Detecting shared physiological arousal events in collaborative problem solving

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ARTICLE INFO

Keywords:
Collaborative problem solving, physiological arousal
Multimodal data
Sequential analysis
Learning analytics

ABSTRACT

Collaborative problem solving (CPS) is a cyclical process in which team members go back and forth between various cognitive and affective phases as they interact with the problem state and each other. An increasing amount of research has been conducted to explore how sequential relationships between the CPS phases affect team performance outcomes. However, detecting CPS phases mainly relies on labor-intensive methods, such as video coding of all team interactions during the problem-solving process. Furthermore, it is challenging to understand the level of sharedness or togetherness among the team members when they go through a specific CPS phase. Consequently, this study aimed to investigate shared physiological arousal events (SPAE) in CPS. We developed and implemented a new method for detecting SPAEs during CPS by utilizing skin conductance response data. Our findings showed that SPAE can be a promising method for detecting the cognitive and socio-emotional CPS phases that are demonstrated as increasing physiological arousal among the team members. Process-mining analysis of the SPAEs revealed different sequential pathways among the successful and less successful teams both in terms of the CPS phases and the problem variables they address during SPAEs. The current study contributes to the timely agenda of CPS and collaborative learning fields in developing multimodal methods to unearth complex team interaction processes during collaboration.

1. Introduction

Collaborative learning can be considered to be a social system in which groups of learners work together to solve problems or construct knowledge (Roschelle & Teasley, 1995). Sharedness is an essential feature of collaborative learning. To succeed in collaboration, learners should develop shared goals (Hadwin, Järvelä, & Miller, 2017), build shared mental representations about the task condition (Fischer & Mandl, 2005; Gijlers & de Jong, 2009), partake in shared monitoring and regulation of the team progress (Zheng, Xing, & Zhu, 2019), share resources, skills, and responsibilities (Griffin, McGaw, & Care, 2012; OECD, 2013), facilitate sharing of positive feelings within the team (Järvenoja, Järvelä, & Malmberg, 2020), and share task outcomes (Johnson & Johnson, 2009). Therefore, studying shared experiences, processes, and artifacts in collaborative settings can provide valuable insights about the quality of collaboration within a team.

In recent years, there has been a growing interest in studying sharedness in collaborative processes by utilizing physiological measures. New technologies allow for unobtrusively capturing the physiological signals of team members as they collaborate on a task. This makes it possible to observe the extent to which collaborative processes are shared by team members by looking at the correspondence between their physiological signals. For example, several studies have employed a variety of methods to identify the extent of physiological synchrony between collaborating students (Dindar et al., 2020b; Pijeira-Díaz, Drachsler, Järvelä, & Kirschner, 2016; Schneider, Dich, & Radu, 2020). However, previous research has primarily utilized methods that yielded metrics about the overall PS within a team during some segments of the collaboration episode or the entire event (Dindar, Alikhani, Malmberg, Järvelä, & Seppänen, 2019; Pijeira-Díaz, Drachsler, Järvelä, & Kirschner, 2016; Schneider, Dich, & Radu, 2020). A current gap in the literature is the lack of studies on how to utilize physiological data to provide temporal information about collaboration. That is, detecting the moments that represent sharing of a specific collaborative process by all team members. Further, the prominent physiological synchrony measures combine the correspondence between the signals of interacting individuals during both high and low arousal episodes when calculating physiological synchrony. However, research has shown that high and...
low arousal indicates different cognitive (e.g. active or passive participation) and affective (enjoyment or boredom) states in learning settings (Pijeira-Díaz et al., 2018). Therefore, another significant gap in the field is development of physiological synchrony metrics that can represent synchrony during high and low arousal moments separately.

A major aim in collaborative problem solving (CPS) (Acronyms and abbreviations used in this study are presented in Table 1) research has been to identify the collaborative processes that lead to successful problem solving (Meier, Spada, & Rummel, 2007). Based on this aim, several frameworks have been developed to explain the distinct qualitative phases in CPS, specifically by focusing on team interaction (Fiore et al., 2010). In general, CPS phases refer to the sub-periods teams go through from the beginning to the end of a problem-solving task (Bales & Strudtbeck, 1951). For example, these phases can be: exploring and understanding, planning and executing, representing and formulating, and monitoring and reflecting (Caspó & Funke, 2017). It is known that CPS is an iterative process in which teams go back and forth between different phases iteratively until the task is completed (Fiore, Rosen, Burke, & Jennoch, 2008). However, in previous studies, limited attention has been given to the sequential relationships between the CPS phases (Wiltshire, Butner, & Fiore, 2018). This is partly due to the challenges of capturing the CPS phases that are qualitative in nature (Gorman, Cooke, Amazeen, & Fouse, 2012). Previous studies have responded to this challenge by utilizing various data modalities, such as log data (Yang, Li, Guo, & Li, 2015) and video data analysis (Dindar et al., 2019; Wiltshire et al., 2018) of team interaction. However, the potential of physiological data in identifying CPS phases has only been explored to a limited extent.

Building on the aforementioned methodological and theoretical challenges in CPS research, the current study developed and implemented a new method to identify the shared physiological arousal events (SPAE) during collaboration and determine the extent of sharedness among team members during the CPS phases. As we will explain further, SPAE refers to a collaborative moment that is reflected as increased physiological arousal in all team members. Based on the electrodermal activity of the team members, the proposed method allows for identifying the temporal location for each SPAE in a CPS episode. To develop an understanding of the relationship between SPAE and the CPS phases, a video analysis was conducted on the SPAE of 18 groups of university students as they collaborated on a computer-based problem-solving task. Furthermore, process-mining analysis was conducted to observe the temporal relationships between the CPS phases and the problem variables across successful and less successful teams. In the following section, we discuss the nature of CPS, the phases of CPS, and the importance of studying the CPS phase transitions. We also present the state-of-the-art research on physiological arousal in collaborative learning and problem solving.

