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Xu Du
Central China Normal University

Lizhao Zhang
Central China Normal University

Jui-Long Hung
Boise State University, andyhung@boisestate.edu

Hao Li
Central China Normal University

Hengtao Tang
University of South Carolina

Yiqian Xie
Central China Normal University

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Understand group interaction and cognitive state in online collaborative problem solving: leveraging brain-to-brain synchrony data

Xu Du[1†], Lizhao Zhang[2†], Jui-Long Hung[2,3*], Hao Li[1], Hengtao Tang[4] and Yiqian Xie[1]

†Xu Du and Lizhao Zhang contributed equally to this work and should be considered co-first authors.

*Correspondence: andyhung@boisestate.edu

[1] National Engineering Research Center for E-Learning, Central China Normal University, Wuhan 430079, China
[2] National Engineering Laboratory for Educational Big Data, Central China Normal University, Wuhan 430079, China
[3] Department of Educational Technology, Boise State University, 1910 University Dr., Boise, ID 83725, USA
[4] Department of Educational Studies, University of South Carolina, Charleston, South Carolina, USA

Abstract

The purpose of this study aimed to analyze the process of online collaborative problem solving (CPS) via brain-to-brain synchrony (BS) at the problem-understanding and problem-solving stages. Aiming to obtain additional insights than traditional approaches (survey and observation), BS refers to the synchronization of brain activity between two or more people, as an indicator of interpersonal interaction or common attention. Thirty-six undergraduate students participated. Results indicate the problem-understanding stage showed a higher level of BS than the problem-solving stage. Moreover, the level of BS at the problem-solving stage was significantly correlated with task performance. Groups with all high CPS skill students had the highest level of BS, while some of the mixed groups could achieve the same level of BS. BS is an effective indicator of CPS to group performance and individual interaction. Implications for the online CPS design and possible supports for the process of online CPS activity are also discussed.

Introduction

Collaborative problem solving (CPS, hereafter) has become a prominent feature in 21st-century learning skills, and it is being researched across many domains (Care et al., 2012). CPS involves two or more people working together to solve a problem. Such capabilities have been recognized as a crucial goal in education (OECD, 2017). Research has indicated that the CPS skill of team members affects the effectiveness of collaboration (Andrews & Rapp, 2015). Groups with at least one student with high CPS skills showed significantly better learning performance (Andrews-Todd & Forsyth, 2020). Therefore, intensive efforts have been motivated to develop related assessments and to activate education reforms to improve the effectiveness of CPS (Stadler et al., 2020). In addition, education practitioners have particularly emphasized the need for building skills for remote collaborations (OECD, 2017; Schulze & Krumm, 2017), as teams have become distributed and as schooling or working from home has become the norm. Therefore, how to design, develop, and implement online CPS activities to improve the effectiveness of online CPS is one of the more important topics in current CPS research.

To better organize a CPS activity, it is necessary to understand students' collaboration processes in CPS learning activities. Then instructors can design and develop more effective CPS activities and can provide personalized support as needed. The first step was to define different phases of the whole CPS process (Hayes, 2013) for advanced analyses/observations. The CPS process can be defined as having two phases: the problem-understanding phase and the solution development phase (Kwon et al., 2019). The problem-understanding phase involves a cognitive structure that corresponds to a problem constructed by a solver (Chi, Feltovich, et al., 1981). Then, in the solution development phase, students work together to develop corresponding solutions based on the collaborative cognitive structure. Therefore, group dynamics (i.e., how students interact with each other) is a critical element during the process (Chi, Glaser, et al., 1981). The two phases form a circular cycle and jointly influence the quality of a solution to the problem. Studies have been conducted to understand how each phase influences learning outcomes (Chang et al., 2017; Kwon et al., 2019; Zheng et al., 2020). However, most of the studies obtained their data through questionnaires or observations. There is a need for additional in-depth analytic results, not from the perceptual data, to understand the details of individual CPS phases, especially from the aspect of the dynamics of the group members.

The development of emerging technologies opens new possibilities to collect and analyze students' behaviors and interactions without interfering in the learning process (Chanel & Muhl, 2015). Physiological data, such as electrodermal activity (EDA, hereafter), heart rate, gesture, body pose, and electroencephalogram (EEG, hereafter), reflect personal physical and psychological states (Cukurova et al., 2020; Sharma & Giannakos, 2020). Such data have been adapted to make up for some gaps in perceptional data analysis (Ashwin & Guddeti, 2020; Dikker et al., 2017; Noroozi et al., 2020). Physiological synchrony (PS, hereafter) is one of the analytic approaches used to obtain insights from physiological data. Studies for years in psychophysiology indicated that human cognition cannot be separated from the body (Critchley et al., 2013). The connection is bidirectional between a person's mental states and his/her physiological signals (Critchley & Garfinkel, 2018; Pecchinenda, 1996). PS is related to learners' beliefs about their cognitions, motivations, emotions, and behaviors (Haataja et al., 2018). The level of PS has been adopted to measure whether the interaction is effective (Dindar, Malmberg, et al., 2020; Sobocinski et al., 2021). As CPS is rooted in the social constructivist view of learning, which assumes that in-depth learning occurs when students engage in building a shared understanding of a problem through social interactions (Jermann & Dillenbourg, 2008; Pear & Crone-Todd, 2002), PS can serve as an indicator of effective interaction in the process of collaborative problem-solving (Dindar, Järvelä, et al., 2020; Sobocinski et al., 2021).

Among the PS instruments mentioned above, brain wave synchrony (or so-called brain-to-brain synchrony, BS) has its advantages in observing CPS processes. Compared with other PS signals, such as EDA and heart rate, BS can reflect students' cognitive state more accurately (Stuldreher et al., 2020a, 2020b). Since collaborative learning involves a high level of interactivity (Davidesco, 2020), BS serves as a more in-depth analytical indicator that reflects interpersonal interaction or common attention from a cognitive state (Nam et al., 2020). Studies have been published that reveal the positive correlation between BS and the level of engagement (Bevilacqua et al., 2019; Dikker et al., 2017) and between BS and academic performance (Davidesco et al., 2019). However, these studies have been limited to individual students; they have not focused on collaborative learning. In addition, these studies analyzed BS through original EEG signals. Since EEG signals can be divided into specific ranges through frequency (Alarcao & Fonseca, 2019), analyzing the BS from different bands is a helpful method to further discover BS characteristics in collaborative learning.

Based on the literature, different CPS phases play different roles in the process of collaboration. In addition, developing a good solution heavily relies on individual students' domain knowledge and CPS skills. BS is an effective indicator of interaction quality, which is proven to have a positive correlation with learning performance in lecturing but is rarely studied in CPS. Therefore, the purpose of this study is to analyze the characteristics of BS in CPS to find a new effective indicator, and understand the collaboration process at different CPS phases and how CPS skills impact the collaboration process from the aspect of BS. The research questions include:

- What are the characteristics of BS in online CPS?
- What are the differences in BS between collaborative groups with different CPS skills?
- What are the differences in group interaction and cognition between groups with different BS levels?

Related works

Collaborative problem solving (CPS)

Collaborative problem solving is defined as "*the capacity of an individual to effectively engage in a process whereby two or more agents attempt to solve a problem by sharing the understanding and effort required to come to a solution and pooling their knowledge, skills, and efforts to reach that solution*" (OECD, 2017, p. 26). (OECD, 2017) developed the PISA survey, which aims to investigate whether a student has acquired the key knowledge and skills for full participation in modern societies near the end of his or her compulsory education. Overall, twelve CPS skills are assessed in the PISA 2015 survey (Herborn et al., 2020). Three social related skills are found to be important in each of the CPS phases, including (1) establishing and maintaining a shared understanding, (2) taking appropriate action to solve the problem, and (3) establishing and maintaining team organization. These skills can help the student better solve a problem collaboratively. Andrews-Todd and Forsyth (2020) proposed a method to evaluate CPS skills based on interactive content and analyzed the performance of collaborative groups with different combinations of CPS skills. The authors found that groups with at least one student with high CPS skills showed significantly better learning performance. This is consistent with findings in areas such as cooperative learning that show that beneficial cooperative behaviors exhibited by team members contribute to team success (Barron, 2003).

