Affective states and regulation of learning during socio-emotional interactions in secondary school collaborative groups

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Abstract

Background: Group affective states for learning are constantly formed through socio-emotional interactions. However, it remains unclear how the affective states vary during collaboration and how they occur with regulation of learning. Appropriate methods are needed to track both group affective states and these interaction processes.

Aims: The present study identifies different socio-emotional interaction episodes during groups' collaborative learning and examines how group affective states fluctuate with regulation of learning during these episodes.

Sample: The participants were 54 secondary school students working in groups across four science learning sessions.

Methods: Multichannel process data (video, electrodermal activity [EDA]) were collected in an authentic classroom. Groups' affective states were measured with emotional valence captured from video data, and activation captured as sympathetic arousal from EDA data. Regulation of learning was observed from the videotaped interactions.

Results: The study disclosed four clusters of socio-emotional interaction episodes (positive, negative, occasional regulation, frequent regulation), which differed in terms of fluctuation of affective states and activated regulation of learning. These clustered episodes confirm how affective states are
INTRODUCTION

The role of affect in learning and collaboration is widely acknowledged (Baker et al., 2013; Barron, 2003). In collaborative learning, group members jointly construct and share their knowledge but also balance shared cognitive processing with socio-emotional aspects of the process (Isohätälä et al., 2018). From a narrow perspective, affect can be seen as individual conditions that influence group members' interactions and behaviours. More broadly, affect plays an active role in the collaboration process and is constantly reset during learning (Bakhtiar et al., 2018; Winne & Hadwin, 2008). For example, socio-emotional interactions between group members can strengthen positive affective states and facilitate high-level cognitive processes (Barron, 2003; Isohätälä et al., 2018; Järvelä, Järvenoja, et al., 2016) while negative affective states jeopardize collaboration if left unregulated (Näykki et al., 2014).

Regulation of learning is needed to make adaptive changes to cognition, motivation, and affect in challenging learning situations. Through co-, and socially shared regulation of learning, students can monitor, control, and redirect their group's affective state (Hadwin et al., 2018). Both go beyond individual group members' self-regulatory actions as they are enacted in interaction between group members. According to Hadwin et al. (2018), individual group members can engage in co-regulation to support their peers or to adapt the group learning process. Socially shared regulation, instead, involves several group members' building on each other's regulatory contributions in synchrony. Winne and Hadwin's (1998) COPES framework models regulation at the micro-level and describes regulation of learning in terms of conditions, operations, products, evaluations and standards. According to COPES, affect has a twofold function. First, it serves as internal condition that influences how students engage in learning. Second, affect is constantly modified by student operations during the learning process, and these affective products in turn become the conditions for ongoing learning activities (Bakhtiar et al., 2018; Winne & Hadwin, 2008). The present study focuses on this interplay occurring in secondary school small groups while they engage in collaborative learning. The study views socio-emotional interactions and regulation of learning as potential means to alter group affective states. That is, socio-emotional interaction refers to intentional interchanges between group members to express affect or shape their perceptions of the group affective state or socio-emotional atmosphere (Bakhtiar et al., 2018; Kreijns et al., 2003; Mänty et al., 2020). In turn, through co-regulation group members can support each other to maintain or restore affective states that are beneficial for learning. The group can also work together constantly reset by socio-emotional interactions and regulation of learning. The results also show that states requiring regulation do not automatically lead to its activation.

Conclusions: By advancing existing understanding of how group level socio-emotional processes contribute to regulation of learning, the study has implications for educational design and psychological practice. Methodologically, it contributes to collaborative learning research by employing multiple data channels (including biophysiological measures) to explore the various dimensions of socio-emotional processes in groups.

KEYWORDS
affect, collaborative learning, co-regulation, self-regulated learning, socially shared regulation, socio-emotional interaction
to enhance the socio-emotional atmosphere or to overcome socio-emotional challenges through socially shared regulation.

