The Promise of Physiological Data in Collaborative Learning: A Systematic Literature Review

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Abstract. Collaborative learning is an important approach in education. Researchers are increasingly interested in using physiological data, such as Electrodermal Activity (EDA), as an objective tool to measure bodily reactions during collaborative activities. However, it remains unclear how physiological data can contribute to our understanding, monitoring and support of the collaborative learning process. To address this gap, a Systematic Literature Review (SLR) was conducted, focusing on the contribution of physiological data to collaborative learning, the features of physiological data that correlate with effective outcomes, and interventions designed to support collaboration based on physiological data. The review identified 13 relevant publications that revealed physiological data can indeed be useful for detecting certain aspects of collaboration including students' cognitive, behavioral, and affective (emotion and motivation) states. Physiological arousal in the form of EDA peaks and physiological synchrony (interdependence or associated activity between individuals' physiological signals) were the most commonly used features. Surprisingly, only one publication presented a prototype of a learning analytics dashboard that used physiological data to guide student reflections. Furthermore, the review highlights the potential for integrating physiological measures with other data sources, such as speech, eye gaze, and facial expression, to uncover psychophysiological reactions and accompanying social and contextual processes related to collaborative learning. Future research should consider embedding methods for the physiological detection and modeling of learning constructs within explicit, feedback-driven interventions for collaborative learning.

Keywords: physiological data, collaborative learning

1 Introduction

Collaboration and collaborative problem-solving (CPS) are increasingly recognized as crucial skills for employment and success in modern society [1]. While, Collaboration involves two or more individuals working together to learn or study a subject [2], CPS refers to the coordinated attempt between two or more people to share their skills and knowledge for the purpose of constructing and maintaining a unified solution to a problem [3]. CPS is thus, at its core, a joint activity that requires the cooperative exchange of information to successfully transform a problem state into a desired goal state. These processes hinges on how well individuals can establish common ground concerning the nature of the problem, develop a solution plan, monitor progress along the way, and accommodate multiple perspectives while respectfully managing disagreements. This requires the ability to understand task goals and constraints and consider others' perspectives and knowledge, along with the ability to communicate this understanding through negotiation, mutual regulation, and shared responsibilities [1]. Hadwin highlights the importance of iteratively fine-tuning cognitive, behavioral, motivational, and emotional states in achieving success within a group, as discussed in socially shared regulation during group interactions [4]. In addition, psychological factors such as cognitive load, attention, and emotion are crucial in the learning process of students, according to Gasevic [5].

Behavioral data captured through log and video recording are commonly utilized in computer-supported collaborative learning. In addition to this objective data, researchers often employ subjective measures such as questionnaires or surveys to gather information about learning constructs that are not directly observable. These measures are commonly used in educational technology research due to their ease and cost-effectiveness [6, 7] and to study constructs related to student engagement and learning, including cognitive, non-cognitive, and meta-cognitive constructs [8–10]. However, subjective measures have two primary limitations. First, they are susceptible to cognitive biases and internal validity issues as the accuracy of responses cannot be easily verified [11]. Second, unlike logs, subjective measures cannot provide continuous and real-time information about users.

The examination of neurophysiological data from individuals, known as neuro measurements, is a different approach for assessing concepts in educational technology and broader information systems. This method has become more prevalent in information systems and has led to the development of a new interdisciplinary field of study called Neuro-Information-Systems (NeuroIS). NeuroIS utilizes neuro measurement tools to collect and analyze neurophysiological data related to the Central Nervous System (CNS) and the Autonomic Nervous System (ANS) of participants, combining knowledge from disciplines such as neurobiology, behavior, and engineering. Riedl et al conducted an extensive review of research on NeuroIS, published between 2008 and 2016, and found that most papers focused on either cognitive or emotional processes [12], which were classified based on Dimoka's approach (cognitive, emotional, social and decision making processes) [13] .

More recently, Schneider and his team conducted a study to investigate how various physiological measures, including EEG (brain), heart rate, and electrodermal activity (EDA), are associated with collaborative outcomes. According to their findings, although physiological data, particularly EDA, are frequently used in research, they are not consistently linked to successful outcomes such as cognitive, affective, and performance outcomes (e.g. completion time, success of task, quality of task, correctness) . They suggested that EDA and the connection to collaborative outcomes could be developed into a collaborative diagnostic system that identifies which outcomes were lacking and which metrics were used to identify them[14].

