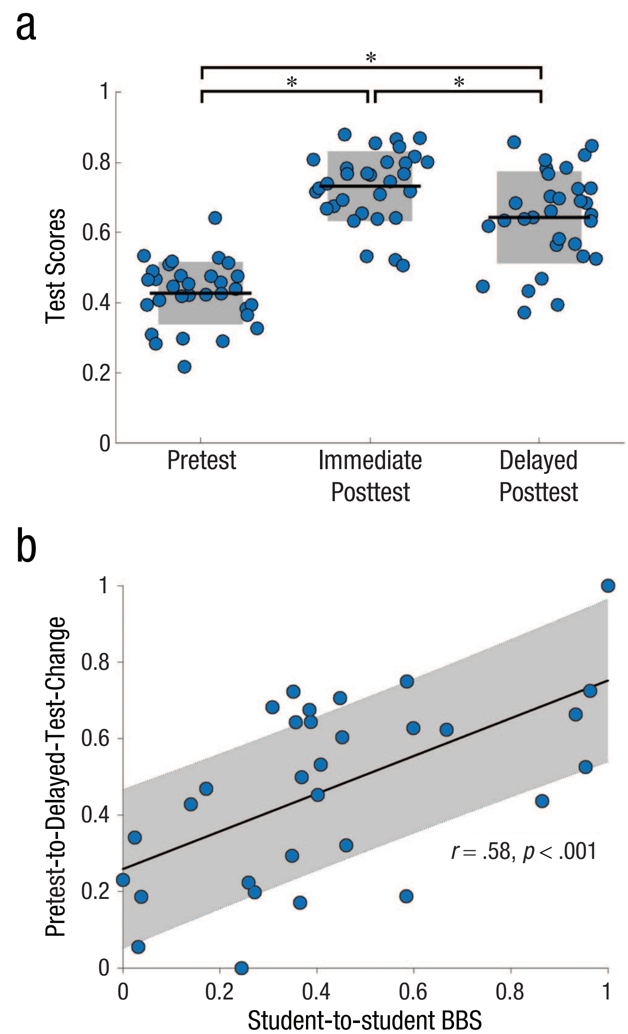

Fig. 2. Association between brain-to-brain synchrony (BBS) and learning outcomes. (a) Averaged scores (proportion of correct answers) in the pretest, immediate posttest, and delayed posttest. Each dot represents one participant, and horizontal lines depict means for all participants; gray regions represent one standard deviation. Asterisks indicate significant differences between mean test scores ($p < .05$). (b) The association between alpha-band BBS and pretest-to-delayed-posttest change. All values were normalized to a scale from 0 to 1 (maximum–minimum) for presentation purposes. Each dot corresponds to the alpha-band BBS in central electrodes between one student and all the other students in the group, averaged across the four lectures. The error band denotes the 1-*SE* prediction interval from a least-square fit.

Results

Behavioral results

Test performance (i.e., proportion of correct answers) significantly increased from pretest ($M = .43$, $SD = .02$) to the immediate posttest ($M = .73$, $SD = .02$), $F(1, 39.51) =$

269.07, $p < .001$, and from the pretest to the delayed posttest ($M = .64$, $SD = .02$), $F(1, 30.27) = 93.01$, $p < .001$. Test performance declined over the course of the week between the immediate and delayed posttests, $F(1, 31.06) = 17.81$, $p < .001$ (Fig. 2a). Pretest performance was a predictor of performance on the delayed posttest, $F(1, 28.22) = 9.67$, $p = .004$, but not on the immediate posttest, $F(1, 28.77) = 1.35$, $p = .255$.

Student-to-student BBS and learning outcomes

We first assessed the statistical significance of BBS by comparing student dyads' BBS across matching (e.g., Lecture 1–Lecture 1) and nonmatching lectures (e.g., Lecture 1–Lecture 2). A nonparametric bootstrap-based *t* test was used to test the hypothesis that BBS in matching lectures would be higher than BBS in nonmatching lectures (see the Method section). Across three frequency bands (theta, alpha, and beta) and three ROIs (posterior, central, and frontal), only alpha-band BBS in central electrodes was statistically significant ($p = .009$, FDR corrected; Fig. S2). Therefore, all subsequent analyses were conducted on this frequency-band–ROI combination.