2. The nature of CPS

CPS is the shared pursuit of team members working together to transform a problem state to a desired goal state. The shared nature of CPS is built on the interactions among the team members engaging in various cognitive states (e.g., knowledge construction, negotiation, coordination, and monitoring of problem-solving strategies) and relational states (e.g., maintaining a positive team atmosphere and dealing with conflicts) (Janssen et al., 2012; Sun et al., 2020). For successful collaboration, team members should regulate their cognitive and relational states, and actively participate in co-construction of knowledge and meaning making by attending to each other’s views, ideas, and feelings (Hadwin et al., 2017; Hesse, Care, Buder, Sassenberg, & Griffin, 2015).

CPS is not a unified process. Team members engage in various phases until they reach an optimum solution. There is no consensual framework on CPS phases (Sun et al., 2020). Several frameworks have been proposed to explain the specific phases that are the indicators of effective problem solving. For example, according to the joint problem space model, monitoring of divergence in understanding and cognitive convergence on task goals, problem state, and possible solutions are the crucial phases of CPS (Roschelle & Teasley, 1995). Another prominent model, Macro Cognition in Teams, summarizes the CPS phases as: “knowledge construction, problem model development, team consensus, outcome evaluation and revision” (Fiore et al., 2010). The Socially Shared Regulation of Learning framework has often been applied in the CPS context. According to that framework, team members go through the phases of task understanding, planning, task enactment, and reflection and adaptation when solving problems collaboratively (Hadwin et al., 2017). The Assessment and Teaching of Twenty-First Century Skills framework explicates the essential phases of CPS as identifying the problem situation, gathering and evaluation information to develop solutions, and conducting strategic problem solving (Griffin et al., 2012). From the perspective of the Generalized Competency Model of Collaborative Problem Solving, the phases of CPS are constructing shared knowledge, negotiation and coordination of solution plan, and sustaining team dynamics (Sun et al., 2020). The team process model asserts that the basic phases in CPS are transition (i.e., mission analysis and planning), situation awareness, information transfer, and tactics application (Hagemann & Kluge, 2017). In addition to these frameworks, Gijlers and De Jong (2009) listed the transformative phases in inquiry-based collaborative problem-solving tasks as orientation, proposition generation, experimentation, and interpretation and conclusion.

Among others, the Program for International Student Assessment (PISA) CPS framework can be considered to be the most widely applied model for measuring CPS competencies due to its worldwide utilization in Organization for Economic Cooperation and Development PISA tests. According to the model, the basic cognitive phases in CPS are defined as exploring and understanding, representing and formulating, planning and executing, and monitoring and reflecting (OECD, 2017). Exploring and understanding involves gaining an understanding of the problem by focusing on the initial information that is present in the problem state. Representing and formulating refers to the selection, organization, and integration of information with prior knowledge. Representing and formulating includes representing information in symbols, words, graphs, and other visual forms, and formulating hypotheses. Planning and executing comprises processes about defining the goals and sub-goals for the problem solution and developing strategies to reach the goals. Monitoring and reflecting consists of evaluating the current situation in relation to the plan, reflecting on the applied strategies, and identifying other possible solutions. According to the framework, successful teams apply some specific collaborative skills (e.g., establishing and maintaining team organization) when going through these CPS phases.

Overall, the underlying processes of CPS are similar among the prominent frameworks in the literature (Sun et al., 2020). They all emphasize that students’ cognitive (i.e. task regulation, knowledge construction, and knowledge application) and social skills (i.e. participation and social regulation) are paramount for effective collaboration (Griffith et al., 2012). Team members should deliberately participate in constructive interactions in each CPS phase to succeed in solving problems together. However, the frameworks differ from each other in terms of focus and complexity. For example, Joint Problem Space model focuses on social aspects of CPS (Teasley et al., 2008). It does not explicate the cognitive CPS phases (e.g. knowledge construction) in detail. Macro Cognition in Teams, Team Process, and Transformative Phases In Inquiry-Based Collaborative Problem-Solving are built from a cognitive perspective and explicates the cognitive mechanisms of CPS.

### Table 1

| Acronym    | Term                                      |
|------------|-------------------------------------------|
| CPS        | Collaborative problem solving             |
| SPAE       | Shared physiological arousal event        |
| PISA       | Program for International Student Assessment |
| SCR        | Skin conductance response                 |
while paying less attention to social regulation in teams. Socially Shared Regulation of Learning, Assessment and Teaching of Twenty-first Century Skills, Generalized Competency Model of Collaborative Problem Solving, and PISA Problem Solving frameworks define both cognitive and social dimensions that underlie the CPS phases. However, CPS phases in Generalized Competency Model of Collaborative Problem Solving and Assessment and Teaching of Twenty-first Century Skills frameworks are defined at a macro level compared to Socially Shared Regulation of Learning and PISA problem solving frameworks. PISA Problem Solving Framework includes the core aspects of Socially Shared Regulation of Learning (OECD, 2017). Therefore, PISA collaborative problem solving has been found as the most comprehensive framework for the purpose of current study.