In another study, Darvishi *et al*. [15] reviewed the literature on physiological measurements in higher education, classified them into ANS (facial expressions, eye movements, heart rate, skin conductance, and blood pressure) and CNS (EEG, fMRI, NIRS, and fNIRS), and mapped them with different types of learning constructs, such as cognitive, non-cognitive, and meta-cognitive. Their findings showed that EEG (CNS) was mainly used to study cognitive constructs, while ANS-related measurements were used to investigate non-cognitive constructs. Recent research has focused on measuring ANS activity because it is less invasive than CNS measures such as EEG. Additionally, advances in ANS measurement instruments have made them more reliable, portable, and affordable.

NeuroIS research suggests that while the relationship between neuro measurements and constructs is intricate, it is possible to capture psychological constructs with neuro measurements. This has the potential to overcome the two limitations of subjective measures. Specifically, it can (1) quantify constructs that cannot be measured accurately with self-reporting techniques and (2) provide nearly real-time and continuous information about a user's psychological constructs [12]. Cognitive outcomes and affective states are notable examples of constructs that can be effectively captured through physiological measures [15].

For instance, collaboration often involves synchrony, an important group feature [16]. While some synchrony behaviors, such as joint attention, are directly observable, others are detected through the physiological responses of group participants. Some research has indicated a positive correlation between physiological synchrony and collaborative learning features, including willingness to collaborate, score of the collaborative report delivered by students, and sum of the individual learning gains [17]. Furthermore, physiological synchrony has been linked to stress [18, 19] and emotional changes [20]. However, as already mentioned, Schneider pointed out that physiological data, including synchrony, has not been consistently associated with cognitive and affective constructs [14]. This raises the question of what physiological data features and metrics researchers can use as a proxy for learning constructs. Additionally, researchers are interested in integrating physiological measures with other types of data to gain a more comprehensive understanding of collaborative learning, known as multimodal analysis.

After detecting and modeling learning constructs, interventions such as feedback and adaptive systems can be developed [15]. High-quality actionable feedback has been shown to positively impact student reflection, performance, and achievement [21]. One potential usage of physiological data is to measure arousal, which indicates excitement and stress levels during learning. Students can utilize this data for reflection purposes, both individually and collaboratively as a group[18]. However, previous research has identified several limitations of current Learning Analytics (LA) to provide effective feedback, including difficulty for non-data experts to understand, ineffective communication of insights, provision of meaningless information, and lack of meaningful impact on education[22]. These challenges might be even more obvious when physiological data is used due to its high frequency, noisy, and difficult-to-interpret nature.

In this paper, our goal is to conduct a systematic review of literature, focusing on three primary areas: (1) investigating how physiological data can help identify learning constructs related to cognition, behavior, and emotion; (2) identifying physiological data metrics and features that serve as indicators for these constructs; and (3) examining the phase where physiological data can be utilized as one of the metrics to support learning interventions.

2 Methods

This systematic literature review (SLR) follows the guidelines of the PRISMA statement [23]. All articles that used physiological data to research collaborative learning were initially within the scope of this review. We restricted our search to a timeframe from 2012 to 2022, knowing that more studies were adopting physiological data collection technologies over the past ten years. Additionally, we concentrate our studies on the ANS (Autonomic Nervous System) rather than the CNS (Central Nervous System).

As already mentioned, our focus in investigating physiological data in collaborative learning will be framed in to three research questions (RQ):

1. What is the contribution of physiological data to our understanding of collaborative learning?
2. What physiological data features correlate with effective collaborative learning outcomes?
3. What interventions are designed to support student learning based on insights from physiological data?

2.1 Search Method

During the identification step, records are identified by database searching utilizing search terms. We conducted our search in the SCOPUS and Web of Sciences (WoS) databases due to their extensive coverage of peer-reviewed academic publications pertinent to the topic of our study as well as their usability as SLR search engines.

The search terms were formulated based on the review's scope and research questions (Table 1). Duplicate items were deleted before the screening step and then title/abstract screening was conducted. In the eligibility step, full-text articles were examined using inclusion–exclusion criteria. The scope of the review determined which papers were included.

A set of search terms was developed based on themes derived from the three research questions above, which are outlined in Table 1.