To assess whether learning outcomes (pretest-to-posttest change) were predicted by BBS during lectures, we constructed a multilevel model (students nested within groups). This analysis revealed that alpha-band BBS significantly predicted both pretest-to-immediate-posttest change, $F(1, 14.32) = 7.73$, $p = .014$, as well as pretest-to-delayed-posttest change, $F(1, 16.43) = 11.14$, $p = .004$ (Fig. 2b). Time (immediate learning vs. delayed learning) did not moderate the main effect of BBS on test change, Time × BBS interaction: $F(1, 29) = 0.67$, $p = .42$.

We also computed the relative alpha power in central electrodes during each lecture (see the Method section). The association between alpha power and pretest-to-posttest change was not significant, immediate posttest: $F(1, 28.49) = 3.72$, $p = .064$; delayed posttest: $F(1, 28.91) = 1.18$, $p = .285$.

BBS within lecture segments

We further examined whether variations in alpha-band BBS throughout the lecture could predict learning at the individual-test-question level. Test questions were classified as either learned (if a student answered correctly in the posttest but not in the pretest) or not learned (if a student's answer had not changed between the pretest and the posttests). Then, BBS was computed separately for lecture segments corresponding with these two categories of questions (Fig. 3a). Alpha-band BBS in central electrodes was significantly higher for learned than for nonlearned information, both for the immediate posttest (learned: $M = .54$, $SD = .02$; not learned: $M = .47$, $SD = .02$), $F(1, 30) = 6.38$, $p = .017$, and the delayed posttest (learned: $M = .54$, $SD = .02$; not learned: $M = .48$, $SD = .01$), $F(1, 30) = 6.38$, $p = .017$ (Fig. 3b).

Student-to-teacher BBS

Because the teacher served as the speaker and the students as listeners, we hypothesized that student-to-teacher BBS would peak at a nonzero lag (i.e., when the teacher's brain activity is shifted backward relative to the student's brain activity; Stephens et al., 2010). To test this hypothesis, we computed time-lagged student-to-teacher BBS and assessed the significance level of each temporal lag using the previously described bootstrapping procedure (see the Method section). Despite the presence of speech-related artifacts in the teachers' EEG data, which required additional preprocessing and epoch removal (Table S3), student-to-teacher BBS was significant at a −300-ms lag (i.e., when the teacher's brain activity preceded the brain activity of students by about 300 ms). This was the only temporal lag at which student-to-teacher BBS reached significance ($p = .015$, uncorrected; Fig. 4a). Student-to-teacher BBS did not significantly differ between the two teachers, $F(1, 6.905) = 0.76$, $p = .41$ (Fig. S3 in the Supplemental Material). Critically, student-to-teacher BBS at the −300-ms temporal lag significantly predicted pretest-to-delayed-posttest change ($r = .46$, $p = .009$; Fig. 4b) but not pretest-to-immediate-posttest change ($r = .27$, $p = .142$).

Discussion

Our aim in the current study was to explore the temporal dynamics of BBS between students and teachers and its relationship with student learning. Although BBS has been previously associated with several learning-related variables, such as student engagement and social dynamics between students and teachers (Babiker et al., 2019; Bevilacqua et al., 2019; Dikker et al., 2017; Ko et al., 2017; Poulsen et al., 2017), there are conflicting results about its relationship with learning itself. Several recent studies provide evidence that BBS is associated with learning outcomes, but most of these studies were constrained to fNIRS and fMRI, which lack temporal specificity (J. Liu et al., 2019; Meshulam et al., 2021; Pan et al., 2020; Piazza et al., 2021; Zheng et al., 2018; Zhu et al., 2021), and/or to individual participants who were not tested simultaneously (Cohen et al., 2018; Meshulam et al., 2021).