To better organize a CPS activity, it is necessary to understand students' collaboration processes in CPS learning activities. Scholars have tried to define different phases of the whole CPS process and to map the required skills in individual phases. For example, (OECD, 2017) defined the CPS process, as starting with (A) exploring and understanding and then moving on to (B) representing and formulating, (C) planning and executing, and (D) monitoring and reflecting. Hayes (2013) categorized the problem-solving process into six phases: finding the problem, representing the problem, planning the solution, carrying out the plan, evaluating the solution, and consolidating gains. Although these definitions have minor differences, the whole process consists of two major phases: problem-understanding and solution development (Kwon et al., 2019). The quality of a solution is strongly influenced by the problem-understanding phase (Simon & Hayes, 1976) which has been referred to as "*a cognitive structure corresponding to a problem, constructed by a solver based on his domain-related knowledge and its organization*" (Chi, Feltovich, et al., 1981). Then students work together to develop corresponding solutions based on the collaborative cognitive structure in the solution development phase. Therefore, group dynamics (i.e., how students interact with each other) is the critical element during the process (Chi, Glaser, et al., 1981). Research efforts have been launched to understand the influencing factors, the quality of learning outcomes, and the collaboration patterns during these two phases. For example, Chi, Glaser, et al. (1981) found that there are considerable differences between novices and experts in problem-solving. Novices will stick to the problem definition or problem-understanding as they work on a solution, whereas experts will move forward toward solution development. Kwon et al. (2019) found that solution-oriented students gained more domain knowledge than problem-oriented students. The authors believe that students' focus more on the problem-solving process rather than on the problem-understanding process is more conducive to the improvement of academic performance. Zheng et al. (2020) coded the online collaboration behaviors of students in their study, used the Apriori algorithm to find the high-frequency jump relationship between CPS behaviors, and analyzed the collaboration patterns of students with different academic performances. Their results show that, at the problem-solving stage, the group with high scores repeatedly modified and improved the solution, while the group with low scores seldom modified the possible solution after it was proposed.

Literature shows that most CPS studies have obtained data through questionnaires or observations. CPS is rooted in the social constructivist view of learning, which asserts that in-depth learning occurs when students engage in building a shared understanding of a problem through social interactions (Jermann & Dillenbourg, 2008; Pear & Crone-Todd, 2002). More analytic results culled not merely from perceptual data, are needed to understand the details of the individual CPS phases, especially from the aspect of group members' dynamics and the mutual effects of two phases on the quality of CPS outcomes.

Physiological synchrony (PS) and brain-to-brain synchrony (BS)

The development of emerging technologies opens new possibilities in collecting and analyzing students' behaviors and interactions without interfering in the learning process (Chanel & Muhl, 2015). Physiological data, such as EDA, heart rate, gesture, body pose, and EEG, reflect the personal physical and/or psychological states of a person (Cukurova et al., 2020; Sharma & Giannakos, 2020). Such data have been adapted to make up for some of the gaps in perceptional data analysis (Ashwin & Guddeti, 2020;

Dikker et al., 2017; Noroozi et al., 2020). PS is one of the analytic approaches used to obtain insights from physiological data. Studies for years in psychophysiology indicated that human cognition cannot be separated from the body (Critchley et al., 2013). This connection is bidirectional, many of the mental states are reflected in the body's physiological signals (Pecchinenda, 1996). On the other hand, the physiology of the body influences human consciousness and cognition (Critchley & Garfinkel, 2018). PS refers to the interdependence of, or the associated activity between, the physiological signals of collaborating individuals. It is an unintentional and spontaneous phenomenon that can be indexed through measures of the human autonomic nervous system (Palumbo et al., 2017). PS appears when there are the same attention objects or when there is effective interaction, and the phenomenon is that the physiological indicators rise or fall simultaneously. Studies have shown that PS can be used to measure whether the interaction is effective or whether students are focused on the same item (Stuldreher et al., 2020a, 2020b). It was found that students who shared their reflected views also showed higher physiological synchrony (Haataja et al., 2018). As CPS is rooted in the social constructivist view of learning, which asserts that in-depth learning occurs when students engage in building a shared understanding of a problem through social interactions (Jermann & Dillenbourg, 2008; Pear & Crone-Todd, 2002). Thus the PS in the CPS process is mainly influenced by the interaction effectivity, and the relationship between PS and learning between students and teachers is worth studying (Davidesco, 2020; Nam et al., 2020). Dindar, Järvelä, et al. (2020) recorded students' EDA in CPS and analyzed the relationship between PS and metacognitive experiences. The PS was calculated through a Multidimensional Recurrence Quantification Analysis (MdRQA). The results show a positive relationship between continuous PS episodes and groups' collective mental effort. Dindar, Malmberg, et al. (2020) investigated the interplay of temporal changes in self-regulated learning processes (i.e., behavioral, cognitive, motivational, and emotional) and their relationship with academic achievement in computer-supported collaborative learning. The PS of the dyads in the collaborating groups was determined by calculating a single session index. The results show that PS among the collaborating students was found to be related to cognitive regulation. Sobocinski et al. (2021) collected heart rate data and videos of students during collaboration. The authors combined video observation and PS as a possible indicator to identify monitoring and adaptation events. The studies have shown that PS is an effective indicator to reflect the process of collaborative learning.

Scalp-recorded electric potentials or electroencephalograms (EEGs) are the most popular instruments to collect a participant's brain wave signals. The signals provide estimates of synaptic action at large scales that are closely related to behavior and cognition. Thus, EEG has been recognized as a genuine "window on the mind" (Nunez & Srinivasan, 2006). The original EEG records electric potentials and can be further divided into specific ranges through the frequency, namely the delta (1–4 Hz), theta (4–7 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (> 30 Hz) bands (Alarcao & Fonseca, 2019). Different wavebands of the EEG reflect different types of activity in the brain (Alarcao & Fonseca, 2019). The literature shows that the delta band is related to signal detection or the unconscious mind (Alarcao & Fonseca, 2019). The theta band is positively correlated with working memory load or cognitive load (Muthukrishnan et al., 2020). The alpha band is related to cognitive load and mediation (Chen & Wang, 2018; Yang et al., 2019). The beta band is related to attention and decision-making (Chen & Wang, 2018; Yang et al., 2019). The gamma band has been demonstrated in a wide range of brain processes, including multisensory and sensorimotor integration, attention, memory formation, and perceptual binding (Chand et al., 2016; Min et al., 2016). The relationships between the EEG bands and brain activities are shown in Table 1.