Table 1. Search Term Structure

Research Question Theme	Search Terms
Physiological data	• “physiological data” OR • “skin temperature” OR • “heart rate” OR • “electrodermal activity” OR • “EDA” OR • “body temperature” OR • “blood volume pulse” OR • “blood pressure” OR • “skin conductance” OR • “multimodal” OR • “multimodal data” OR • “multi channel data” AND
Collaborative Learning	• “learn” OR • “educate” OR • “collaborate” OR • “collaboration learning” OR • “regulated learning” OR • “computer-supported collaborative learning*” OR • CSCL OR • “Socially shared regulation” AND
Learning Outcome	• “learning outcome” OR • “educational outcome” OR “learning output” OR • “educational output” OR • “learning objective” OR • “educational objective” OR “learning performance” OR • “academic achievement” AND
Intervention	• “intervention” OR • “supporting” OR • “feedback” OR • “understand” OR • “improvement” • OR “enhancement”

As such, our query was designed to find papers on physiological data in collaborative learning and the interventions used to enhance collaboration quality or learning outcomes. Upon reflection on initial limited results, we deemed that we should modify our search strategy. After further discussion, we decided to conduct a 2nd search by limiting the search terms to only two themes, namely physiological data and collaborative learning. We also indicated to the database our categories in educational research/education scientific disciplines/psychology education/education special. For full search strings both of 1st and 2nd round search, please refer to our supplementary materials document (link provided after the references).

Below, we outline the data items (metrics) that were extracted from each study, structured based on the general characteristics of studies and our three research questions. An overview of our research questions and corresponding metrics is given in Table 2.

Table 2. Overview of Research Questions and Metrics

Question	Label
General Characteristic	1. Learning Environment 2. Learning domain 3. Collaboration Types 4. Collaboration Scenario 5. Group Counts 6. Group Size
What is the contribution of physiological data to our understanding of collaborative learning?	1. Psychological Construct 2. Construct Label 3. Sub Construct 4. Independent Variables 5. Dependent Variables 6. Contribution of Collaborative Learning
What physiological data features correlate with effective collaborating learning outcomes?	1. Construct to investigate 2. Physiological data analysis 3. Indices correlate with effective collaborative learning outcome 4. Multimodal data 5. Physiological Indices
What interventions are designed to support student learning based on insights from physiological data?	Type of Intervention/Support

We divided *learning environment* into three categories: online, face-to-face/co-located learning, and blended learning. *Learning domain* is the domain subject being taught/discussed. *Collaboration type* in this paper divided into three: verbal interaction, hands-on activity, and virtual experimentation. With regards to *collaboration scenario*, we used the 13 collaboration scenarios proposed by Praharaj [2]. *Group counts* refers to the total number of groups used as the experimental sample, while *group size* refers to the number of group members.

2.2 Data analysis for RQ1

To better understand the contribution of physiological data in collaborative learning, we are using Darvishi classification that categorized psychological constructs into three high level groups of cognitive, non-cognitive and meta-cognitive constructs[15]. The cognitive construct includes attention, cognitive load, and skill; the non-cognitive construct includes attitudes and beliefs, social and emotional factors, habits and processes, and personality traits, based on the work by Lipnevich et al [24] and the meta-cognitive construct includes knowledge about cognition and self-regulation of cognition.

For further clarification, we have categorized an exploratory independent and dependent variable, which can be found in Table 1 of our supplementary material. Additionally, we have described the contribution of collaborative learning, which is the finding of each paper.

2.3 Data analysis for RQ2

To facilitate effective collaboration, it is essential for team members to engage in joint attention, transactive interaction (i.e., building on each other's ideas), and behavioral synchronicity [25, 26]. The purpose of this inquiry is to provide an overview of the construct being studied (cognitive, behavioral, affective), the physiological data being analyzed (arousal and synchrony), and the indices that correlate with effective collaboration and learning outcomes (exploratory). In addition, we created a data table (Table 2 in supplementary material) that combines subjective, objective, and physiological data to better understand collaborative learning through the lens of multimodal data.

2.4 Data analysis for RQ3

High quality actionable feedback can have a strong positive effect on student reflection, performance, and achievement[21]. Therefore, we are interested in identifying what kind of feedback have been developed based on insight from physiological data.