The current study substantially extends previous fMRI/fNIRS research by demonstrating that BBS between students and teachers measured at the millisecond level

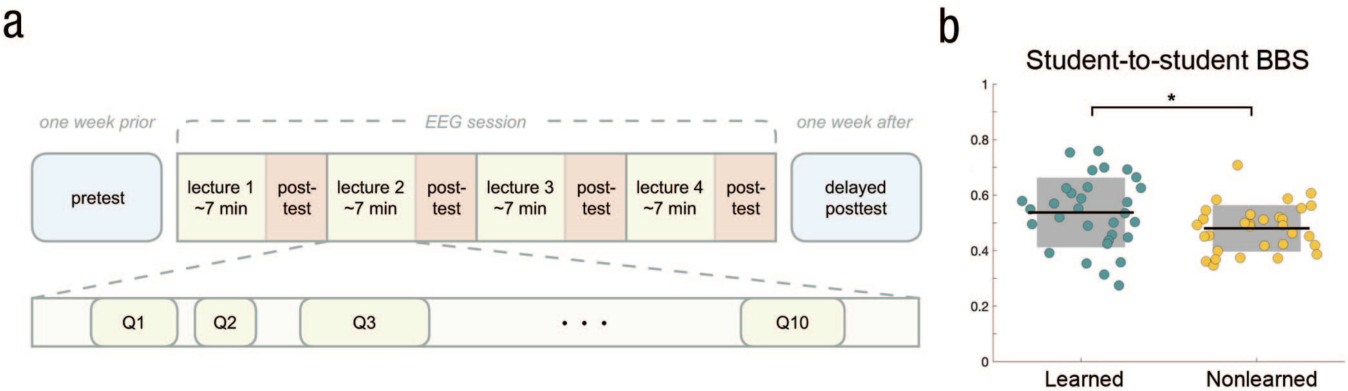

Fig. 3. Lecture segment analysis. (a) Question-specific time intervals where relevant content was delivered by the teacher were identified on the basis of the lecture transcript. (b) Alpha-band brain-to-brain synchrony (BBS) in central electrodes was measured separately for lecture segments associated with learned and nonlearned items. The difference between learned and nonlearned items is plotted for the delayed posttest (similar findings were obtained using the immediate posttest; see the main text). Minimum–maximum normalized brain-to-brain synchrony values are shown (see the Method section). Each dot represents one participant, and horizontal lines depict means for all participants; gray regions represent one standard deviation. The asterisk indicates a significant difference between means for learned and nonlearned items ($p < .05$).

captures student learning. In line with prior research (Dumas et al., 2010), our findings indicate that the alpha band is the most robust frequency range for BBS. Our findings are also consistent with prior research linking alpha oscillations with attention (Dikker et al., 2020; Haegens, Händel, & Jensen, 2011; Haegens, Nácher, et al., 2011; Jensen & Mazaheri, 2010; Klimesch et al., 2007; Palva & Palva, 2007) and memory (Meeuwissen et al., 2011), and with the view that the alpha rhythm is involved in actively suppressing task-irrelevant processing (Haegens, Händel, & Jensen, 2011; Haegens, Nácher, et al., 2011; Jensen & Mazaheri, 2010; Klimesch et al., 2007; Palva & Palva, 2007).

Whereas previous EEG research has demonstrated that increases in alpha power are associated with inattention (e.g., Boudewyn & Carter, 2018), our findings indicate that increases in alpha-band BBS are associated with better learning outcomes. Critically, the BBS metric we used was based on phase rather than power. More precisely, circular correlation (our index of BBS) measures the extent to which phase variance covaries between two EEG channels (Burgess, 2013). As demonstrated by previous EEG studies, BBS increases when students are engaged in a task and decreases when students disengage (Bevilacqua et al., 2019; Cohen et al., 2018; Dikker et al., 2017). Although the phenomenon of BBS is not yet fully understood, it is thought that when task engagement increases, students' alpha oscillations are attenuated but become more phase entrained with the external stimulus (in this case, the lecture), leading to higher BBS across students (Dikker et al., 2017). Intriguingly, our findings suggest that alpha-band synchrony across students might be a better predictor of learning outcomes than alpha power within individual students (see Balconi et al., 2017, for related findings). This finding merits further investigation in future studies.