BS is a type of PS. It refers to the synchronization of brain activity between two or more people (Nam et al., 2020). Compared with PS reflected by EDA and heart rate data, BS can reflect students' cognitive states more accurately (Stuldreher et al., 2020a, 2020b). Dikker et al. (2017) studied the relationship between BS and the self-reported engagement of twelve students in a traditional classroom. BS was computed using the method of total interdependence (Wen et al., 2012). The authors found that students with a higher level of BS had higher levels of engagement and social dynamics during the lecture. Bevilacqua et al. (2019) came to a similar conclusion in their study. The authors calculated the level of BS between students and the teacher and studied the relationship between the level of BS and self-reported engagement level of twelve students in an offline lecture. The results show that students with a higher level of BS with the teacher had higher levels of perceived engagement and closeness. Davidesco et al. (2019) studied the relationship between BS and academic performance. The authors calculated the BS between students and between students and teachers in a traditional classroom. The results show that students with high performance had higher BS with teachers and that the BS between students was more pronounced when they learned what they got wrong on the pretest and right on the posttest. Due to the limitations of devices, the sample sizes of the above studies were between twelve and thirty-six. These studies have shown that BS is an indicator that reflects academic performance and the learning process. The above studies showed that BS can provide more insights and make up some gaps in studies that rely on perceptional data only. However, the studies discussed the relationship between BS and the learning process in a traditional classroom without collaboration. More research efforts should be expended, to understand the CPS process, and to study the unique findings that can be extracted from BS. The literature shows that most CPS studies analyze the process through PS (Dindar, Järvelä, et al., 2020; Dindar, Malmberg, et al., 2020; Sobocinski et al., 2021). As CPS is a process of building a shared understanding (Jermann & Dillenbourg, 2008; Pear & Crone-Todd, 2002), BS can better serve the research, since it can reflect students' cognitive state more accurately (Stuldreher et al., 2020a, 2020b). Most of the studies have a limit on analyzing the original EEG

Table 1 Relationships between EEG bands and brain activities

EEG bands	Related brain activity
Delta (δ)	The unconscious mind, signal detection
Theta (θ)	Positively correlated with cognitive load
Alpha (α)	Negatively correlated with cognitive load, related with mediation
Beta (β)	Related with attention and decision making
Gamma (γ)	Related with multisensory and sensorimotor integration, memory formation, and perceptual binding

signals (Bevilacqua et al., 2019; Davidesco et al., 2019; Dikker et al., 2017). Since different wavebands of the EEG reflect different types of activity in the brain (Alarcao & Fonseca, 2019), analyzing the BS through different wavebands, rather than through the original signal, will help reveal the CPS in more detail.

Methods

Participants

The participants comprised thirty-six undergraduates (15 males and 21 females) from a higher education institution in China. The participants were recruited from one class and were randomly assigned into groups with three students. The average age of the participants was 21.35. All students self-assessed their CPS skills through the social problem-solving inventory revised survey (SPSI–R) (D'Zurilla et al., 2002) during the pretest. Each participant was informed of the purpose and procedure of the experiment, and each signed an informed consent form for the experiment. Everyone became used to wearing an electroencephalograph in class after a semester of adaptation.

Materials

The experiment was carried out in a simulated online CPS environment in a Computer Networking course that adopted a network simulator called Cisco Packet Tracer for online collaboration. The visualization and network simulation tool allows students to construct and program network devices collaboratively and observe the outcomes in a real-time matter.

The CPS task was a simulation task in which students, acting as the network administrators of the school, discussed how to construct a network to enable network interactions among three colleges and, at the same time, to meet the needs of each college for the use of the network. To better solve the task, students needed to consider how to allocate a CIDR address block to three colleges and meet the requirements of the number of IPs in each college. Since each college had different IP numbers and LAN requirements, each student in the group needed to set up a college network and select the right number of routers, switches, and servers. To explore the process of online CPS, the collaborative task was divided into two stages [i.e., the collaborative problem-understanding stage (PUS) and the collaborative problem-solving stage (PSS)] (Jermann, 2004). The problem-solving question given at the problem-understanding stage was "*The university's IT office is going to assign the following subnet, 192.0.64.0/22, to four colleges. As a network administrator of the IT office, you oversee allocating these IP addresses to meet the needs of individual colleges and at the same time, simplify network management and optimize network performance. The total numbers of IP addresses needed by individual colleges are School of Mathematics (required 126 IPs), School of Physics (required 120 IPs), School of Chemistry (required 500 IPs), and School of Biology (required 240 IPs). In addition, each college needs its subnet. You need to work with your group members to compile a table to list the needs of individual colleges after group discussion, including the following table columns— the binary number required for the host number, the design-assigned network number, the subnet mask, the maximum available address, and the minimum available address.*" At the problem-solving stage, each group needs to complete the network configurations of individual colleges and the necessary configurations to enable communications among colleges and devices. All networking tasks were completed on the Cisco Packet Tracer, which allows multiple users to configure a network independently or collaboratively. Therefore, a group can choose to allocate each of the group members different tasks, or they can just work on the same task together, depending on their problem-solving strategies. As part of the learning outcomes, each group needs to complete a network topology for individual colleges with configured network devices, including routers, switches, and end-user devices. All activities were completed fully online and students used the VooV meeting (https://voovmeeting.com/) for group discussion. The tool provided real-time video conferencing with functions of a whiteboard, screen share, and collaborative annotations. All meetings were recorded for discussion content analysis.

The EEG signals were collected through portable EEG devices during the collaborative activity. Both traditional electroencephalograph and portable EEG devices can measure EEG. The portable EEG device has fewer channels than a traditional electroencephalograph, but it offers similar results (Li et al., 2020). Moreover, the portable EEG device is easy to wear, and it can be applied on a large scale in a real classroom environment, which a traditional electroencephalograph cannot do (Xu & Zhong, 2018). In this experiment, we used a type of brain wave monitoring device, the core component of which was the ThinkGear Asic Module (TGAM). The sampling frequency of the device is 512 HZ and, in research, it can be used on the forehead (referred to as the FP1 area in neuroscience) to measure high-precision electroencephalogram signals. The reliability and the accuracy of the equipment have been verified by relevant studies (Rebolledo-Mendez et al., 2009; Yasui, 2009). The device adopted in this study generates the following EEG signals: delta, theta, low alpha, high alpha, low beta, high beta, low gamma, high gamma, attention, and mediation. The first eight signals were separated from the original EEG signal and the rest of the two were computed from the device's built-in algorithms.

Procedure

At the beginning of the experiment, students wore portable EEG devices and were told about the procedure. After that, students had ten minutes to finish the SPSI–R survey. Next, during the problem-understanding stage, each group had fifteen minutes to understand the problem by observing and analytical reasoning before starting with the problem-solving task by experiment design and hypothesis verification. Each of the groups was asked to submit a worksheet that lists key information of their group-generated solution in IP address range, the number of usable devices, subnet masks, broadcast IDs, and network IDs. Then, at the problem-solving stage, each group had another thirty minutes to complete the network configurations on Cisco Packet Tracer. The performance of the group was evaluated by the instructor and two teacher assistants based on the following criteria: (1) whether the group fully listed the overall networking needs and the needs of individual colleges; (2) whether all devices can communicate with each other; (3) whether the network speed is optimized; (4) whether the network layout is easy to manage and maintain. The procedure of the CPS activity is shown in Table 2.

Table 2 Procedures of the CPS activity

Procedure	Time length	Operation
Prepare	5 min	Inform the students of the process and purpose of the experiment, and wear and adjust the EEG equipment for the students
Questionnaire	10 min	The students finish the SPSI–R
Problem-understanding stage (PUS)	15 min	The groups understand the collaborative learning task and answer the questions in the report
Problem-solving stage (PSS)	30 min	The groups work together on the solution and present their solution in the report

Data analysis

Brain to brain synchrony

To compute BS between students, we employed a synchrony measure known as phase locking value (PLV) (Perez et al., 2017), which was calculated for every pair of students in the group, across all brain wavebands. The PLV is an indicator of the level of BS within the value range from zero to one. A higher PLV value means a higher level of BS. This measure reflects the mean phase coherence of angular distribution. The PLV is expressed in Eq. (1), where T is the number of time points, $\varphi_{(t,n)}$ is the phase of trial at time t in band n, in student φ, $\psi_{(t,n)}$ in student ψ.

$$PLV_{(t,n)} = \frac{1}{T}\left|\sum_{t=1}^{T} e^{i(\varphi_{(t,n)} - \psi_{(t,n)})}\right| \tag{1}$$

Statistical analysis

The EEG data were collected during problem-understanding and problem-solving stages, each student collected 45 min of EEG data and generated a record containing all band intensities every second. A total of 97,200 pieces of EEG data were collected in this experiment. This research focuses on the analysis of the characteristics of BS in CPS. To eliminate the interference of the individual signal strength, the intensity of each band was transformed via range transformation (Wang et al., 2021). The PLV was used to measure the level of BS between group members. Therefore, the PLV between any of two students in the same group was calculated.