CPS is a cyclical process. During collaboration, team members go back and forth between different phases in order to adapt to the changes in the condition of the problem (Hagemann & Kluge, 2017; Kapur, 2011). Research on self-regulated learning has shown that the sequential order of the CPS phases might represent the quality of collaboration better than the frequency of their occurrences (Schoor & Bannert, 2012; Sobociński, Malmberg, & Jarvelä, 2017). Therefore, there has been increasing emphasis on studying the CPS phases with respect to their temporal and sequential order. For example, (Chang et al., 2017) compared the CPS phases for successful and less successful teams in a collaborative simulation. Their findings revealed significant transitions between monitoring and reflecting, representing and formulation, and exploring and understanding among the successful teams. Among the less successful teams, the only significant transition was observed between monitoring and reflecting and planning and executing. Their findings showed that less successful teams embraced a trial-and-error approach; the successful teams applied more analytical reasoning by visiting multiple CPS phases. (Zhu, Xing, & Popov, 2019) studied patterns of the CPS phases for successful and less successful teams in a physics task simulation. Their findings revealed that the probability of transitions between the proposition generation-orientation, interpretation and conclusion-regulation, and interpretation and conclusion-sustaining mutual understanding was significantly higher for the successful team. However, the probability of a transition between proposition generation-experimentation, proposition generation-regulation was significantly higher in the less successful team than the successful team. Additionally, more instances of the experimentation to experimentation phase transition were observed in the less successful team, indicating that the team members were applying a trial-and-error strategy. (Yang et al., 2015) compared the collaboration patterns of high-scoring and low scoring teams in a collaborative English-to-Chinese translation task. In that study, the high-scoring teams displayed significant transitions between the specific collaboration phases (i.e., discovery of dissonance among the participants and negotiation), but no significant transitions were observed among the low-scoring teams. In an earlier study, (Schoor & Bannert, 2012) applied a process-mining method to explore the collaboration patterns in successful and less successful teams in a statistics task. They found no difference between the successful and unsuccessful teams in terms of the transitions between the regulatory phases (e.g., planning, monitoring, and evaluation). (Wiltshire et al., 2018) applied a sliding window entropy method to investigate the relationship between the CPS phase transitions and team performance. A negative relationship was observed between the entropy peaks (i.e., amount of disorder and complexity in the conversation) at the transition points and task performance. Overall, the literature suggests that successful teams switch between different CPS phases to a greater extent than less successful teams. Nevertheless, the research on the sequential aspects of CPS is limited to the utilization of specific data modalities, namely transcribed conversation data (Wiltshire et al., 2018) or log data (Chang et al., 2017; Schoor & Bannert, 2012; Yang et al., 2015; Zhu et al., 2019). This calls for further research that utilizes the potential of other data modalities for detecting and understanding the CPS phases.

3. Physiological arousal in collaborative learning and problem solving

Effective collaboration necessitates joint attention, transactive interaction (i.e., building on another person’s ideas), and behavioral synchronicity among team members (Cukurova, Luckin, Millán, & Mavrikis, 2018; Noroozi, Biemans, Weinberger, Mulder, & Chizari, 2013; Schneider et al., 2018). This is not easy to accomplish; it requires team members to commit to the task with an active state of mind. It is well known that the mind and the body are connected (Critchley, Eccles, & Garfinkel, 2013). Cognitive and affective changes in the mind are reflected in physiological signals. For example, physiological arousal has its origins in preparing individuals to act when need for this occurs (Dawson et al., 2016). Though this process serves a general purpose, it also means that arousal is evoked especially when appraisal about the events meaningful in relation to one’s goals is made (Kreibig et al., 2012). Therefore, arousal of collaborating group members could be considered to occur in situations which are especially meaningful, such as phase transitions in CPS. Thus, one way to gain an understanding of and add to the existing methods on studying group interactions in CPS would be to look at the team members’ physiological arousal during their collaboration.

In the current study, physiological arousal refers to alterations in the electrophysiological activity. Electrophysiological activity is a measure of the skin’s electrical properties, which reflects activation in the sympathetic branch of the autonomic nervous system (Benedek & Kaernbach, 2010). It represents the state of activation as a fight or flight response to the stimuli in the environment (Critchley & Garfinkel, 2018). Electrophysiological activity has two basic features: a slow varying skin conductance level and a fast, varying phasic skin conductance response (SCR). As changes in skin conductance level take time, it is rarely used to study temporally unfolding events such as collaboration. However, SCR reacts within seconds and can reflect stimulus-specific responses; it is impacted by the intensity, novelty, and significance of a stimulus (Dawson et al., 2016). Due to its fast-changing nature and its sensitivity to external stimuli, SCR has become a popular electrophysiological activity feature to study momentary cognitive and affective changes within students (Noroozi et al., 2020).

SCR is measured at the individual level. Thus, several analytical methods have been developed to infer the physiological arousal at the group level based on the individual SCR of the team members. These methods have primarily focused on the real-time correspondence between the SCR time series of the team members (Schneider et al., 2020). In the literature, this correspondence has often been referred to as physiological synchrony (Palumbo et al., 2016). Instantaneous derivative matching, signal matching, Pearson’s correlation, directional agreement, and recurrence quantification analysis are some of the popular methods used to calculate physiological synchrony among team members (Dindar, Jarvelä, Ahola, Huang, & Zhao, 2020a; Pijeira-Díaz, Drachslér, Jarvelä, & Kirschner, 2016). Recently, (Schneider et al., 2020) developed a new method to quantify physiological synchrony during different CPS task phases in a collaborative robot programming task. They found that successful groups switched between high and low physiological synchrony to a greater extent during different task phases than less successful teams. The aforementioned methods mostly yield session-based physiological synchrony metrics. They provide information about the overall physiological concordance among the team members within a specific time period. Thus, the common physiological synchrony methods provide little information about the momentary changes during CPS (Dindar et al., 2020).