A number of studies have recently adopted a process-oriented approach to address the fluctuation of affective states during learning (e.g., Goetz et al., 2016; Ketonen et al., 2017; Li et al., 2021; Moeller et al., 2020). For example, Mänty et al. (2020) studied the relationship between negative socio-emotional interactions, emotion regulation, and self-reported emotional experiences of collaborative learning among sixth grade students. Their results indicate that negative interactions had a negative impact on students’ emotional experiences of collaboration and that emotion regulation does not always make a difference to these negative interactions. It remains unclear how this variation of affect occurs together with regulation of learning. The present study examines how group affective states vary in socio-emotional interactions and with group-level regulation. Novel process-oriented methods, including video and biophysiological data (electrodermal activity [EDA]), were used to capture the fluctuation of affective states and regulation in an authentic learning context. By complementing the video analysis with EDA, this study sought also to track the ‘invisible’ markers of affect and regulation of learning contextualized in the learning situations where they occur.

Valence and activation as dimensions of group affective states

In learning contexts, affect has been operationalized in terms of the dimensions of emotional valence and activation (Pekrun et al., 2002). In the affective circumplex (Russell & Barrett, 1999), valence separates positive affect from negative, and activation refers to the extent of physiological arousal caused by an affect (Ben-Eliyahu & Linnenbrink-Garcia, 2013; Boekaerts & Pekrun, 2016). During a learning situation, a student may feel positively activated (e.g., enjoyment), negatively activated (e.g., anxiety), positively deactivated (e.g., relief) or negatively deactivated (e.g., boredom) (Pekrun, 2016). Rather than seeking to detect distinct emotions, this study specifies varying affective states during learning in terms of valence and activation. Affective states, including emotions, can be defined as situation-specific responses to the changing environment (Rosenberg, 1998). When learners collaborate as a group, their affective states are likely to converge (Duffy et al., 2015), promoting synchronous and interactive experiences of shared group affect (Barsade & Knight, 2015). Previous research has identified emotional contagion (i.e., the transfer of affect from one person to another) as one of the mechanisms through which group members’ affect can spontaneously become shared (Barsade & Gibson, 2012), and group interactions serve as the main context for this to occur. However, group members may also differ in how they approach and interpret the same situation, leading to mixed affective states (Lobczowski, 2020; Törnänen et al., 2021b). As these situations can be detrimental for joint learning processes (Barsade & Gibson, 2012), regulation is needed to restore shared affective conditions for collaboration. That is, socially shared regulation is another type of mechanism to influence the development of shared affective state (Järvenoja et al., 2019). It differs from emotional contagion as it includes intended efforts to influence affective states and interactions within the group (Hadwin et al., 2018).

The present study utilizes video data of observable emotional expressions and interactions as indicators to track emotional valence within a group of learners (Linnenbrink-Garcia et al., 2011; Porayska-Pomsta et al., 2013). In terms of emotional valence, there is evidence that positive task-related emotions support learning by enhancing student engagement, motivation and interest and encouraging the use of deep learning strategies (Pekrun, 2016). Negative emotions often have the opposite effect but can also drive engagement when successfully regulated—for example, by triggering extra effort to avoid failing a test (Harley, Pekrun, et al., 2019; Pekrun & Stephens, 2010). Only a few studies have explored the consistency and variation of affective states during learning (see e.g., Li et al., 2021), and still fewer have examined this fluctuation in collaborative learning settings (Pietarinen et al., 2019, 2021; Törnänen et al., 2021b). Nevertheless, the available evidence highlights the need to account for both consistency and variation in group members’ affective states. Emotional contagion and related emotional consistency within groups have been detected...
by observing group members' facial expressions, body language, verbal tone (Barsade et al., 2018) and physiological reactions (Pijeira-Díaz, Drachsler, Järvelä, et al., 2018). The years of research conducted especially in the studies of work organizations emphasize that emotional consistency within the group influences group members' behaviours, group processes, as well as outcomes of the group work (Barsade et al., 2018). Furthermore, in the context of collaborative high school students, Pietarinen et al. (2020) studied group affective states using self-reports and video observations, and found that group affect, as such, was not related to group learning outcomes. Instead, extremely high- and low-performing groups exhibited greater within-group emotional consistency while affect was more ambiguous in average-performing groups.