Results

The characteristics of BS in online CPS

Initially, to analyze the difference in the BS characteristics between the problem-understanding and problem-solving stages, T-tests were conducted to compare BS levels among students between two CPS stages (see Table 3). Table 3 shows there are significant BS level differences in the brain activities including attention (β), mediation (low α), cognitive load (θ and low α), decision making (β), memory (γ), and perception (γ) between CPS stages. In these bands, the problem-understanding stage had a significantly higher BS level than the problem-solving stage.

Table 3 Comparison of BS level between problem-understanding and problem-solving stages

Band	Mean value	Standard value	T	P value
Attention	0.0142	0.0479	1.775	0.085
Mediation	0.0085	0.0470	1.129	0.267
Delta	0.0065	0.0433	0.901	0.374
Theta	0.0152	0.0358	2.539	0.016*
Alpha_low	0.0107	0.0246	2.602	0.014*
Alpha_high	0.0102	0.0346	1.771	0.085
Beta_low	0.0203	0.0300	4.060	0.000*
Beta_high	0.0226	0.0392	3.451	0.001*
Gamma_low	0.0239	0.0409	3.508	0.001*
Gamma_high	0.0290	0.0346	5.025	0.000*

*p < 0.05

Table 4 Results of linear regression in identifying important performance predictors from BS levels in brainwave signals

Band	Beta	T	P
Attention(PUS[1])	− 0.199	− 1.329	0.195
Alpha_low(PUS)	0.256	1.618	0.117
Beta_low(PUS)	− 0.350	− 1.210	0.237
Attention(PSS[2])	− 0.383	− 2.528	0.018*
Delta(PSS)	0.493	2.875	0.008*
Theta(PSS)	− 0.291	− 1.822	0.079
Alpha_high(PSS)	− 0.430	− 1.566	0.129
Gamma_high(PSS)	0.435	2.250	0.033*

[1] PUS: Problem-understanding stage

[2] PSS: Problem-solving stage

*p < 0.05

Secondly, to analyze the relationship between the level of BS and task performance. The linear relationship between task performance and BS in each band was analyzed. The task performance was scores of collaborative task reports graded by the teacher. The dependent variable was task performance. The independent variables were the level of BS in each stage and each band. Factors extracted from the Linear Regression model through the backward method can explain 51.3% of the variances in groups' task performance (see Table 4). Significant factors were the level of BS in brain activities including unconscious mind (δ), attention (attention), memory (high γ), and perception (high γ) at the problem-solving stage.

All of the significant factors were from the problem-solving stage. That means BS levels at the problem-solving stage directly influenced the CPS task performance. Moreover, the synchrony in attention was negatively correlated with the CPS task performance.

The differences in BS between collaborative groups with different CPS skills

To reveal how CPS skills influenced group performance from the aspects of BS levels in different brainwave signals, ANOVA was conducted to compare BS levels of different group constitutions at two CPS stages. To understand the constitutions of students with different CPS skills in groups, the overall average was used as the baseline. CPS skills were higher than the baseline called high CPS students. CPS skills were lower than the baseline called low CPS students. The high group (HG, hereafter) represents a group consisting of all high CPS students, and the low group (LG, hereafter) represents a group consisting of all low CPS students. Then the High-Low Group (HLG, hereafter) represents a group with a mix of high and low CPS students. After random grouping, there were two HGs, one LG, and ten HLGs in this study.

After figuring out the CPS skills of each group, ANOVA was used to analyze the characteristics of BS across different wavebands in different types of collaborative groups. The results are shown in Table 5. It can be found that, at the problem-understanding stage, three types of collaborative groups showed a significant difference in the level of BS in the brain activities including unconscious mind (δ), attention (high β), decision making (high β), memory (high γ), and perception (high γ). At the problem-solving stage, three types of collaborative groups showed a significant difference in the level of BS in the brain activities including unconscious mind (δ), memory (high γ), and perception (high γ). The Scheffe post-hoc method was used for further comparisons. The following bands show significant results.

- The problem-understanding stage
  - Delta: LG > HLG > HG, only LG > HG and HLG > HG were significant

Table 5 Comparison of BS level between different types of groups at problem-understanding and problem-solving stages

Band	F	P-value
Attention (PUS[1])	0.421	0.660
Mediation (PUS)	0.007	0.993
Delta (PUS)	10.369	0.000*
Theta (PUS)	1.731	0.193
Alpha_low (PUS)	2.787	0.076
Alpha_high (PUS)	1.815	0.179
Beta_low (PUS)	1.994	0.152
Beta_high (PUS)	3.963	0.029*
Gamma_low (PUS)	1.123	0.337
Gamma_high (PUS)	4.815	0.015*
Attention (PSS[2])	1.171	0.323
Mediation (PSS)	0.968	0.390
Delta (PSS)	5.594	0.008*
Theta (PSS)	0.696	0.506
Alpha_low (PSS)	0.816	0.451
Alpha_high (PSS)	1.065	0.356
Beta_low (PSS)	2.509	0.097
Beta_high (PSS)	3.285	0.050
Gamma_low (PSS)	1.650	0.208
Gamma_high (PSS)	3.315	0.049*