In general, the existing electrophysiological activity-based physiological synchrony methods calculate synchrony by looking at the correspondence of the electrophysiological activity signals between team members for every measurement point in the time series data. Consequently, differences in the signal starting level, SCR amplitudes, and varying time delay between the team members might affect the results. Different
standardization and lag analysis procedures have been developed to overcome these challenges. However, many of them are applied to full recordings and demand intensive computation; therefore, they are difficult to apply, for example, for real-time analysis. Moreover, many of the physiological synchrony indices reflect the extent of the correspondence between the signals in terms of both increasing physiological arousal and decreasing physiological arousals. Consequently, it is not possible to understand whether a physiological synchrony score refers to, for example, shared engagement, active participation, or shared boredom among the team members. This makes it challenging to understand the relationship between physiological synchrony, the CPS processes, and the outcomes (Dindar et al., 2020b; Verdiere, Albert, Dehais, & Roy, 2020). Some studies have tried to overcome this limitation by observing how physiological synchrony unfolds in specific CPS task phases through video coding of group interactions (Haataja, Malmberg, & Järvelä, 2018; Schneider et al., 2020) or by using both arousal and its synchrony as separate variables in the analysis (Haataja, Malmberg, Dindar, & Järvelä, 2021). Although these studies have yielded valuable insights about the manifestation of physiological synchrony during CPS, their findings are limited to the overall alterations in PS of the group members for specific periods of CPS. More fine-grained and efficient methods that can utilize SCRs to detect the critical time points that are relevant to the productive or unproductive CPS processes must be developed.

CPS is a social phenomenon. When solving problems together, team members make their thoughts, ideas, and arguments explicit to one another (Webb, Troper, & Fall, 1995). They negotiate meanings and strategies and they deal with the conflicts that may arise (Baker, 2003). Therefore, during CPS, the cognitive and affective states are not confined within individuals; they are shared and distributed among the group members (Avry, Chanel, Betrancourt, & Molinari, 2020). Considering this, and the association of SCRs with goal-relevant events (Kreibig et al., 2012), we argue that the SCRs of the group members are likely to correspond to each other and events relevant for shared goals rather than occurring independently. Therefore, it is important to gain an understanding of the nature of the group interactions that occur during SPAEs. The study discussed in this paper aimed to investigate SPAEs in CPS. We explored which type of CPS phases successful and less successful teams participate in during SPAEs. To achieve these aims, we implemented a new method for detecting the correspondence between the SCRs of collaborating students. Rather than solely providing session-based physiological synchrony scores, our method can detect the time windows in which an increased physiological arousal is shared by all the team members. The research questions are:

RQ1. Can we detect the shared physiological arousal events (SPAE) in CPS?
RQ2. Is there a difference between the successful and less successful teams in terms of the CPS phases they engaged in during SPAEs?
RQ3. Is there a difference between the successful and less successful teams in terms of the sequential relationships between the CPS phases engaged in during SPAEs?
RQ4. Is there a difference between the successful and less successful teams with regard to the sequential relationships between the problem state variables addressed during SPAEs?
RQ5. The sequential relationships in CPS phases engaged during SPAE differ between successful and less successful groups.
RQ6. Are there differences between the successful and less successful groups in the physiological synchrony indices?

4. Methodology

4.1. Participants

Seventy-seven students from the University of Oulu in Finland participated in the study (females = 33; males = 41). Their mean age was 27.8 (SD = 5.43). The participants were Finnish (f = 7) and international (f = 70) students who were enrolled in the bachelor’s (f = 5), master’s (f = 52), and doctoral (f = 16) programs at the university.

4.2. The CPS task

Tailorshop, a computer-based complex problem simulation, was used in the current study (Danner et al., 2011; Dorner, Kreuzig, Reither, & Stäudel, 1983). In Tailorshop, the simulation is about running a shirt production company by addressing the complex relationship between 24 variables. However, only half of those variables can be directly manipulated by the participants. In the simulation, the ultimate aim is to increase the company value as much as possible at the end of 12 simulated months. Company value includes the amount of money in the company’s bank account, the value of its machine sales values, the value of its store sales, and the value of the raw materials and shirts in the company’s store. The simulation updates the company value after each month based on the participant’s input. Fig. 1 presents the Tailorshop interface. In order to check the significance of the CPS task for the participants, a single-item task interest questionnaire was presented to them after the CPS task completion. Participants graded their interest towards the CPS task from 1 to 10. The mean score in the whole sample was 8.37 (SD = 1.87).

4.3. Procedure

To recruit the participants, the researchers posted announcements on social media sites and distributed fliers on the university campus. In the announcements, a free lunch ticket was offered for participation. The volunteering participants were students in different degree programs at the university. Thus, the dates of their availability varied, so it was not possible to form the collaborative teams in a randomized manner. Instead, the participants that were available on the same date were randomly assigned to their collaborative team. Data was collected using the LeaF research infrastructure (https://www.oulu.fi/leaf-eng/) at the university of Oulu. LeaF has a high technology infrastructure that is specifically designed for collecting data from collaborative learning activities. The participants were presented with consent forms upon their arrival at the LeaF facility. After completing the forms, the researchers installed Shimmer 3GSR + electrodermal activity sensors on the non-dominant hand of the participants. The sensors were attached to the thenar and hypothenar eminences of the palm (Dawson et al., 2016). The participants were then introduced to their team members and guided to the data collection room. In that room, the team members were seated in front of a desktop computer. The researcher read aloud the instructions about the team task from a pre-written text and then left the room. The participants completed the Tailorshop simulation on their desktop computer as a team. No time limit was set for completing the task. All the team interactions during the CPS task were recorded using a video camera. Furthermore, screen recording software was used to record how the team members navigated the simulation environment.

