

Brain-to-Brain Synchrony in the STEM Classroom

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ABSTRACT

Cognitive neuroscience research is typically conducted in controlled laboratory environments that hold very little resemblance to science, technology, engineering, and mathematics classrooms. Fortunately, recent advances in portable electroencephalography technology now allow researchers to collect brain data from groups of students in real-world classrooms. Even though this line of research is still new, there is growing evidence that students' engagement, memory retention, and social dynamics are reflected in the brain-to-brain synchrony between students and teachers (i.e., the similarity in their brain responses). In this *Essay*, I will provide an overview of this emerging line of research, discuss how this approach can facilitate new collaborations between neuroscientists and discipline-based education researchers, and propose directions for future research.

INTRODUCTION

With the transition from lecture-based to active-learning formats, science, technology, engineering, and mathematics (STEM) undergraduate classrooms are becoming more social (Linton *et al.*, 2014; Eddy *et al.*, 2015). Yet social interactions and their impact on student learning, especially at the undergraduate level, are vastly underexplored. Discipline-based education researchers typically collect data from large *groups* of students, but the emphasis is on how pedagogy affects *individual* students (Grunspan *et al.*, 2014). There is relatively a small (but growing) number of discipline-based education research (DBER) studies that focus on social interactions. These studies suggest that social interactions can help explain shifts in students' self-efficacy (Dou *et al.*, 2016), persistence in introductory courses (Zwolak *et al.*, 2017), and academic performance (Theobald *et al.*, 2017; Vargas *et al.*, 2018).

Similarly, there is very limited neuroscience research on social interactions. In fact, the study of real-world social exchanges has been dubbed the “dark matter of social neuroscience” (Schilbach *et al.*, 2013). The lack of studies investigating these phenomena is most likely due to the high cost and fragility of traditional cognitive neuroscience methods, limiting the vast majority of research on the human brain to studies in which one participant at a time performs a task in a highly constrained environment (e.g., inside a brain scanner). In the past few years, researchers have begun to approach the neural basis of social interactions by comparing the brain responses of multiple individuals during a variety of tasks (Hasson *et al.*, 2012; Babiloni and Astolfi, 2014; Wheatley *et al.*, 2019). In pioneering research, Hasson and colleagues (2004) used functional magnetic resonance imaging (fMRI) to demonstrate that the brains of different people who watch the same movie show increasingly similar activity patterns over time (a phenomenon called “brain-to-brain synchrony”). Other research has found that successful communication is associated with similar brain activity between a speaker and a listener: the more similar the listener's brain activity with that of the storyteller, the better the listener remembers a story (Stephens *et al.*, 2010). However, participants in these studies were not tested simultaneously (i.e., there was no social interaction). The few truly interactive studies that exist demonstrate a relationship

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between social factors and brain-to-brain synchrony. For example, face-to-face dialogues have been shown to induce more brain synchrony compared with back-to-back dialogues or monologues (Jiang *et al.*, 2012). It has also been demonstrated that conversational leaders show more synchronous brain activity with “followers” than followers do among one another (Jiang *et al.*, 2015).

In this *Essay*, I will discuss how social interactions in STEM classrooms can be studied from a neuroscience perspective. Though this line of research is still at an early stage, I will argue that it holds great potential for cross-disciplinary research in biology education. I will first describe how portable technologies can be used to measure the brain activity of groups of students in classrooms and review several recent studies that used this approach. These studies suggest that students exhibit synchronized brain activity patterns, and the extent of brain synchrony reflects students’ engagement, social closeness, and learning outcomes. I will then discuss what might drive brain synchrony between students in classrooms and conclude with suggestions for future research.

PORTABLE BRAIN TECHNOLOGIES IN STEM EDUCATION RESEARCH

This *Essay* focuses on electroencephalography (EEG), because it is currently the only brain-measuring technology that allows the recording of students’ and teachers’ brain activity in classrooms at just a fraction of the cost of laboratory-based neuroscience equipment. Other neuroimaging techniques, such as fMRI, positron emission tomography, and magnetoencephalography, require stationary brain scanners that cost millions of dollars. Another neuroimaging method that is gaining popularity is functional near-infrared spectroscopy (fNIRS), which uses near-infrared light to measure brain activation. Although wireless fNIRS devices are now becoming available, almost all fNIRS research to date has been conducted in laboratory settings (Cui *et al.*, 2011).