2.5 SLR Procedure

A visual representation of the study selection process under PRISMA statement can be found in Figure 1.

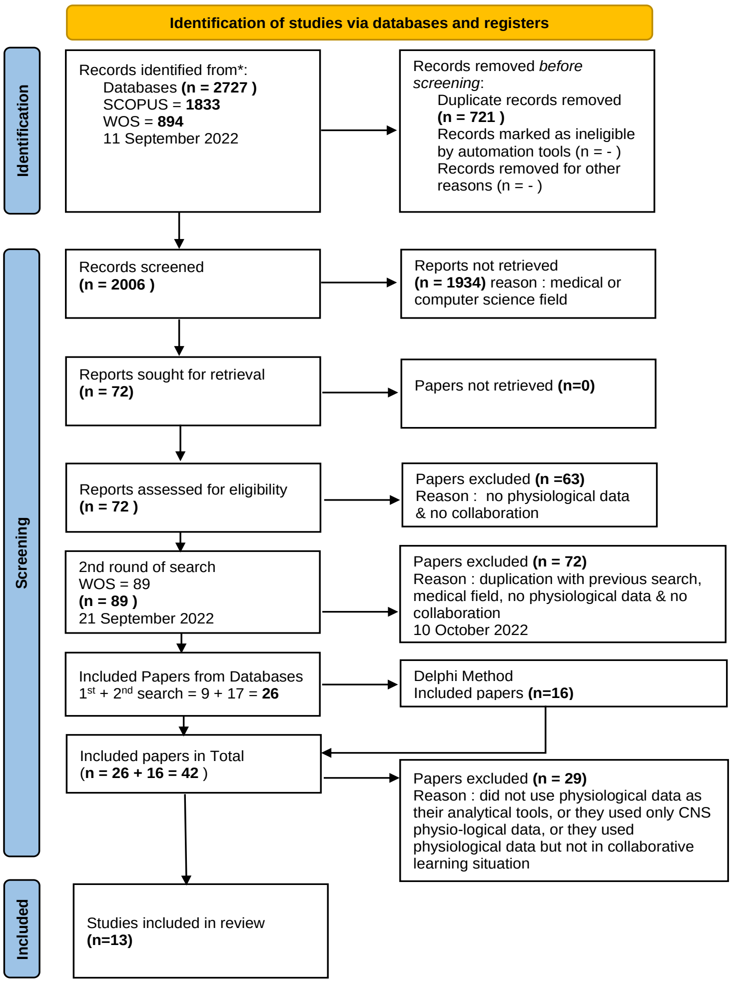

Fig. 1. PRISMA diagram showing SLR Procedure

2.6 Excluded and Included Studies

A search was conducted on WoS and Scopus, resulting in 894 and 1833 papers respectively. After eliminating 721 duplicates and conducting a preliminary screening, 72 articles were left. After a second search on WoS and parallel exclusion verification with a second researcher, 42 papers were selected for full-text review. Of these, 29 papers did not use physiological data as their analytical tools, used only CNS physiological data, or did not involve physiological data in a collaborative learning situation. The remaining 13 papers were included in the study.

2.7 General Characteristics of studies

Learning Environment and Learning Domain. Most of the learning environments were face-to-face/co-located learning with the help of computer supported collaborative learning (CSCL) (n=11), the rest were face-to-face/co-located learning without CSCL (n=2). The most common subject/learning contexts were business simulation (n=3) and nutrition (n=3). Other subjects included nursing, advanced physics course, impact of social media, programming and strategic management of information system.

Collaboration Type and Collaboration Scenario. The papers identified verbal communication as the primary collaboration type (n=9), followed by hands-on activities (n=4). Among collaboration scenarios, learning and knowledge acquisition was the most frequently used (n=7), followed by collaborative problem solving (n=3). Two papers focused on healthcare simulation and one on programming as collaborative scenarios.

Group Counts and Group Size. Dyadic and Triadic (2-3 group members) collaboration was the most common grouping of the research conducted (n=10), while only two studies looked at groups of 4-5 members and one study examined groups of up to 6 members.