[1] PUS: Problem-understanding stage

[2] PSS: Problem-solving stage

*$p < 0.05$

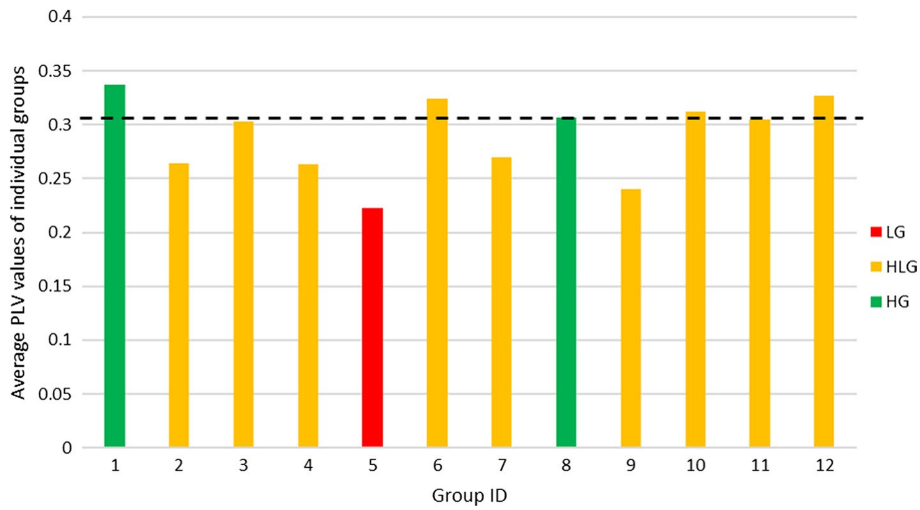

Fig. 1 The mean of PLV values of beta bands at the problem-understanding stage

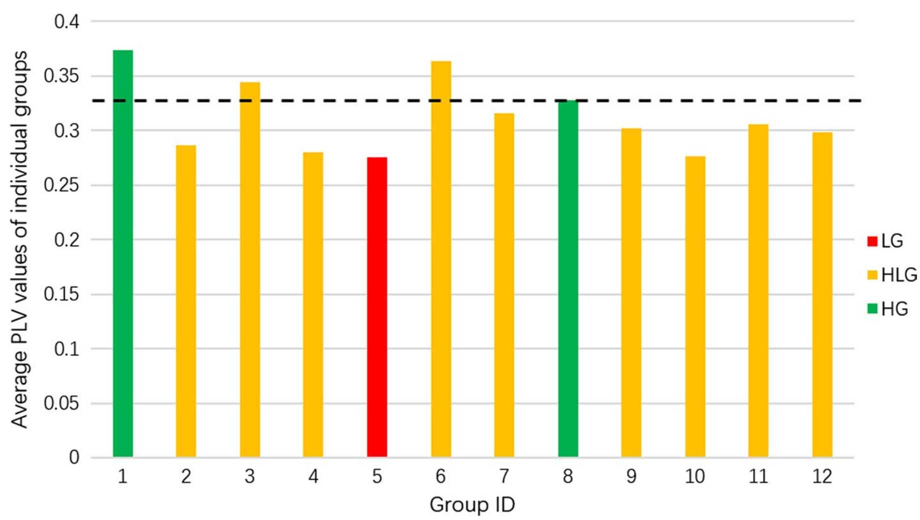

Fig. 2 The mean of PLV values of high gamma bands at the problem-understanding stage

- High beta: HG > HLG > LG, only HG > LG and HLG > LG were significant
- High gamma: HG > HLG > LG, only HG > HLG and HG > LG were significant

- The problem-solving stage

  - Delta: LG > HLG > HG, only HLG > HG was significant
  - High gamma: HG > HLG > LG, only HG > LG was significant

Because Table 5 found significant BS level differences in the following aspects—unconscious mind (δ), attention (high β), decision making (high β), memory (high γ), and perception (high γ), these signals' average PLV values were computed to further explore the characteristics of BS in the HG, LG, and HLG groups. The delta band was excluded from the comparisons because its effect on learning is still unknown.

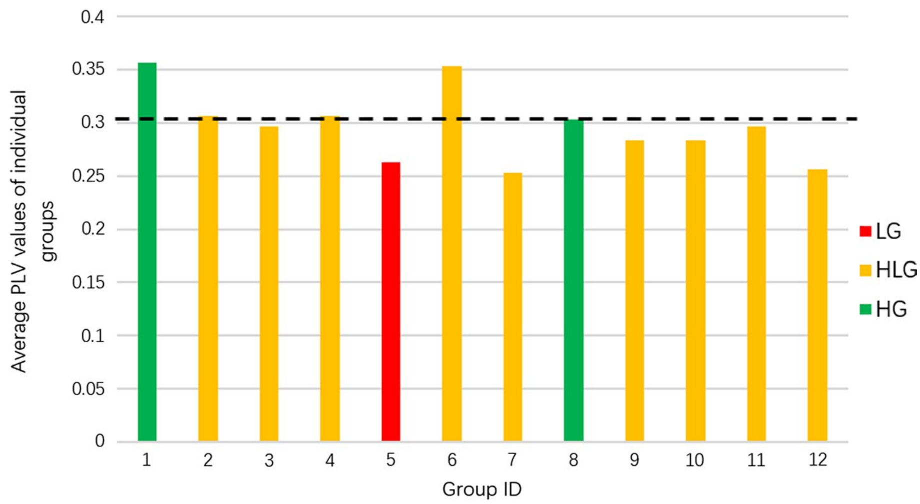

Fig. 3 The mean of PLV values of high gamma bands at the problem-solving stage

Figures 1, 2, 3 compare the average PLV values of individual groups in beta (problem-understanding), gamma (problem-understanding), and gamma (problem-solving) respectively. HG, HLG, and LG are coded in green, yellow, and red. The dashed lines represent the lowest average PLV values among HG groups. Generally speaking, HG groups show higher BS levels and LG groups show lower BS levels in the following aspects—unconscious mind (δ), attention (high β), decision making (high β), memory (high γ), and perception (high γ). However, HLG can be divided into two conditions—HLG with higher BS levels and HLG with lower BS levels. HLG groups with higher BS levels represent the groups' BS levels that are over the dashed line, such as group 3 in Fig. 2. After examining other data, HLG groups with higher BS levels have the following characteristics. Each of the groups contains at least one high CPS skill student. In Fig. 1, the high CPS skill student showed a higher level of beta-band intensity. That means the student was very focused and tended to be positive thinking. The student led the group discussions resulted in a higher BS level. In Figs. 2 and 3, the high CPS skill student showed a higher level of gamma-band intensity. That means the student was trying to understand the discussion contents and recall the knowledge related to the problem.

Qualitative analysis of group discussions

To further validate or interpret analytic results from the EEG signals, all group conversations were recorded and transcribed. The qualitative part mainly focuses on comparing discussion frequencies and contents in HG, LG, and HLG groups. In the previous section, groups of HG, LG, and HLG show significant differences in the following signals—the high gamma (at both stages) and the low beta (at the problem understanding stage). These signals were used to further divide HLG groups into HLG with high BS levels (if the group showed similar average BS levels as the HG groups) and HLG groups with low BS levels (if the group showed lower average BS levels than the HG groups). The results of interaction frequency (see Table 6) show that HG groups had the highest average frequencies of interactions, while LG groups

Table 6 The average number of interaction times in HG, HLG, and LG

Group type	The average number of interaction times		
	At whole process	At PUS[1]	At PSS[2]
HG	490.5	294	196.5
LG	140	35	105
HLG	274.5	100	174.5
HLG with high BS levels	424	170	254
HLG with low BS levels	200	57	143

[1] PUS: Problem-understanding stage

[2] PSS: Problem-solving stage

had the lowest average frequencies of interactions. HLG groups with high BS levels show higher interaction frequencies than HLG with low BS levels. Overall, groups with higher BS levels had intensive oral discussions at both stages. Moreover, HG groups had higher interaction frequencies at the problem-understanding stage than in the problem-solving stage, while the other groups had higher interaction frequencies at the problem-solving stage. From the aspect of discussion contents, HG groups focused on the discussions of knowledge related to the problem-solving, for strategy confirmation or knowledge exchange at the problem-solving stage. For example, HG students had the conversions like "*The maximum address here is 67. So, so the 8-bit is 255.0, right?*" and "*Why do we need to change the subnet mask? I don't think we need to change the subnet mask.*" At the problem-solving stage, in addition to discussing the knowledge related to the problem and the solution, they also frequently shared screens to better explain their ideas or network configurations. On the other hand, the LG groups had fewer oral discussions at both stages. At the problem-understanding stage, LG students mainly discussed task allocation, but not the strategies or knowledge related to problem-solving. At the problem-solving stage, LG students mainly focused on completing their tasks. For example, LG group students had the following conversations. "*What is your gateway?*" and "*I will ping you.*" The HLG with high BS levels had similar collaboration patterns to the HG groups. The HLG groups also focused on the discussions of knowledge related to the problem-solving, for strategy confirmation or knowledge exchange at the problem-solving stage. In addition, the students with high CPS skills led most of the discussions. At the problem-understanding stage, HLG with high BS levels had conversions like "*I don't think the third is 255 since all the ones in front and all the zeros in the back.*" At the problem-solving stage, they discussed the knowledge related to the solution and shared their screens frequently. The HLG with low BS levels acted like the LG group. The students in HLG with low BS levels had little verbal interactions. The students with high CPS skills try to lead the discussion, but other students in the group responded with very short answers and just obeyed the orders without rich discussions. For example, the students with high CPS gave orders "You put in two PCs and one switch. Yeah. Two. Yeah." and "You can click setting, setting, and set the gateway to 192.0.65.1." Another situation in HLG groups with low BS levels is that one student tried to solve the problem alone. There were conversions like "I'll figure everything out and then I'll tell you how to fill the blanks.". Based on the results, HG and HLG with high BS levels had better discussions on the aspects of interaction frequencies and content quality.