What does EEG measure? EEG measures the brain’s electrical activity from electrodes placed on the scalp (typically 32–256 electrodes). The EEG signal is thought to reflect the summation of postsynaptic potentials across thousands of neurons (Biasiucci *et al.*, 2019; Brienza and Mecarelli, 2019). The EEG signal is primarily generated by cortical pyramidal neurons. Due to their anatomical geometry, when these neurons are activated in synchrony, their electrical signals summate and propagate to the scalp. Thus, the EEG signal varies according to the synchronized or desynchronized activity of large populations of neurons. Biasiucci *et al.* (2019) propose the following analogy: EEG is similar to measuring the roar of a crowd from *outside* a stadium. It cannot identify individual conversations, but it can detect changes in the overall activity of the crowd (for a recent primer on EEG, see Biasiucci *et al.*, 2019).

Whereas other neuroimaging tools, such as fMRI, can detect brain activations within a range of a few millimeters, with EEG, it is mathematically very difficult to infer where in the brain the EEG signal originates. Another limitation of EEG is that the signal is often contaminated by other sorts of physiological electrical activity (e.g., ocular and other muscular activity) and environmental noise (e.g., computer screens). This is particularly a concern when using EEG in classrooms, and therefore, EEG

data should be closely examined and artifacts should be identified and removed (see Dikker *et al.*, 2017). On the other hand, EEG is very useful in determining *when* a certain brain response is happening, making EEG a rich source of data when it comes to disentangling different stages of information processing (Luck, 2014).

Most EEG research is still being conducted in laboratory settings, but with recent developments in low-cost, portable, wireless, and dry (i.e., gel-free) EEG technology, researchers can now conduct neuroscience investigations outside the laboratory in ecologically valid environments, such as classrooms. Biology education researchers might be especially interested in smartphone-based EEG systems that combine an off-the-shelf EEG device with a smartphone or a tablet (Debener *et al.*, 2012; Stopczynski *et al.*, 2014; Poulsen *et al.*, 2017) as well as EEG systems that offer less obtrusive electrode configurations (Debener *et al.*, 2015). However, one should note that portable EEG devices have fewer electrodes, which might restrict data analysis and the types of research questions that can be answered. Also, data acquired with portable EEG devices are more susceptible to artifacts, such as head motion and eye movement artifacts, resulting in a higher percentage of data exclusion. Nonetheless, it has been demonstrated that portable EEG devices can yield comparable data to laboratory-grade systems (at least with tasks that are known to generate robust EEG effects; Badcock *et al.*, 2013; Ries *et al.*, 2014; Grummett *et al.*, 2015).

BRAIN-TO-BRAIN SYNCHRONY IN CLASSROOMS

Several recent studies have used portable EEG methods to collect brain data from groups of students in simulated and real-world classrooms. Poulsen *et al.* (2017) measured the brain activity of a group of 12 young adults in a classroom setting while they were presented with short video clips. The videos elicited synchronized brain activity patterns across participants compared with randomly scene-scrambled versions of the same videos. While this study helped validate the method of recording EEG in a classroom, its educational relevance is limited due to the type of materials that were used (segments of popular movies) and the fact that the participants were not an organic group of students.

In another recent study, Dikker *et al.* (2017) recorded EEG activity from a group of 12 students in a biology high school classroom. Students’ brain activity was recorded throughout various classroom activities, such as lectures, instructional videos, and group discussions (Figure 1). The extent to which brain activity was synchronized across students was found to predict self-reported student engagement: Students who reported being more engaged exhibited higher brain synchrony with their peers. Further, brain-to-brain synchrony between pairs of students reflected how close they felt toward each other: pairs of students who demonstrated higher brain synchrony also reported higher social closeness (Dikker *et al.*, 2017).