4.4. Data analysis

In this study, the data was collected from 26 teams. Twenty-five of these teams consisted of three participants and one team consisted of two participants. In some of the teams, one participant left the room before the CPS task was completed (n = 3), the electrodermal activity data of a team member displayed poor quality (n = 3), or the screen recording software did not record the computer screen (n = 1). Thus,
these teams were not included in the analysis. The data analysis included 18 teams that each consisted of three team members from the beginning of the task until its completion.

4.4.1. CPS performance and clustering for the successful and less successful teams

In Tailorshop, a common method used to measure team CPS performance has been to calculate the monthly trend score from the company value (Danner et al., 2011). The trend score is calculated by adding up the number of months the team succeeded in increasing the company value. The simulation was comprised of 12 months. Thus, the trend score could vary between 0 and 12. To identify the successful and less successful teams in terms of their Tailorshop trend scores, cluster analysis was conducted. K-mean clustering was conducted using the trend scores to classify the teams into the successful and less successful categories.

4.4.2. SCR peak detection and SPAE

SPAE is based on the common SCR peak detection method used in physiological research. An SCR is characterized by a steep incline followed by an exponential decline in the electrodermal activity signal (Fig. 2) (Benedek & Kaernbach, 2010). The SCR peaks refer to heightened physiological arousal in the body. An SCR peak occurs within 1 to 5 s following the presentation of a stimuli (Dawson et al., 2009). In the time series electrodermal activity data, the exact time point of the SCRs can be calculated using several standardized methods such as peak-to-peak detection (Boucsein, 2012). In the current study, the SCRs were detected with the Ledalab toolbox (Benedek & Kaernbach, 2010). Before the detection, a Butterworth low pass filter with a frequency of 1 Hz and order 5 was used to remove the small movement artifacts from the signal (Kelsey et al., 2017). Then, SCRs with a minimum amplitude of 0.05 μS were detected using classic trough-to-peak analysis.

In this study, the correspondence between the SCRs of the team members is referred to as the SPAE. We define SPAE as a time window in which an SCR is manifested by all the team members. As seen in Fig. 2, a latency occurs between a stimuli/event and the SCR to that stimuli/event. This latency differs from one individual to another. Thus, it is highly unlikely that the SCRs of collaborating team members would occur at the exact same time point. Consequently, we define SPAE as a time window not a time point. Fig. 3 depicts the sample SPAEs on a timeline.

To decide on the optimum time window for SPAE detection, we followed a data-driven, three-step approach. In the first step, we calculated the SPAE counts for each team for 20 different time windows. The time windows ranged from 0.25 s to 5 s with an increment of 0.25 s in each consecutive calculation. The increment value was based on sampling frequency (i.e., 4 Hz = 4 measurements per second). The minimum and maximum time window was based on the maximum latency between the stimuli and the SCR suggested in the literature (Dawson et al., 2009). For each time window, the SPAE count was calculated by moving the window from the beginning to the end of the time series data, within steps of 0.25 s (i.e., by each measurement point). Considering that the teams completed the CPS task in different amounts of time, we calculated the SPAE count/minute scores for each time window to make the findings comparable among the different teams (Boucsein, 2012). In the second step, we created a surrogate dataset by randomly shuffling the SCR time points for each team member (Lancaster, Iatsenko, Pidde, Ticcinelli, & Stefanovska, 2018). Similar to the first step, we then calculated the SPAE count/minute for the surrogate teams for 20 different time windows (0.25 s to 5 s). In the third step, we
compared the SPAE count/minute scores of the actual and surrogate teams for each time window with independent samples t-tests. This allowed us to detect the optimum time window for SPAE detection.

4.4.3. Video analysis
A video coding scheme was developed to gain an understanding of the characteristics of the team interactions during the SPAEs. The coding scheme included four problem-solving phases in the PISA Problem Solving Framework (i.e., exploring and understanding, representing and formulating, planning and executing, and monitoring and reflecting) (OECD, 2017), socio-emotional expressions and off-task or no interaction categories. The definitions and sample utterances or behaviors for each category is presented in Appendix 1. The first author used the scheme to characterize the team interactions that occurred during each SPAE. Furthermore, the first author coded the simulation variables (e.g., shirt price, wage, worker satisfaction, or advertisement) that were mentioned during each SPAE. To check the reliability of the coding, the fifth author independently applied the same coding procedure that was used on the first five teams in terms of alphabetical order. Cohen’s Kappa scores displayed good interrater reliability across the video coding categories (Kexploring and understanding = 0.72; Krepresenting and formulating = 0.73; Kplanning and executing = 0.82; Kmonitoring and reflecting = 0.90; Ksocio-emotional expressions = 0.58; Koff-task or no interaction = 0.71). Good interrater reliability was observed in terms of the addressed simulation variable during the SPAE (K = 0.80).

4.4.4. Process-mining analysis
We conducted process-mining analysis to identify and describe the flow of interactions for the cognitive phases in CPS. Fuzzy Miner approach for process-oriented analysis (Günther & van der Aalst, 2007) was adopted for the exploration of the time-related pathways of CPS phases between the successful and less successful groups. The process-mining analysis was conducted using Fluxicon’s Disco analysis software (https://fluxicon.com/disco/), a process mapping software program commonly used in previous studies to assess the process of learning events (Jarvenoja, Nâykki, & Törämäen, 2019; Juhanâk, Zoune, & Rohlíková, 2019). The results were visualized to show the most frequent pathways of interactions between the CPS phases. We also explored the pathways between the simulation variables that the successful and less successful teams went through during the collaborative session.