3 Results

3.1 RQ 1. What is the contribution of physiological data to our understanding of collaborative learning

To answer the research question, we first explore and categorize the synthesis of studies on collaborative learning into psychological constructs as categorized by Darvishi[15], and further detailed into their respective sub-constructs. Our analysis reveals that the *emotional* sub-construct, including stress, emotional state, challenge, and engagement, has been the most extensively studied (n=5), followed by the *cognitive* sub-construct of learning gain (n=4) and the *meta-cognitive* sub-construct of monitoring (n=4).

We then delve deeper into the contribution of physiological data to collaborative learning by breaking it down into independent and dependent variables and mapping it to the learning constructs of cognitive, affective, and behavior. Most of the reviewed papers utilize Electrodermal Activity (EDA) as an objective measure to detect affective constructs such as stress [18, 19], emotion [20, 27], and mental effort [28]. Other contributions include the detection of cognitive aspects such as learning outcomes [17], learning gain, and collaboration quality[29]. Several papers also focus on metacognitive monitoring using physiological data[30–32].

3.2 RQ 2. What physiological data features correlate with effective collaboration learning outcomes?

Regarding physiological data, all papers reviewed utilized physiological arousal and synchrony as the primary proxies to detect learning constructs. In cognitive constructs, EDA Peak [33], [31], Directional Agreement (DA) [17], [29], and Single Session Index (SSI) [31], [32] are the most commonly used indices (2 papers each), followed by Instantaneous Derivative Matching (IDM) [17], Pearson Correlation (PC) [29], Shared Physiological Arousal Events (SPAE) [34], and Hidden Markov Model (HMM) [30] (1 paper each). All indices, except for SPAE and HMM, showed a positive relationship with measuring cognitive constructs.

In affective constructs, EDA Peak is used in three papers [18, 19, 31], while SSI [31, 32] and Multidimensional Recurrence Quantification Analysis (MdRQA) [27, 28] are used in 2 papers each, IDM [20] and SPAE [34] are used in 1 paper each. All the metrics showed positive correlation with affective or emotional constructs, for instance EDA Peak to detect stress-related incidents, IDM as a gauge for emotional changes, and MdRQA change refer to the groups' collective mental effort.

In terms of behavior constructs, one paper [31] utilized EDA Peak and SSI. The results indicated a correlation between EDA Peak and behavior in monitoring situation (awareness of learning progress against learning goals in socially shared regulation phase) but there was no straightforward connection between monitoring events and SSI.

Multimodality refers to the use of multiple sources of data to gain a more complete understanding of a particular phenomenon. In the context of research papers, 10 studies have utilized video data in combination with EDA (Electrodermal Activity) data to collect observational activities such as dialogue (voice/speech) [17, 18, 27, 29–35], facial expressions [33, 35], and gaze recognition [20]. Four of these studies collected objective data in the form of pre and posttests [17, 18, 29, 32], while four papers used subjective data in the form of self-report questionnaires [17, 28, 32, 33].

In general, cognitive, affective, and behavioral constructs exhibited a positive correlation with physiological data indices, including EDA Peak, SSI, and IDM. It is important to note most of these studies were conducted in a laboratory setting (classroom-like research space) and the majority of them focused on small-sized groups consisting of 2-3 members per group.

3.3 RQ 3. What interventions are designed to support student learning based on insights from physiological data?

Only one study by Fernandez-Nieto et al. [18] was discovered that examines interventions designed to support student learning through the utilization of insights derived from physiological data. This paper aims to provide actionable feedback to students during clinical training by utilizing multimodal data, including EDA, observation logs, and video, through the means of data stories and learning analytics. The feedback is designed to support students directly in their learning process. The role of physiological data is to leverage changes in physiological arousal to detect stress-related incidents and present this information visually to students. During reflection sessions, students found the use of data stories to be beneficial. The data stories helped guide the students' reflections on the evidence by simplifying the representation of complex data, which reduced the likelihood of incorrect interpretation. Moreover, the students recognized and valued the advantages of enhancing the timeline of action with explanatory annotations and visual elements. These annotations and visual elements clarified the errors they made and the extent of their arousal during the reflection process. As a result, students used these stories to reflect on their arousal status and understand the reasons behind their feelings of excitement or stress during specific periods of time. The intention behind using these tools was to enhance the provision of feedback by utilizing concrete evidence rather than solely relying on the teacher’s memory during debriefing sessions. The ultimate aim was to improve student’s clinical practice.