In another study, EEG activity was recorded not only from the students, but also from their teacher, which is a challenging task due to the sensitivity of EEG to head movement and speech-related artifacts. By instructing the teacher to be mindful of their head motion and sufficiently preprocessing the data, the authors were able to measure the brain synchrony between

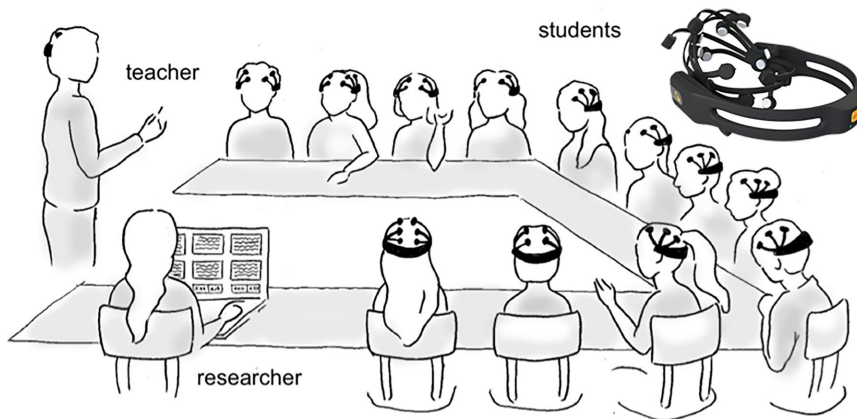


FIGURE 1. Portable EEG recordings in a classroom (from Dikker *et al.*, 2017). Inset: An example of a portable EEG device (EMOTIV EPOC+).

students and their teacher. Student-to-teacher brain synchrony was significantly correlated with students' self-reported engagement: Students who were more engaged showed higher brain synchrony with the teacher. Further, students who reported feeling closer to the teacher exhibited more student-to-teacher brain synchrony (Bevilacqua *et al.*, 2019).

Taken together, these two studies suggest that the social dynamics among students and their teacher are, to some extent, reflected in their brain-to-brain synchrony. This is intriguing, because students in these studies were not prompted to think about their social relationships *while* EEG data were being collected. This finding is consistent with recent fMRI research, which reported that neural responses to naturalistic movies were highly similar among friends, with similarity of neural responses decreasing as social distance increased (Parkinson *et al.*, 2018).

So far, I have focused on student engagement and social dynamics—but how does brain-to-brain synchrony relate to learning outcomes? Bevilacqua *et al.* (2019) did not find a significant association between brain synchrony and students' memory retention, but two other studies indicate otherwise (Cohen *et al.*, 2018; Davidesco *et al.*, 2019). Cohen *et al.* (2018) demonstrated that brain-to-brain synchrony between students who watched science-related instructional videos predicted their performance in a memory test. In another study, brain activity was concurrently measured from four non-science major students and their instructor in a simulated classroom throughout a sequence of four mini-lectures in biology and chemistry. Students' knowledge was measured a week before, immediately after, and a week following the EEG session. Both student-to-student and student-to-teacher brain synchrony significantly predicted students' memory retention a week after the lesson took place. Interestingly, moment-to-moment variations in brain synchrony throughout the lecture indicated what *specific* information students retained: Brain synchrony was higher for test questions for which students demonstrated learning (i.e., answered incorrectly in the pretest and correctly in the posttest) compared with test questions for which students' answers remained unchanged (Davidesco *et al.*, 2019).

WHAT MIGHT GIVE RISE TO BRAIN-TO-BRAIN SYNCHRONY DURING CLASSROOM INTERACTIONS?

While the underlying mechanisms of brain-to-brain synchrony are not well understood, Dikker *et al.* (2017) proposed that shared attention plays a crucial role. At the most basic level, brain-to-brain synchrony is driven by the fact that all students were exposed to the same stimulus (e.g., the instructor's voice). When confronted with an external stimulus, brain activity becomes temporally aligned to the rhythm of the input, a phenomenon called "stimulus entrainment" (Lakatos *et al.*, 2008). In a classroom, because all students have similar sensory-motor systems designed to apprehend the world, their brains all become entrained to the instructor's voice or to

any other shared stimuli, thus syncing with one another.

Critically, stimulus entrainment only provides a partial explanation to brain synchrony in classrooms. Our brains act as a selective filter of the external world (Enns and Lleras, 2008; Berkes *et al.*, 2011); thus, sharing the same audiovisual input does not guarantee that we all "see" the world the same way. For example, instructors may trigger completely different responses in each of their students' brains depending on students' attention. Attention has a critical role in the learning process, as it controls the flow of incoming information by suppressing irrelevant information while enhancing sensitivity to task-relevant information (Kanwisher and Wojciulik, 2000).