To the best of our knowledge, only one previous hyperscanning EEG study addressed the relationship between BBS and learning outcomes. Surprisingly, this study did not find a significant association between BBS during instructional videos and live lectures and test performance (Bevilacqua et al., 2019). There are several factors that could explain this null finding, including insufficient power (only 12 students were measured) and the use of commercial-grade EEG devices in a classroom setting, which could result in low signal-to-noise ratio. Furthermore, unlike in the current study, BBS was measured across a wide frequency range (1–20 Hz), and learning was assessed using only an immediate posttest without considering students' preexisting knowledge.

Relatedly, whereas most previous studies only measured test performance immediately after learning, here, student knowledge was assessed a week before the lecture (to account for preexisting knowledge) and a week after the lecture had taken place. Interestingly, students' preexisting knowledge was associated only with delayed rather than with immediate posttest performance. This suggests that delayed posttest performance is a more meaningful measure of learning, which could reflect the integration of new content with existing knowledge rather than pure short-term recall. Furthermore, in contrast to previous studies that measured BBS only over extended periods of time (e.g., the entire duration of a lecture or a video; Bevilacqua et al., 2019; Cohen et al., 2018; Dikker et al., 2017), here we demonstrated that BBS during specific lecture segments was

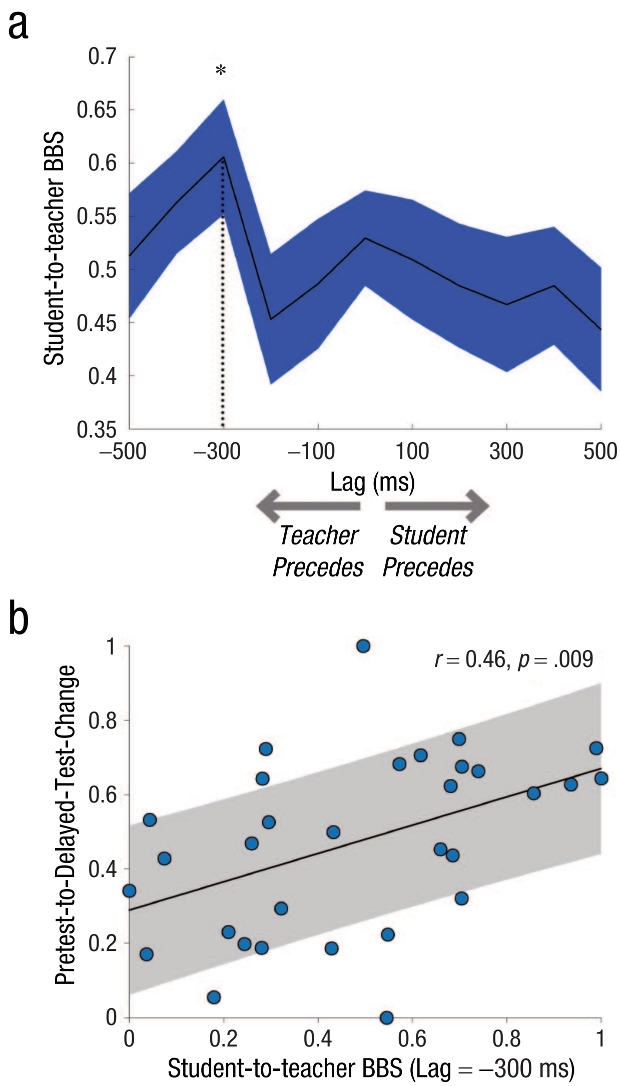

Fig. 4. Temporal analysis of student–teacher brain-to-brain synchrony (BBS). (a) Student-to-teacher alpha-band BBS in central electrodes as a function of temporal lag between the student's and teacher's brain activity. Negative lag values correspond to the teacher's brain activity preceding the students' brain activity. The shaded area reflects the standard error of the mean. BBS values were normalized to a scale from 0 to 1 (maximum–minimum) before they were averaged across dyads. The statistical significance of BBS at each lag was assessed using a bootstrapping test. The asterisk indicates a significant BBS value (p < .05, uncorrected). (b) The association between alpha-band student-to-teacher BBS in central electrodes and pretest-to-delayed-posttest change. Each dot corresponds to the BBS between one student and the teacher at a –300-ms lag (marked by the dashed line in panel a). The error band denotes the 1-*SE* prediction interval from a least-square fit.

associated with learning at the individual-test-question level (Fig. 3).

Student-to-teacher BBS peaked at an approximately 300-ms lag in the students' brain activity relative to the teacher's brain activity (Fig. 4). This finding is consistent with previous fMRI/fNIRS studies (Dikker et al., 2014; Y. Liu et al., 2017; Stephens et al., 2010; Zheng et al., 2018), but these studies could not accurately estimate the speaker–listener delay. A delay of roughly 300 ms, as reported here, is consistent with the time course of language comprehension in spoken discourse (Gwilliams, 2020). Student-to-teacher BBS at this temporal lag significantly predicted delayed (but not immediate) learning (Fig. 4b). It is possible that the association between student-to-teacher BBS and immediate learning did not reach significance because of the lower signal-to-noise ratio in the teacher data.