Discussion

The problem-understanding stage had a significantly higher level of brain-to-brain synchrony than the problem-solving stage

Table 3 compared the BS levels of different brainwave signals at different CPS stages. Below summarizes significant results and their corresponding brain activities.

- The problem-understanding stage > the problem-solving stage in the following signals:

  - Theta: positively correlated with cognitive load
  - Low alpha: negatively correlated with cognitive load, related with mediation
  - Low and high beta: related to attention and decision making
  - Low and high gamma: related to multisensory and sensorimotor integration, memory formation, and perceptual binding

The problem-understanding stage had a significantly higher level of BS than the problem-solving stage. The significant difference in the gamma band has been analyzed before; students try to understand the same problem, so that has a higher synchronization in memory and perception (Chand et al., 2016; Min et al., 2016). The theta band is positively correlated with the cognitive load (Muthukrishnan et al., 2020). The higher level of synchrony of the theta band at the problem-understanding stage may also be since students read the same question and try to reach a consistent understanding of the question during this process, so they have a higher level of synchrony in the cognitive load. The beta band is related to the attention and decision-making activities of the human brain (Chen & Wang, 2018; Yang et al., 2019). Students at the problem-understanding stage show a higher level of synchrony in this band, which may be because students have common attention objects and are thinking about the same problem. Previous studies showed the BS level is highly corrected with oral interaction. At the problem-understanding stage, students tried to understand the same questions and requirements as a group. However, individual students might be assigned to focus on different tasks at the problem-solving stage. Therefore, the levels of BS were decreased. Because of the characteristic differences between these two stages, it might be better to design a CPS with two or more stages. In addition, supporting or encouraging group discussions is crucial at the problem-understanding stage. Strategies like question prompt or role-play strategies might be used to support group discussions.

The brain-to-brain synchrony of the attention, delta, and high gamma bands at the problem-solving stage is significantly correlated with task performance

Table 4 identified what brainwaves' BS levels are significant predictors at both CPS stages toward the quality of the final solutions proposed by individual groups. Below are summaries of significant performance predictors:

- The problem-understanding stage:
  - None
- The problem-solving stage:
  - Attention (related to focusing attention): the BS is significantly negatively correlated with performance.
  - Delta (related to the unconscious mind, signal detection): The BS is significantly positively correlated with performance.
  - High gamma (related to multisensory and sensorimotor integration, memory formation, and perceptual binding): the BS is significantly positively correlated with the performance.

The results indicate all significant predictors came from the problem-solving stage. The results implied the importance of CPS skills during the problem-solving stage. As each of the group members might be assigned different tasks, how coordinating the collaboration process and integrating everyone's work into the final solution is the key to success. Therefore, group members' CPS skills might play an important role at this stage. The inference is also supported by comparing BS levels and performance among different group constitutions. The BS of Attention at the problem-solving stage is negatively correlated with task performance, which may be because group members no longer need to focus on a specific content together at the problem-solving stage. Instead, individuals focused and worked on different points. The BS in the gamma band at the problem-solving stage is positively correlated with task performance. The gamma band is related to brain memory perception and other activities. The BS in this band indicates that students memorize or understand at the same time when discussing solutions, and such BS in memory and understanding is conducive to collaborative learning. The findings consisted of conclusions from related works. Kwon et al. (2019) found that investment at the problem-solving stage was more conducive to improving collaboration performance than an investment at the problem-understanding stage. Further, through the exploration of the collaborative learning mode, relevant studies have found that the main reason for the difference in the performance of the collaboration group lies in whether the plan is effectively discussed and improved at the stage of problem-solving (Chang et al., 2017; Zheng et al., 2020). In addition, the BS of the delta band is also positively correlated with task performance. Delta band is related to subconscious brain activity (Alarcao & Fonseca, 2019). The meaning of the BS of the delta band and its significance in collaborative learning remains to be further explored.

Since the BS at the problem-solving stage is more important to the performance of collaborative tasks than that at the problem-understanding stage, it is necessary to strengthen students' collaboration in this portion or to add appropriate guidance when designing online collaborative learning. The detection of the BS in online collaborative activities and the intervention based on collaborative efficiency obtained through the BS should also focus on the problem-solving stage.

Different types of collaboration groups have significant brain-to-brain synchrony differences in the delta and high gamma bands during the problem-understanding stage and the problem-solving stage

Table 5 compares the BS levels of different brainwave signals among three group constitutions at both BS stages. The significant signals and their corresponding brain activities can be summarized as follows:

- The problem-understanding stage:
  - Delta (related to the unconscious mind, signal detection): LG > HG and HLG > HG
  - High beta (related to attention and decision making): HG > LG and HLG > LG
  - High gamma (related to multisensory and sensorimotor integration, memory formation, and perceptual binding): HG > HLG and HG > LG
- The problem-solving stage:
  - Delta (the unconscious mind, signal detection): HLG > HG
  - High gamma (related to multisensory and sensorimotor integration, memory formation, and perceptual binding): HG > LG

Only HLG and LG groups had significant BS levels in delta signals. These findings might imply the delta signal is correlated with the low prior CPS experiences or low CPS skills. However, as mentioned earlier, how this signal is related to learning is still unclear (Alarcao & Fonseca, 2019). Therefore, additional studies can be conducted to reveal their relationships. In the high gamma band, the HG had higher BS, indicating that the collaborative group composed of students with high CPS skills had a common focus on memory and the perception of content. In addition, at the problem-understanding stage, the HG had higher BS in the high beta band, which did not appear at the problem-solving stage, indicating that the students in HG had a higher level of synchrony of attention in the problem comprehension. Every group member was clear about their role and tasks.

The high-low groups could have similar brain-to-brain synchrony levels to the high group

By plotting the PLV values and the mean band intensity of any two students in each group (see Figs. 1, 2, 3), it was found that the HLG had polarization in PLV values. In the high beta and high gamma bands of both stages, several of the HLG had similar BS levels to the HG. In these groups, it was found that the students with high CPS skills were more active in brain activity, played a leading role in the process of collaboration, and guided the rest of the students to cooperate. The results consisted of the findings of (Andrews-Todd & Forsyth, 2020), that collaborative groups were more likely to have better academic performance when there was at least one student with strong CPS ability in the group.

The qualitative analyses show that the HG and HLG with high BS levels had higher conversation frequencies and discussion quality, while the LG and HLG with low BS levels had low conversation frequencies and discussion quality. This means that groups with a higher level of BS have more effective interactions. The result validated our findings, (a) BS levels can be an effective indicator to evaluate the process of CPS, and (b) groups with different CPS skills have different characteristics on BS levels. In addition, HLG groups might not always have effective discussions. As HLG might be the most common group constitution in CPS, how to support and facilitate an HLG group conducting effective discussions is important in the CPS activity. Moreover, HG groups had higher interaction frequencies at the problem-understanding than the problem-solving stage, while the other groups had a higher interaction frequency at the problem-solving stage. Based on the conversation observation, HG groups had discussed the problems sufficiently at the problem-understanding stage, so group members mainly focused on the solution-related discussions at the problem-solving stage. On the other hand, the rest of the groups often overlooked or missed some key discussion points at the problem-understanding stage, and had to discuss these missing parts at the problem-solving stage. Therefore, instructors might consider providing additional guidance to support group discussions on the problem-understanding.