Many studies have demonstrated that attention can modulate how the brain processes information (e.g., Davidesco *et al.*, 2013). For example, in a cocktail party-like scenario, when participants are confronted with two speakers and asked to direct attention to only one of them, brain activity in high-order auditory regions tracks only the attended speaker's voice (Mesgarani and Chang, 2012; Golumbic *et al.*, 2013). Similarly, as students pay close attention to a lecture, their brains become entrained to the lecturer's voice, and thus their brain activity aligns with the brain activity of the instructor and other students. In contrast, as students lose interest, their brains become less entrained to the lecturer (and possibly more entrained to other stimuli), resulting in decreased similarity in neural responses to the instructor and other students (Dikker *et al.*, 2017).

BRAIN SYNCHRONY AS A REFLECTION OF INTERPERSONAL COORDINATION

During social interactions, not only do people's brains become synchronized, but also their behaviors become aligned (Cornejo *et al.*, 2017). For example, during conversations, people tend to imitate each other's choices of speech sounds, grammatical forms, and words, a process known as "interactive alignment" (Garrod and Pickering, 2004). Interpersonal coordination also occurs nonverbally: Interlocutors tend to synchronize their facial expressions, manual gestures, and noncommunicative postures. This typically happens spontaneously, unconsciously, and rapidly (within a few seconds after the onset of an interaction; Louwerse *et al.*, 2012).

Even though teaching and learning are highly social processes, with students and teachers interacting constantly with one another, there is very little research on interpersonal coordination in classrooms. In one of the few studies that addressed this issue, Bernieri (1988) measured the movement synchrony and behavioral matching in video recordings of high school students. The students were videotaped in pairs as they attempted to teach each other a set of imaginary words. Ratings of movement synchrony and behavioral matching were higher in genuine interaction video clips compared with control video clips. Further, the degree of movement and behavioral synchrony were positively correlated with rapport ratings between students. In another more recent study, bilingual undergraduate and graduate students engaged in teaching-like tasks, where one person was required to transmit information that was unknown to their partner in order to achieve a shared goal. An independent group of native English speakers rated the degree of alignment between interlocutors. Interactive alignment in both linguistic (e.g., word stress placement in multisyllabic words) and nonverbal behaviors was found to be significantly higher at the end of the conversation compared with the beginning, suggesting that interpersonal coordination increases over time (Trofimovich and Kennedy, 2014; Trofimovich *et al.*, 2014).

Interpersonal coordination relies on our ability to anticipate both our own linguistic and behavioral actions and those of others (Ramnani and Miall, 2004; Sebanz *et al.*, 2006; Konvalinka *et al.*, 2010; Sanger *et al.*, 2011; Romero *et al.*, 2012; Pickering and Garrod, 2013). For example, using fMRI, Stephens *et al.* (2010) reported that neural responses in the frontal cortex of the listener's brain preceded the responses in the speaker's brain. These anticipatory responses suggest that listeners are actively generating predictions of what the speaker is about to say. Interestingly, the extent of brain areas where the listeners' activity preceded the speaker's activity was found to be the best predictor of listeners' comprehension of the story to which they listened (Stephens *et al.*, 2010). Similarly, Davidesco *et al.* (2019) demonstrated that in frontal and central EEG locations, student-to-teacher brain synchrony best predicted learning outcomes when the students' brain responses *preceded* the teachers' brain responses. However, the role of prior knowledge in this process is not clear. It is possible that students who knew more about the topic *before* the lecture were better able to generate predictions about what the instructor was about to say, and that allowed them to learn more efficiently.

CONCLUSIONS AND NEXT STEPS

Social interactions in STEM classrooms as well as how they are reflected in students' brain activity seem to be promising directions for interdisciplinary research in biology education. Social interactions are often overlooked in DBER, despite having a direct impact on students' academic performance (Linton *et al.*, 2014; Theobald *et al.*, 2017; Vargas *et al.*, 2018). Similarly, social interactions are understudied in human neuroscience, where most research is conducted on individual participants in controlled laboratory environments.