5. Results

5.1. RQ1. Can we detect SPAE in CPS?

According to the independent samples t-test results, the most significant difference between the actual and surrogate teams in terms of SPAE count/minute occurred at the 1.5-second time window (t_{360} = 2.893; p = .006; Cohen’s d = .94). Fig. 4 displays the p value chart for all the time windows. Based on these results, 1.5 s was designated as the time window for the SPAE. That is, if an SCR was observed in all the team members within a 1.5-second time window, it was regarded as an SPAE. Further analyses were conducted based on the SPAEs observed within the 1.5-second time window. Overall, the findings indicate that it is possible to detect SPAEs. Moreover, SPAEs do not occur at a random time and they indicate team interaction processes.

The mean SPAE frequency was 103.56 (Min = 21; Max = 251; SD = 62.55) in the whole sample. For the successful teams, the mean SPAE frequency was 123.22 (Min = 43; Max = 251; SD = 70.32). For the less successful teams, it was 83.89 (Min = 21; Max = 156; SD = 49.99). The Mann-Whitney U test showed no significant difference between the successful (Mdn = 9.67) and the less successful teams (Mdn = 9.33) in terms of SPAE/minute scores (U = 39; p = .931). The SPAE count for each team is presented in Table 2. The table further presents the frequency of each CPS phase observed during the SPAEs. In order to check whether SPAEs refer to meaningful interactions, we totaled the frequency of the cognitive and socio-emotional phases and compared them to the frequency of the off-task or no interaction phase with a paired samples t-test. According to the test results, the observed cognitive and socio-emotional phases were significantly higher than the off-task or no interaction phase (t_{17} = 6.566; p < .001; Cohen’s d = 1.55; M_{cognitive & socio-emotional phases} = 96.2; SD_{cognitive & socio-emotional expressions} = 57.8; M_{off-task or no interaction} = 7.33; SD_{off-task or no interaction} = 5.980). This finding confirms that SPAEs mostly refer to the meaningful and shared team interaction phases in CPS.

5.2. RQ2. Is there a difference between the successful and less successful teams in terms of the CPS phases engaged in during SPAEs?

According to the Mann-Whitney U test results, no difference was observed between the successful and less successful teams in terms of the CPS phase frequencies or the CPS phase frequencies weighed by team task time (see Table 3).
5.3. RQ3. Is there a difference between the successful and less successful teams in terms of the sequential relationships between the CPS phases engaged in during SPAEs?

The process-mining analysis results revealed significant differences between the successful and less successful teams in terms of the CPS phase pathways they went through. Fig. 5 and Fig. 6 present the pathways of the CPS phases in the process maps for the successful and less successful teams with the most dominant process flows among those phases. The CPS phases are represented by boxes and the process pathway between two phases is visualized by an arrow. The dashed arrows point to the CPS phases that occurred at the beginning or at the end of the most dominant process. The map shows the absolute frequencies of the number of CPS phases and the connections among them.

In the successful teams, the members started by participating in the exploring and understanding phase. Then, they went through a linear path in the following sequence: planning and executing, off-task or no interaction, representing and formulating, and socio-emotional expressions. The successful teams also engaged in specific CPS phases (exploring and understanding (f = 51), planning and executing (f = 129), representing and formulating (f = 195), monitoring and reflecting (f = 68) repeatedly before or after participating in other phases. From the most dominant process flows among the shown activities, we observed no connection between the successful and less successful teams in terms of the CPS phases.

In the less successful teams, the number of connected activities in the most dominant process flows are limited in comparison to the successful teams. In the less successful teams, the CPS phases do not exhibit a clear process pattern throughout the session. The following pathways were observed: 1) socio-emotional expression and exploring and understanding, and off-task or no interaction was followed by planning and executing. Furthermore, it was observed that the less successful teams also repeatedly engaged in exploring and understanding (f = 99). No other pathways were observed in the most dominant process flows of the CPS phases.

5.4. RQ4. Is there a difference between the successful and less successful teams with regard to the sequential relationships between the problem state variables addressed during SPAEs?

Fig. 7 and Fig. 8 present the process-mining results for the most dominant pathways between the simulation variables in the successful and less successful teams. Overall, complex patterns of pathways were observed in both teams. However, a closer look at the relationship between the simulation variables revealed different patterns in terms of the teams’ focus in the simulation. In the successful teams, the most frequently mentioned variables were shirt price (n = 113), machines (n = 98), shirts sold (n = 63), shirts in stock (n = 60), company value (n = 48), retail stores (n = 48), workers (n = 38), bank account (n = 37), customers interested (n = 33), and advertisement (n = 33). Among the less successful teams, the most frequently mentioned variables were machines (n = 93), workers (n = 50), material ordered (n = 44), shirt price (n = 41), retail stores (n = 44), worker satisfaction (n = 35), shirts in stock (n = 31), shirts sold (n = 29), advertisement (n = 28), and wage (n = 24). Evaluating the pathways between the most frequently mentioned variables, it appears that the less successful teams primarily focused on production (i.e., machines, workers, material ordered, worker satisfaction, shirts in stock, and wage), whereas the successful teams focused on both production (i.e., machines, shirts in stock, workers) and sales (i.e., shirt price, shirts sold, customers interested, advertisement, retail stores, and bank account). The less successful teams focused on both production (i.e., machines, shirts in stock, workers) and sales (i.e., shirt price, shirts sold, customers interested, advertisement, retail stores, and bank account).