As the activation dimension of affect refers to the physiological arousal caused by the affect (Ben-Eliyahu & Linnenbrink-Garcia, 2013; Boekaerts & Pekrun, 2016), it is not directly observable from the students' visible behaviour. Thus, capturing both valence and activation requires complementing video data with a physiological data channel that allows tracking students' physiological reactions as well. To capture emotional activation, the present study measures activation of the sympathetic nervous system through EDA (Palumbo et al., 2017), since the physiological component of affect is closely linked to the autonomic nervous system activity (Kreibig, 2010). There is an emerging body of research (e.g., Harley et al., 2015; Harley, Jarrell, et al., 2019; Törmänen et al., 2021a) that has investigated sympathetic arousal in connection with the activation dimension of the affective circumplex model (Russell & Barrett, 1999), which reflects the degree to which an affect is physiologically arousing (Pekrun, 2016). Previous research has shown that sympathetic arousal and fluctuations in the level of arousal can illuminate students' affective and cognitive processes during learning. However, the previous findings also demonstrate that the relationship between arousal and learning processes is not straightforward. In general, the available evidence suggests that students in learning situations experience quite low levels of arousal and that simultaneous high arousal among group members seems rare (Harley, Jarrell, et al., 2019; Malmberg et al., 2019; Pijeira-Díaz, Drachsler, Kirschner, et al., 2018). Instances of high arousal have been linked to both negative and positive affective states (Ahonen et al., 2018; Harley, Jarrell, et al., 2019; Malmberg et al., 2019; Törmänen et al., 2021b), to learning challenges and regulation of learning (Malmberg et al., 2019; Törmänen et al., 2021a), and to both low and high performance (Harley, Jarrell, et al., 2019; Mason et al., 2018; Pijeira-Díaz, Drachsler, Kirschner, et al., 2018; Pizzie & Kraemer, 2018). Also, changes in physiological states have been studied in relation to regulation of learning and emotion regulation. For example, Sobociński et al. (2020) reported that high school physics students showed more physiological state transitions in heart rate (i.e., significant changes in groups' aggregated heart rate state) during sequences when the collaborative learning process was on-track. Sobociński et al. related the number of transitions positively to task progress; when a group was on-track, progress could be made without frequent regulation, and smooth task progress was reflected as more state transitions in groups' heart rate. In terms of emotion regulation, according to previous studies emotion regulation may increase or reduce sympathetic arousal, depending on the regulatory goal (Kinner et al., 2017; Matejka et al., 2013; Pizzie & Kraemer, 2018). To conclude, to understand more thoroughly how affective states as conditions contribute to group learning processes, methods unravelling both valence and activation dimensions, as well as their interplay with regulation of learning are needed.

**Aims of the study**

Based on the assumption that affective states in collaborative learning groups are constantly reset through socio-emotional interaction and regulation of learning (Bakhtiar et al., 2018; Winne & Hadwin, 1998), the present study examines how group emotional valence and activation fluctuate with regulation of learning during such interactions. To that end, the study addresses two research questions.

1. What types of socio-emotional interaction episodes can be identified during collaborative learning?
2. How do group emotional valence and activation fluctuate with regulation of learning during socio-emotional interaction episodes?