A group with only high CPS skill students could have better collaborative performance in online collaborative learning. However, this kind of group is not conducive to the learning of all students. Rather, organizing the group with students at different levels of CPS skills is better for all students and this model can achieve BS levels similar to those of the HG. To make this kind of mixed type group achieve better collaborative performance, it is necessary to conduct effective guidance. How to evaluate the interaction quality through the students' BS levels, and how to provide intervention so that all the groups can better collaboratively learn are questions to be studied.

Limitations

This study also has the following limitations. To capture the actual brainwave activities during the CPS activities, this study did not group students based on their CPS skill levels. The random grouping generated unbalanced numbers in HG, HLG, and LG groups. This study was limited to the maximum number of concurrent Bluetooth device connections, and only recruited thirty-six participants in a computing course (i.e., Computer Network course). Although the sample size is similar to related studies, larger sample size may help to discover more interesting and generalizable findings. In addition, findings in this study might not be generalized to different subject areas.

Conclusion

This study analyzed students' learning processes in the CPS activity from the aspects of cognitive neuroscience. First, BS shows as an effective indicator for observing group interactions during collaborative problem-solving and provides insights for teachers and researchers to further understand the CPS process. Second, the analytic results show common and unique characteristics at the problem-understanding and problem-solving stages. The problem-understanding stage had a significantly higher BS level than the problem-solving stage in most of the EEG bands. The results show expectations and requirements of these two stages are different and might require different CPS skills to achieve better learning outcomes. Therefore, how to support or evaluate individual students at these two stages more effectively would be a follow-up study. BS can still serve as an indicator to observe how personalized supports impact students' EEG signals. Third, although the problem-solving stage had a lower BS level in most of the EEG bands, the results indicate the BS levels at the problem-solving stage directly influenced the CPS task performance. The findings also validated the conclusions from other studies. Finally, groups with higher BS levels showed more effective interactions in terms of discussion frequencies and discussion quality. Instructors should avoid assigning a group with all low CPS skill students or should provide basic CPS skill training before working on the CPS activity. However, this study also found that HLG groups (i.e., a mix of high and low CPS skill students) might lead to totally different interactions. As the combination is likely to be the most common type in practice, how to provide in-time and personalized support to foster effective interactions becomes an important research topic. Future studies can concentrate on the development of early-warning mechanisms or effective discussion interventions by tracking group BS levels, especially focusing on the HLG group constitution.

As an instructional approach, a CPS activity aims to get students engaged in the instructional activity and cultivate students' CPS skills. This study provides evidence from aspects of cognitive neuroscience to support its effectiveness as an instructional approach in online learning. With the development of emerging technologies, more and more wearable devices can be used to track students' physiological changes during the learning process. This study serves as a starting point in this endeavor. More research efforts in this area can be expected in near future.

Abbreviations

CPS	Collaborative problem solving
BS	Brain-to-brain synchrony
EDA	Electrodermal activity
PS	Physiological synchrony
EEG	Electroencephalogram
HG	High group
LG	Low group
HLG	High-low group

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Author contributions
XD conceptualized and designed the work; writing-reviewing and editing; participated in acquisition, analysis, and interpretation of data. JH designed the work; writing-reviewing and editing; participated in analysis, and interpretation of data. LZ designed the work; writing-original draft preparation and editing; participated in acquisition, analysis, and interpretation of data. HL writing-reviewing and editing; participated in analysis, and interpretation of data. HT writing-reviewing and editing; participated in analysis, and interpretation of data. YX participated in analysis, and interpretation of data. All authors read and approved the final manuscript.

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Availability of data and materials
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Declarations

Competing interests
There is no issue related to journal's policy and no conflicts of any potential competing interests.

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References

Alarcao, S. M., & Fonseca, M. J. (2019). Emotions recognition using EEG signals: A survey. *IEEE Transactions on Affective Computing, 10*(3), 374–393. https://doi.org/10.1109/taffc.2017.2714671

Andrews, J. J., & Rapp, D. N. (2015). Benefits, costs, and challenges of collaboration for learning and memory. *Translational Issues in Psychological Science, 1*(2), 182.

Andrews-Todd, J., & Forsyth, C. M. (2020). Exploring social and cognitive dimensions of collaborative problem solving in an open online simulation-based task. *Computers in Human Behavior, 104*, 105759.

Ashwin, T. S., & Guddeti, R. M. R. (2020). Automatic detection of students' affective states in classroom environment using hybrid convolutional neural networks. *Education and Information Technologies, 25*(2), 1387–1415. https://doi.org/10.1007/s10639-019-10004-6

Barron, B. (2003). When smart groups fail. *The Journal of the Learning Sciences, 12*(3), 307–359.

Bevilacqua, D., Davidesco, I., Wan, L., Chaloner, K., Rowland, J., Ding, M., Poeppel, D., & Dikker, S. (2019). Brain-to-brain synchrony and learning outcomes vary by student-teacher dynamics: Evidence from a real-world classroom electroencephalography study. *Journal of Cognitive Neuroscience, 31*(3), 401–411. https://doi.org/10.1162/jocn_a_01274

Care, E., Griffin, P., & McGaw, B. (2012). *Assessment and teaching of 21st century skills*. Springer.

Chand, G. B., Lamichhane, B., & Dhamala, M. (2016). Face or house image perception: Beta and gamma bands of oscillations in brain networks carry out decision-making. *Brain Connectivity, 6*(8), 621–631. https://doi.org/10.1089/brain.2016.0421

Chanel, G., & Muhl, C. (2015). Connecting brains and bodies: Applying physiological computing to support social interaction. *Interacting with Computers, 27*(5), 534–550. https://doi.org/10.1093/iwc/iwv013

Chang, C. J., Chang, M. H., Chiu, B. C., Liu, C. C., Chiang, S. H., Wen, C. T., Hwang, F. K., Wu, Y. T., Chao, P. Y., Lai, C. H., & Wu, S. W. (2017). An analysis of student collaborative problem solving activities mediated by collaborative simulations. *Computers Education, 114*, 222–235.

Chen, C. M., & Wang, J. Y. (2018). Effects of online synchronous instruction with an attention monitoring and alarm mechanism on sustained attention and learning performance. *Interactive Learning Environments, 26*(4), 427–443. https://doi.org/10.1080/10494820.2017.1341938

Chi, M. T., Feltovich, P. J., & Glaser, R. (1981). Categorization and representation of physics problems by experts and novices. *Cognitive Science, 5*(2), 121–152.

Chi, M. T., Glaser, R., & Rees, E. (1981b). Expertise in problem solving.

Critchley, H. D., Eccles, J., & Garfinkel, S. N. (2013). Interaction between cognition, emotion, and the autonomic nervous system. In *Handbook of clinical neurology* (Vol. 117, pp. 59–77): Elsevier.

Critchley, H. D., & Garfinkel, S. N. (2018). The influence of physiological signals on cognition. *Current Opinion in Behavioral Sciences, 19*, 13–18.

Cukurova, M., Giannakos, M., & Martinez-Maldonado, R. (2020). The promise and challenges of multimodal learning analytics. *British Journal of Educational Technology, 51*(5), 1441–1449. https://doi.org/10.1111/bjet.13015

D'Zurilla, T. J., Nezu, A. M., & Maydeu-Olivares, A. (2002). Social problem-solving inventory-revised. *APA PsycTests*.

Davidesco, I. (2020). Brain-to-brain synchrony in the STEM classroom. *CBE Life Sciences Education, 19*(3), es8.