Table 3
Comparison of the successful and less successful teams in terms of the video coding category frequencies.

| E/U | E/U/Task time | R/F | R/F/Task time | P&E | P&E/Task time | M&R | M&R/Task time | SE | SE/Task time | Off | Off/Task time |
|-----|--------------|-----|--------------|-----|---------------|-----|---------------|----|--------------|-----|--------------|
| Mean rank | 20.67 | 12.83 | 15.23 | 21.23 | 23.23 | 29.30 | 31.35 | 21.35 | 23.35 | 20.35 | 22.35 |
| p value | 0.194 | 0.566 | 0.133 | 0.122 | 0.536 | 0.895 | 0.095 | 0.627 | 0.424 | 0.690 | 0.169 | 0.427 |

E&U: exploring and understanding; R&F: representing and formulating; P&E: planning and executing; M&R: monitoring and reflecting; SE: socio-emotional expression; Off: off-task or no interaction; Task time: team CPS task time.
teams also discussed sales issues (i.e., shirt price, retail stores, shirts sold, and advertisement). However, a linear pathway was observed from the sales-related variables to worker satisfaction. This finding indicates that the less successful teams might have prioritized worker satisfaction when deciding on the sales-related issues. However, in the successful teams, customer interest played a central role in deciding on issues related to production and sales. Furthermore, the main objective of the CPS task was to increase company value as much as possible. The less successful teams discussed company value to a lesser extent than the successful teams. Thus, it can be claimed that the successful teams focused on the final task goal when progressing in the simulation. However, the less successful teams paid less attention to the task goal, and they eventually failed to identify the relationships that have the most influence on the final task outcome. Overall, these findings imply that successful teams develop a more comprehensive understanding of the problem situation by focusing on the relationships that are more relevant to the task objectives; in contrast, less successful teams lack perspective in reaching task goals since they overlook some of the crucial relationships in the problem state.

6. Discussion

This study aimed to detect SPAEs in CPS and explore how SPAEs are manifested in successful and less successful teams. Toward that end, we first tested the utility of the SPAE method for identifying the shared physiological arousal moments during CPS. To understand whether SPAEs occur by chance, we created surrogate teams by shuffling the SCR time points within the team members and we used this surrogate dataset to compare the surrogate SPAEs with the actual SPAEs observed in real teams. Our findings showed that temporal manifestation of SPAEs does not occur by chance.

Extensive research on human physiology has yielded multiple
methods for studying PS between interacting individuals (Palumbo et al., 2016; Pijeira-Díaz et al., 2016; Schneider et al., 2020). These methods have primarily studied physiological synchrony in terms of coupling of the signals during the cycles of both decreasing and increasing physiological arousal. In the education literature, high arousal has been associated with active participation in learning and low arousal has been associated with boredom and disinterest (Pijeira-Díaz et al., 2018). Drawing on this, we argue that combining high and low physiological arousal events when calculating physiological synchrony might be problematic. In the literature, the contradictory findings of the association between physiological synchrony and collaborative learning constructs can be considered to support to our argument. For example, some studies reported a positive relationship between physiological synchrony and team cohesion (Monster, Håkonsson, Eskildsen, &
emotional challenges before, during, or after the collaboration (Dindar, Malmberg, 2020; Kirschner, Kreijns, Phielix, 2005), primarily refer to cognitive or socio-emotional CPS phases rather than physiological arousal moments during collaboration. Effective and shared regulation of cognitive and socio-emotional processes are crucial for successful collaboration (Järvelä et al., 2014). However, team members often fail to regulate themselves or others during collaborative learning or problem-solving tasks (Hadjidemetriou et al., 2017). Thus, there has been a growing interest in employing technological tools to support learners when they collaborate (Fischer, Kollar, Stegmann, & Wecker, 2013). These tools mainly prompt team members to become aware of their cognitive, motivational, and emotional challenges before, during, or after the collaboration (Dindar, Malmberg, Järvelä, Haataja, & Kirschner, 2020; Järvenoja, Järvelä, & Malmberg, 2020; Kirschner, Kreijns, Phielix, & Fransen, 2015). How-ever, these tools primarily serve as a reflection apparatus since they rely on team members’ self-reported experiences (Järvelä et al., 2016). In collaborative learning research, a current challenge is to capture cognitive and socio-emotional team processes objectively and unobtrusively during collaboration (Järvelä, Gasević, Seppänen, Pechenizkiy, & Kirschner, 2020). Moreover, collaboration occurs through verbal turn-taking of the team members. Thus, it is difficult to detect the extent to which cognitive or socio-emotional processes are shared among all the team members when one of the team members is speaking. To tackle these challenges, researchers in the field of collaborative learning has been increasingly embracing advanced technologies, multimodal data, and process-oriented methodologies to detect shared team processes. As a contribution to these efforts, the current study demonstrates that SPAEs can help detect the shared cognitive and emotional processes during collaboration unobtrusively and provide information about their time of occurrence. Detection of the shared cognitive and socio-emotional processes in real time can lead to the development of a new generation of collaborative tools that can provide real-time support to team members during CPS. However, more research is necessary to develop a thorough understanding of the nature of the cognitive and socio-emotional CPS phases that are exhibited during SPAEs.