4 Discussion

In previous research on collaborative learning, physiological data has mainly been used to measure affective (e.g., stress, emotions) and cognitive (e.g., mental effort, learning outcomes, learning gain, collaboration quality) aspects of learning. This is in line with a previous literature review by Riedl, which found that out that, out of 103 empirical papers in NeuroIS research from 2008-2016, 50% focused on cognitive processes and 32% on emotional processes [12]. Another recent literature review from 2014-2018 on the use of neuro measurement, specifically skin conductance, showed that 5 articles studied non-cognitive constructs such as social and emotional processes, while 2 articles researched cognitive constructs such as attention and cognitive load [15].

Regarding physiological data features that are associated with successful collaborative learning outcomes, physiological arousal and synchrony were the main factors identified through various indices including EDA peak, DA, SSI, IDM, SPAE, HMM, PC, and MdRQA. Many of these indices were created by researchers themselves, and most of them have been evidenced to be useful predictors of specific learning constructs. However, these findings appear to contradict the results of a previous systematic literature review by Schneider [14], who examined 74 papers published between 2010 and 2020. According to Schneider's review, physiological data is commonly used in research to identify the link between metrics and outcomes, such as the relationship between EDA and affective or cognitive engagement. However, the review found that metrics were more often unsuccessful in establishing such associations [14]. The observed differences may be attributed to researchers currently using more stable indices compared to previous studies. Another point to note is that, currently, there are no studies that can align physiological data features or characteristics with a collaboration quality framework. A few noteworthy examples are the rating scheme in computer-supported collaboration processes quality [36] and the more recent studies by Chen Sun et al., who developed a generalized competency model of collaborative problem solving [1]. Both of these studies utilized primarily verbal (utterance/dialogue) and non-verbal behavioral data, captured through video and audio recordings, which served as indicators of collaboration quality. It would be intriguing to explore in the future whether physiological data features can be incorporated as additional indicators within a collaboration quality framework.

In addition, ten studies were identified that leveraged both video and EDA data to observe various activities such as dialogue, facial expressions, and gaze recognition. These studies were made possible by the development of machine learning algorithms that enable automatic detection of these behaviors. Video data is easy to be collected, is unobtrusive, and is frequently combined with speech/voice recognition for the analysis of the dialogue that occurred during collaborative learning. The increasing use of multimodal data is a positive sign that researchers are using different sources of data to gain a more comprehensive understanding of collaborative learning [37, 38].

However, only one study was found that used physiological data to provide feedback to students on their learning [18]. This study used a combination of multimodal data, including EDA, observation logs, and video, to provide students with actionable feedback on their learning process. Our results suggest that more research is necessary to investigate how to effectively incorporate physiological data into feedback interventions for students, to complement existing learning analytics.

4.1 Limitation and Further Research

This review has a few limitations that are worth acknowledging. Firstly, we only searched for papers in WoS and Scopus databases, which means we may have missed some papers that were published elsewhere. Secondly, we used a specific framework to classify the learning construct based on physiological data, and other frameworks may have different classifications. Despite its limitations, this review has provided significant insights into the role of physiological data, particularly EDA, in collaborative learning.

Future research should explore how physiological data, such as EDA, can be used to create feedback mechanisms that help students reflect on their learning and make adjustments to their collaborative behavior. This could lead to more effective and efficient learning, as well as improved collaboration skills among students.

5 Conclusion

This systematic literature review highlights the growing interest in utilizing physiological data, particularly Electrodermal Activity (EDA), in the study of cognitive and emotional processes related to collaborative learning. The use of EDA has been shown to measure stress, emotions, mental effort, learning outcomes, learning gain, and collaboration quality. Physiological arousal and synchrony were identified as the main factors associated with successful collaborative learning outcomes, as measured by various EDA indices. However, the effectiveness of these metrics in establishing associations between EDA and learning outcomes has been debated, with some studies showing limited success in this area. While there is limited research on using physiological data to provide feedback to students on their learning, there is a clear need for further exploration of this area to complement existing learning analytics.

6 Acknowledgements

This research was partially funded by The Indonesia Endowment Fund for Education (LPDP) and the European Union's Horizon 2020 research and innovation programme under grant agreement No 101004676.

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Supplementary Material: Supplementary Material (The Promise of Physiological Data in Collaborative Learning).pdf