This study had several limitations. First, students were measured in a simulated laboratory classroom rather than a real-world classroom. Second, the current findings are limited to lectures, in which information is conveyed in one direction from the instructor to the students. The focus on lectures (rather than group discussions, for example) was driven by our intent to minimize EEG artifacts and to examine the temporal lag between students and teachers' brain activity, but this limits the generalizability of our findings. Third, this study cannot dissociate the contribution of shared sensory input (i.e., all students viewing the same lecture) from the social interactions between students and teachers (Hamilton, 2021). Fourth, this study cannot speak to any behavioral correlates of BBS because only EEG activity was collected. Future research is needed to extend these findings to real classrooms, where students and teachers interact with one another in a variety of ways, and to other populations (e.g., K–12 students). Further, tracking eye movements, body motion, and physiological signals (e.g., heart rate) in addition to EEG can provide a more holistic view on BBS between students and teachers (Hamilton, 2021; Redcay & Schilbach, 2019). Relatedly, further work is needed to understand the neural dynamics that give rise to BBS, for example, by examining not only what conditions enhance BBS but also under what circumstances BBS is diminished. Finally, given that group size has a critical effect on group dynamics (Rifkin et al., 2012; Shultz & Dunbar, 2007), future studies could assess the impact of group size on BBS between students and teachers. Future studies with larger samples could also distinguish between different profiles of learners and teachers (e.g., students with high vs. low prior knowledge; novice vs. experienced teachers).

The methods we currently have to study the human brain do not permit more neurobiologically granular, mechanistic characterization of BBS. That being said, the measures that we used here yielded unanticipated new insights into how learning in a group context is reflected in the brain dynamics of teachers and learners.

Transparency

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Author Contributions

Ido Davidesco: Conceptualization; Formal analysis; Investigation; Writing – original draft.
Emma Laurent: Formal analysis; Investigation; Writing – original draft.
Henry Valk: Formal analysis; Investigation; Writing – original draft.
Tessa West: Formal analysis; Writing – original draft.
Catherine Milne: Conceptualization; Funding acquisition; Writing – review & editing.
David Poeppel: Conceptualization; Funding acquisition; Supervision; Writing – review & editing.
Suzanne Dikker: Conceptualization; Supervision; Writing – review & editing.

Declaration of Conflicting Interests

The author(s) declared that there were no conflicts of interest with respect to the authorship or the publication of this article.

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Supplemental Material

Additional supporting information can be found at http://journals.sagepub.com/doi/suppl/10.1177/09567976231163872

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