METHOD

Participants

The participants were 54 secondary school students (aged ~13 years; 31 female) from Finland working in 18 groups of three across four collaborative learning sessions, yielding data from 68 learning sessions (four missing sessions due to absences). The students were from five classrooms of one secondary school located in an urban area in the Northern Finland and had similar socio-economic backgrounds. The original sample included 94 students, but since the data analysis was done on a group level, five groups of four members and one dyad were excluded from the analysis to align both the video data coding and the EDA data aggregation between the different groups. Also, the EDA recordings with missing electrode contact were removed from the data set leading to the exclusion of six groups due to the missing data of some group members. Prior to the data collection, the study was reviewed and approved by the Ethics Committee of Human Sciences of the University of Oulu.

Data collection and pre-processing

The data (Järvelä, Järvenoja, et al., 2021) were collected during weekly science lessons. The students were divided into heterogeneous groups on the basis of science grades, and the groups remained the same throughout the sequence of four lessons on the topic of light and sound. Each lesson followed a specific collaborative learning design (for more information, see Järvenoja, Malmberg, et al., 2020). Each group collaboration was videotaped using Insta360 Pro 360° cameras; audio was recorded using separate table microphones. Shimmer 3 GSR+ sensors (Realtime Technologies Ltd) were used to record students’ EDA at a sampling rate of 128 hz, placing gel electrodes at the thenar and hypothenar eminences on the palm of the non-dominant hand (Dawson et al., 2007).

Video data were used to observe group emotional valence as well as regulation of learning and were processed using Observer XT software (Noldus Information Technology). The data were split into 30-s segments, as this was long enough to properly capture interactions and supported valid judgements and detailed observations of behaviour (Porayska-Pomsta et al., 2013). As the study focused on collaborative working, any other segments (e.g., teacher instructions) were excluded from the analysis. In total, this process yielded 5622 30-s segments.

Since emotional activation dimension cannot be captured from the video recordings, video observations were supplemented with EDA data. A MySQL database was constructed to organize the EDA data. To begin, the data were downsampled from 128 to 16 Hz to accelerate the analysis (Kelsey et al., 2018). Any recordings in which electrode contact was missing were removed from the data set. A Butterworth low-pass filter (frequency 1, order 5) was used to remove small movement artefacts from the signal (Realtime Technologies Ltd, 2018). Non-specific skin conductance response (NS-SCR) peaks with a minimum amplitude of .05μS were then identified in each student’s signal, using the trough-to-peak method (Boucsein, 2012; Dawson et al., 2007). NS-SCR peaks were selected because they are strongly related to emotional response and are more sensitive than slowly varying skin conductance level (SCL) to variations in experimental conditions (Christopoulos et al., 2019; Dawson et al., 2007). In situations involving continuous stimuli (such as collaborative learning), frequency of NS-SCR peaks serves as an indicator of current arousal (Braithwaite et al., 2013). The threshold was set to .05μS, since it is the most used (Braithwaite et al., 2013) and thus enabled the comparability of the peak detection results. Different methods for peak detection (continuous decomposition analysis and discrete decomposition analysis) available in Ledalab were first tested (Benedek & Kaernbach, 2010a, 2010b). Ultimately, the
peaks were derived with the traditional trough-to-peak method because, even after several rounds of testing, decomposition-based methods seemed to provide unrealistically high frequency of peaks as a result.

Data analysis

The analysis involved four phases (see Figure 1). In phase 1, socio-emotional interactions were identified from the video data. In phase 2, group affective states during socio-emotional interactions were identified and coded; emotional valence was captured from the video footage while emotional activation was captured from EDA data. In phase 3, regulation of learning during socio-emotional interaction was located using video data. Finally, in phase 4, the various episodes of socio-emotional interaction were identified using multichannel sequence mining and clustering based on mixture hidden Markov models (MHMM). This analytical procedure is described in more detail below.