This emerging line of research provides an opportunity for cross-disciplinary collaborations between discipline-based education researchers and cognitive and social neuroscientists (Davidesco and Milne, 2019; Mestre *et al.*, 2018). The connec-

tion between neuroscience and education has been described in the past as "a bridge too far" (Bruer, 1997). Since then, there has been growing interest and debate regarding the relevance of cognitive neuroscience to education research and practice (Ansari and Coch, 2006; Goswami, 2006; Sigman *et al.*, 2014; Bowers, 2016). Bridging neuroscience and education is challenging, because these disciplines have very different goals and research traditions. Neuroscientists typically adopt a reductionist approach and study cognitive functions in isolation. Educational researchers, on the other hand, focus on the learner as a whole and how the learner is embedded in a context, such as a classroom. A common concern is that traditional cognitive neuroscience methods (e.g., fMRI) are conducted in artificial laboratory environments and therefore cannot provide useful data to understand real-world learning. From a more pragmatic standpoint, the concern is that neuroscience methods are just too expensive to apply to educational research (Varma *et al.*, 2008).

This *Essay* highlighted recent developments in portable and wearable brain technologies, such as portable EEG, which now allow researchers to use neuroscience methods in classroom-based research at just a fraction of the cost (Dikker *et al.*, 2017; Bevilacqua *et al.*, 2019). These methods can complement other measures used in DBER, such as achievement tests, self-reports, and think-aloud interviews, and can deepen our understanding of the learning process in several important ways. First, neuroscience methods provide continuous data without interfering with naturally occurring learning activities. Using these methods, we can better explore the cognitive processing that is taking place *during* learning, rather than just before and after learning (Mayer, 2017). Further, these methods can potentially measure implicit processes that learners are unaware of or unable to report accurately, such as lapses of attention (Dahlstrom-Hakki *et al.*, 2019). Finally, neuroscientific data can be used to explore individual differences that mediate learning and predict how students would benefit from different pedagogies (Gabrieli, 2016; Mayer, 2017).

Brain-to-brain synchrony is an example of what can be measured in neuroscience research in STEM classrooms, but this phenomenon is not unique to STEM. In fact, it is not unique to classrooms at all, but likely occurs in any type of social interaction (Hasson *et al.*, 2012). But in the case of classroom learning, brain-to-brain synchrony can be an informative measure of student engagement, social dynamics, and learning outcomes (Dikker *et al.*, 2017; Cohen *et al.*, 2018; Bevilacqua *et al.*, 2019; Davidesco *et al.*, 2019).

However, there are several inherent limitations associated with classroom-based EEG research. First, EEG is a correlative method, where neural activity is associated with behavioral measures (e.g., test scores). Thus, EEG cannot assess causal relationships. Second, the low spatial resolution of EEG limits the information available to researchers. Questions about what specific brain regions are involved in classroom learning cannot currently be addressed with EEG. Third, EEG recordings are sensitive to muscle-related artifacts caused by head motion, eye movements, and speech. For this reason, classroom-based EEG research to date has focused primarily on passive forms of learning, such as listening to lectures and watching instructional videos, where student movement and speech are limited (Dikker *et al.*, 2017; Bevilacqua *et al.*, 2019). However, now

that this method has been successfully deployed in classrooms, future research can start exploring more interactive forms of learning, such as small-group work.

Recent calls to enhance active learning in STEM education have emphasized group work based on the understanding that collaborative groups can enhance learning, improve students' attitudes toward science, and reinforce their social identity as scientists (Springer *et al.*, 1999; Tanner *et al.*, 2003; National Research Council, 2012; President's Council of Advisors on Science and Technology, 2012). However, groups can be dysfunctional, and we do not know enough about how to best use group learning in STEM education, especially at the college level (Theobald *et al.*, 2017). Future cross-disciplinary research teams can collect both EEG and audio-video data from small groups of students during collaborative learning tasks. Whereas previous work has typically measured brain-to-brain synchrony throughout the entire duration of an activity, the high temporal resolution of EEG allows researchers to examine how brain synchrony (as well as other EEG measures) unfolds over time. For example, researchers can identify moments of high and low synchrony in the EEG data and examine the corresponding audio and video recordings to identify any recurring patterns. This research might generate new insights into what makes group learning effective.

In summary, I believe that neuroscience research in classrooms provides an exciting opportunity for both discipline-based education researchers and cognitive and social neuroscientists. From a DBER perspective, this research will hopefully yield a deeper, more mechanistic understanding of STEM learning by illuminating what is happening in students' brains during the learning process and what factors mediate learning. From a neuroscience perspective, this research provides a unique opportunity to study the brain mechanisms that support learning in real-world classroom environments.

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