Davidesco, I., Laurent, E., Valk, H., West, T., Dikker, S., Milne, C., & Poeppel, D. (2019). Brain-to-brain synchrony between students and teachers predicts learning outcomes. *BioRxiv*, 644047.

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. *Current Biology, 27*(9), 1375–1380. https://doi.org/10.1016/j.cub.2017.04.002

Dindar, M., Järvelä, S., & Haataja, E. (2020). What does physiological synchrony reveal about metacognitive experiences and group performance? *British Journal of Educational Technology, 51*(5), 1577–1596.

Dindar, M., Malmberg, J., Järvelä, S., Haataja, E., & Kirschner, P. A. (2020). Matching self-reports with electrodermal activity data: Investigating temporal changes in self-regulated learning. *Education Information Technologies, 25*(3), 1785–1802.

Haataja, E., Malmberg, J., & Järvelä, S. (2018). Monitoring in collaborative learning: Co-occurrence of observed behavior and physiological synchrony explored. *Computers in Human Behavior, 87*, 337–347.

Hayes, J. R. (2013). *The complete problem solver*. Routledge.

Herborn, K., Stadler, M., Mustafić, M., & Greiff, S. (2020). The assessment of collaborative problem solving in PISA 2015: Can computer agents replace humans? *Computers in Human Behavior, 104*, 105624.

Jermann, P. R. (2004). *Computer support for interaction regulation in collaborative problem-solving.* Verlag nicht ermittelbar,

Jermann, P., & Dillenbourg, P. (2008). Group mirrors to support interaction regulation in collaborative problem solving. *Computers Education, 51*(1), 279–296.

Kwon, K., Song, D., Sari, A. R., & Khikmatillaeva, U. (2019). Different types of collaborative problem-solving processes in an online environment: Solution oriented versus problem oriented. *Journal of Educational Computing Research, 56*(8), 1277–1295. https://doi.org/10.1177/0735633117740395

Li, Q., Ren, Y., Wei, T., Wang, C., Liu, Z., & Yue, J. (2020). A Learning Attention Monitoring System via Photoplethysmogram Using Wearable Wrist Devices. In *Artificial Intelligence Supported Educational Technologies* (pp. 133–150): Springer.

Min, L., Guang, M., Wenming, Z., Wade, J., & Sarkar, N. (2016). Brain gamma oscillations of healthy people during simulated driving. *Intelligent Robotics and Applications. 9th International Conference, ICIRA 2016. Proceedings: LNAI 9835*, 453–458. https://doi.org/10.1007/978-3-319-43518-3_43

Muthukrishnan, S. P., Soni, S., & Sharma, R. (2020). Brain networks communicate through theta oscillations to encode high load in a visuospatial working memory task: An EEG connectivity study. *Brain Topography, 33*(1), 75–85. https://doi.org/10.1007/s10548-019-00739-3

Nam, C. S., Choo, S., Huang, J., & Park, J. (2020). Brain-to-brain neural synchrony during social interactions: A systematic review on hyperscanning studies. *Applied Sciences, 10*(19), 6669.

Noroozi, O., Pijeira-Díaz, H. J., Sobocinski, M., Dindar, M., Järvelä, S., & Kirschner, P. A. (2020). Multimodal data indicators for capturing cognitive, motivational, and emotional learning processes: A systematic literature review. *Education Information Technologies, 25*, 5499–5547.

Nunez, P. L., & Srinivasan, R. (2006). A theoretical basis for standing and traveling brain waves measured with human EEG with implications for an integrated consciousness. *Clinical Neurophysiology, 117*(11), 2424–2435.
OECD. (2017). PISA 2015 Results (Volume V). Collaborative Problem Solving.
Palumbo, R. V., Marraccini, M. E., Weyandt, L. L., Wilder-Smith, O., McGee, H. A., Liu, S., & Goodwin, M. S. (2017). Interpersonal autonomic physiology: A systematic review of the literature. *Personality Social Psychology Review, 21*(2), 99–141.
Pear, J. J., & Crone-Todd, D. E. (2002). A social constructivist approach to computer-mediated instruction. *Computers Education, 38*(1–3), 221–231.
Pecchinenda, A. (1996). The affective significance of skin conductance activity during a difficult problem-solving task. *Cognition & Emotion, 10*(5), 481–504.
Perez, A., Carreiras, M., & Dunabeitia, J. A. (2017). Brain-to-brain entrainment: EEG interbrain synchronization while speaking and listening. *Scientific Reports, 7*, 12. https://doi.org/10.1038/s41598-017-04464-4
Rebolledo-Mendez, G., Dunwell, I., Martínez-Mirón, E. A., Vargas-Cerdán, M. D., De Freitas, S., Liarokapis, F., & García-Gaona, A. R. (2009). *Assessing neurosky's usability to detect attention levels in an assessment exercise.* Paper presented at the International Conference on Human-Computer Interaction.
Schulze, J., & Krumm, S. (2017). The "virtual team player": A review and initial model of knowledge, skills, abilities, and other characteristics for virtual collaboration. *Organizational Psychology Review, 7*(1), 66–95. https://doi.org/10.1177/2041386616675522
Sharma, K., & Giannakos, M. (2020). Multimodal data capabilities for learning: What can multimodal data tell us about learning? *British Journal of Educational Technology, 51*(5), 1450–1484. https://doi.org/10.1111/bjet.12993
Simon, H. A., & Hayes, J. R. (1976). The understanding process: Problem isomorphs. *Cognitive Psychology, 8*(2), 165–190.
Sobocinski, M., Malmberg, J., & Järvelä, S. (2021). Exploring adaptation in socially-shared regulation of learning using video and heart rate data. *Technology, Knowledge Learning*, 1–20.
Stadler, M., Herborn, K., Mustafić, M., & Greiff, S. (2020). The assessment of collaborative problem solving in PISA 2015: An investigation of the validity of the PISA 2015 CPS tasks. *Computers Education, 157*, 103964.
Stuldreher, I. V., Thammasan, N., Van Erp, J. B., & Brouwer, A.-M. (2020a). Physiological synchrony in EEG, electrodermal activity and heart rate detects attentionally relevant events in time. *Frontiers in Neuroscience, 14*, 1257.
Stuldreher, I. V., Thammasan, N., van Erp, J. B., & Brouwer, A.-M. (2020b). Physiological synchrony in EEG, electrodermal activity and heart rate reflects shared selective auditory attention. *Journal of Neural Engineering, 17*(4), 046028.
Wang, Y. W., Yang, X., Yao, X. Q., & Fu, C. (2021). Computational methods of brain-to-brain coupling during human interaction. *Chinese Science Bulletin-Chinese, 66*(4–5), 501–514. https://doi.org/10.1360/tb-2020-0642
Wen, X. T., Mo, J., & Ding, M. Z. (2012). Exploring resting-state functional connectivity with total interdependence. *NeuroImage, 60*(2), 1587–1595. https://doi.org/10.1016/j.neuroimage.2012.01.079
Xu, J. H., & Zhong, B. C. (2018). Review on portable EEG technology in educational research. *Computers in Human Behavior, 81*, 340–349. https://doi.org/10.1016/j.chb.2017.12.037
Yang, X. M., Zhao, X. S., Tian, X. S., & Xing, B. B. (2019). Effects of environment and posture on the concentration and achievement of students in mobile learning. *Interactive Learning Environments*. https://doi.org/10.1080/10494820.2019.1707692
Yasui, Y. (2009). A brainwave signal measurement and data processing technique for daily life applications. *Journal of Physiological Anthropology, 28*(3), 145–150.
Zheng, Y., Bao, H., Shen, J., & Zhai, X. (2020). Investigating sequence patterns of collaborative problem-solving behavior in online collaborative discussion activity. *Sustainability, 12*(20), 8522.

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