Phase 1: Identifying socio-emotional interaction from the video data

To begin, socio-emotional interactions involving group members' verbal or behavioural actions related to expressions of affect or shaping of emotional atmosphere through e.g., group formation or group dynamics were coded in 30-s segments (Bakhtiar et al., 2018; Kreijns et al., 2013; Kwon et al., 2014). These were coded when at least two group members used clear verbal or bodily cues to indicate affect or engaged in emotionally charged interactions (see Table 1 for examples). Using Cohen's kappa statistic, interrater reliability was assessed for 10% of the coded videos, and substantial agreement was indicated ($\kappa = .77$; Landis & Koch, 1977). The disagreements between the coders were then discussed to reach a consensus for the final codes. Socio-emotional interactions were identified in the 2029 segments selected for further analysis and emotionally neutral segments ($n = 3593$) were excluded.

FIGURE 1 Analysis of episodes of socio-emotional interaction in terms of group emotional valence, activation and regulation of learning
### TABLE 1  Coding of group emotional valence during 30-s video segments of socio-emotional interaction

<table>
<thead>
<tr>
<th>Valence</th>
<th>Coding criteria</th>
<th>Indicators</th>
<th>Example behaviour</th>
<th>Example utterances</th>
</tr>
</thead>
<tbody>
<tr>
<td>Positive</td>
<td>Positive indicators from two group members; No indications of negative affect</td>
<td>Verbal expressions</td>
<td>Positive content, positive tone of voice, laughing, singing</td>
<td>Oh la laa, quite cool!</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Bodily expressions</td>
<td>Smiling, dancing</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Positively charged</td>
<td>Joking, praising, encouraging</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>interaction</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Negative</td>
<td>Negative indicators from two group members; No indications of positive affect</td>
<td>Verbal expressions</td>
<td>Negative content, negative tone of voice, groaning, whining</td>
<td>I hate these. I wish this would be over already</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Bodily expressions</td>
<td>Sighing, facepalm, lack of focus (playing with equipment, wandering around)</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Negatively charged</td>
<td>Arguing, criticizing, teasing</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>interaction</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Physical discomfort</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mixed</td>
<td>Positive indicator from a group member and negative indicator from another group member</td>
<td>Positive + negative</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>expressions</td>
<td></td>
<td></td>
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<td></td>
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</tr>
</tbody>
</table>

[Group is testing how sound travels on the string bound to a metal spoon]  
I will hit it with such a swing that the spoon will fly out of the window (joking, making a swing movement)  
How are you able to draw such straight lines without a ruler? Look! She didn’t even use a ruler to do this line! (praising)  

[S1 is dazzling the eyes of S2 and S3 with a flashlight]  
S2: Stop!  
S3: Stop you piece of…  
S2: Give me the flashlight…  
[S1 does not stop]  
S2: Give it now!  

[Group is laughing and testing the paper cup phone]  
S1: Make sure it doesn’t fall down, come a little bit closer. Oh no! If (the wire) will come off now!  
S2: No it won’t, don’t ruin it. *laughing*  
S1: Don’t ruin it, very nice… *laughing*
Phase 2: Identifying group valence and activation during socio-emotional interactions

In this phase, the valence and activation dimensions of group affective states were specified for each segment. From the video data, valence was coded as one of three categories (positive, negative, mixed) based on group members' emotional expressions. The academic emotions framework (Pekrun et al., 2002) and the affective circumplex model (Russell & Barrett, 1999) provided the theoretical basis for differentiating expressions of positive and negative affect. The video coding scheme was based on the authors' previous work (Törmänen et al., 2021a; Törmänen et al., 2021b). Before proceeding to final coding, seven videos (10%) were coded by two researchers, and unclear cases were discussed to refine the coding scheme. Group valence was coded as positive when at least two group members expressed clear signs of positive affect or made a positive comment, and vice versa. In cases where valence was mixed within one group member (e.g., individual displayed a negative verbal expression and a positive bodily expression) or when two students’ expressions conflicted (i.e., positive vs. negative), valence was coded as mixed (see Table 1 for examples). The interrater reliability analysis performed for 10% of the coded videos indicated substantial agreement (\( \kappa = .68 \)) (Landis & Koch, 1977). Again, the discrepancies between the coders were discussed to agree on the final codes. The valence coding procedure is detailed in Table 1.