The current study also explored the SPAEs of successful and less successful CPS teams. Our findings showed no significant differences between these two teams in terms of SPAE frequency. Furthermore, we found no significant differences between the teams across the frequency of CPS phases engaged in at the time of the SPAEs. These findings imply that the less successful teams did not perform as well as the successful teams. Successful teams did not have a higher degree of shared physiological arousal or because they went through specific CPS phases to a limited extent than the successful teams. Rather, the temporal order of the CPS phases made a difference between the performance of the successful and less successful teams. More sequential pathways were observed between the CPS phases in the successful teams (exploring and understanding -> planning and executing -> off-task or no interaction -> representing and formulating -> socio-emotional expressions) than the less successful teams (off-task or interaction -> planning and executing: socio-emotional expressions - > exploring and understanding). These findings show that, in successful teams, the CPS phases occur in a more structured way and in a sequential relationship to each other. In the less successful teams, the CPS phases occur in a more random order with less sequential relationships. This result is in line with the findings reported in previous research. For example, (Wiltshire et al., 2018) found a negative relationship between entropy (i.e., the extent of disorder in team discourse) and CPS performance. (Chang et al., 2017) observed frequent sequential relationships between monitoring and reflecting, representing and formulating, and planning and executing in the successful teams. In the less successful teams, the most dominant process of the CPS phases only showed pathways between monitoring and reflecting and planning and executing. Several other studies have also reported more sequential relationships between the CPS phases in successful teams in comparison to less successful teams (Yang et al., 2015; Zhu et al., 2019). Based on these findings, it can be claimed that successful teams adapt their performance by participating in specific CPS phases, sequentially. In contrast, less successful teams follow a more random order when engaging in CPS phases.

Another striking finding of the current study was that successful teams repeatedly went through the same cognitive CPS phase (i.e., exploring and understanding, planning and executing, representing and formulating, or monitoring and reflecting) before or after participating in a different CPS phase. However, less successful teams only repeatedly engaged in planning and executing. Planning and executing involves deciding on a strategy and applying it. It seems that the less successful teams embraced a trial-and-error approach. They primarily focused on deciding on and applying a strategy rather than developing a better representation of the problem situation or monitoring and reflecting on the outcomes of their strategy. (Zhu et al., 2019) also showed that less successful teams primarily repeat the phase of experimenting different strategies rather than, for example, building a shared understanding. Considering these findings, one way to support collaborative teams would be to embed intelligent systems in the simulations that can prompt teams to consider participating in specific CPS phases (e.g., monitoring and reflecting or representing and formulating) when they get trapped in a vicious cycle of trial-and-error.

Our findings showed that it is not only the sequential order of CPS phases that differ between successful and less successful teams. Successful and less successful teams also differ from each other in terms of the sequences of the problem state variables they discuss during SPAEs. Causal reasoning, identifying causal relationships between problem state variables, is essential for successful problem solving (Novick & Bassok, 2005). In order to develop effective problem solving strategies, learners should be able to predict or infer the covariational and mechanistic relationships among the variables (Jonassen & Joas, 2008; Steyvers et al., 2003). This is usually done by observing the changes in problem state in relation to the input or actions of the learners (Steyvers et al., 2003). However, it is challenging to draw causal inferences in complex problem situations in which there are many interacting elements (Funke, 2012). The Tailorshop simulation utilized in this study includes a large number of interrelated variables. Thus, it can be considered to be a highly complex problem-solving task (Ollinger, Hammon, von Grundherr, & Funke, 2015). We found that successful teams develop a better representation of the problem state by focusing on the interconnectivity between the variables that are essential to achieving the task goals. In other words, successful groups were better at causal reasoning. However, less successful teams tend to focus on the associations between the variables that have limited impact on attaining the task goals (i.e. increasing the company value).

Our findings highlight the potential benefit of representational tools in collaborative learning/problem solving. Representational tools are pictorial or diagrammatic tools that can help learners map the interconnectivity and causal relationships among the variables (Fischer & Mandl, 2005). Concept maps or interactive whiteboards are examples of representational tools. Several studies have shown that representational
tools facilitate successful problem solving by assisting learners in their efforts to develop shared conceptions, and visualize, monitor, and evaluate their problem-solving process (Kolodoff, Eysink, & de Jong, 2011; Lajoie & Lu, 2012; Sangin, Molinari, Nüssli, & Dillenbourg, 2011). Thus, a possible approach to assist less successful teams would be to provide them with representational tools and ask them to draw causal relationships between all the variables they observe in the simulation. Then, the teams can be prompted to identify the variables that have the greatest impact on achieving the task goals. This funneled approach and emphasis on the task goals might help less successful teams focus on the relationships that are more important for attaining the task goals.

Previous process-oriented research on CPS has looked for meaningful interactions or behaviors during the team collaboration by mostly coding of all the learner discourse (e.g., Chang et al., 2017) or behavioral actions (e.g. Dindar et al., 2020a). Coding team interaction and behavior is a labor-intensive process. Unlike previous studies, the current study focused on the interactions among the team members that only occurred during the SPAEs. Solely analyzing the SPAEs still allowed us to detect the sequential differences between the problem-solving processes of the successful and less successful teams. Considering this, the SPAE method might be a promising approach to detect critical CPS phases from the team discourse data with less effort, for example, in comparison to analyzing every utterance. Future research is necessary to test this potential.

To summarize, the demonstrated results reflect the theoretical assumption that CPS is the process of building and sustaining joint problem space through shared processes (Fischer & Mandl, 2005). These processes can include sharing of knowledge, shared monitoring and regulation of task progress and shared emotional states. Extending the previous findings that studied CPS at the discourse level, the current study has evidenced that shared cognitive and affective processes during the current study utilized electrodermal activity to capture shared physiological arousal. This opportunity identifies new frontiers for educational researchers to unearth the convergence and divergence between different data modalities and link them with the theory. We hope that this study represents a step forward in that direction.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This research was granted by Academy of Finland. Grant No. 275440 and No: 324381. Data collection was carried out with the support of Leaf Research Infrastructure (https://www.oulu.fi/leaf-eng/), University of Oulu, Finland.

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