Group activation during each socio-emotional interaction segment was measured in terms of EDA data, based on frequency of NS-SCR peaks for individual group members (Braithwaite et al., 2013). First, the frequency of NS-SCR peaks for each group member was calculated for every 30-s segment of collaboration. To account for the individual differences, the average number of peaks during one segment was then calculated for each group member separately, along with standard deviations; if the number of peaks during the segment was more than one standard deviation above the individual's average, the group member was considered to be in a state of high arousal. Individuals' limit values for high arousal varied between 5 and 9 peaks/30-s. Individual levels of arousal were then aggregated into a group-level activation variable. If all group members were in a state of low arousal, group-level activation was categorized as low; if some group members were in a state of high arousal, group-level activation was categorized as divergent, and if all group members were in a state of high arousal, group-level activation was categorized as high.

Phase 3: Locating regulation of learning during socio-emotional interactions

The emergence of group level regulation during each segment of socio-emotional interaction was observed from the video footage, defining regulation of learning as co- and socially shared activities addressing group members’ cognition, motivation, affect and behaviours (Hadwin et al., 2018). Activities were coded as regulation when the group faced a cognitive, motivational or emotional obstacle in their learning process, and an individual group member engaged in co-regulation, or group members engaged in shared strategic negotiation (socially shared regulation), followed by a strategic change in action (e.g., see Table 2). When regulation sought to maintain or strengthen affective state or motivation, no obstacle or change in action was needed (e.g., encouragement, social reinforcement; Järvenoja et al., 2019). Interrater reliability was assessed for 10% of the coded videos, and substantial agreement was indicated (\( \kappa = .79 \)) (Landis & Koch, 1977). The final codes were then discussed and agreed between the two coders.

Phase 4: Identifying socio-emotional interaction episodes of different kinds

Sequence mining was used to identify the various kinds of socio-emotional interaction episodes. This process typically involves constructing a sequence according to a time scheme and then studying sequences or patterns that constitute homogeneous subgroups of behaviours (Abbott & Tsay, 2000). As the multichannel data were temporally aligned, the study employed a novel method of multichannel sequence mining; after coding each data channel as a sequence, all sequences were temporally
To construct these sequence data, chronological 30-s segments of socio-emotional interaction were treated as single socio-emotional interaction episodes. Performing this procedure for the three data channels—valence (video), activation (EDA) and regulation (video)—yielded 447 socio-emotional interaction episodes with a mean length of 11.22 segments (SD = 15.04). Using MHMM for clustering (Helske & Helske, 2019), socio-emotional interaction episode clusters were differentiated in terms of valence, activation and regulation patterns. Observed states from the three data channels were regarded as probabilistic functions of hidden states that fluctuate during episodes of socio-emotional interaction. First, several MHMM models with different numbers of clusters and hidden states were estimated using the EM algorithm—repeating the process 1000 times from random starting values in order to find the global optimum (see Helske & Helske, 2019). Finally, the optimal number of hidden states and clusters were determined using the Bayesian Information Criterion. Consequently, the model was fitted for four clusters with two hidden states; the four clusters were named in terms of dominant patterns of valence, activation and regulation, and the hidden states were interpreted and named as affective states within the clustered episodes. Fluctuations in valence and activation as components of these affective states were measured in terms of Shannon’s entropy, using the TraMineR R package.
(Gabadinho et al., 2011), where larger entropy values indicate larger fluctuation. Furthermore, *proportions of positive valence and divergent activation* were calculated for each cluster using the seqipos function in TraMineR. Differences between the clusters were explored using the Kruskal–Wallis (KW) test and the Dunn–Bonferroni post hoc test with Holm adjustment.

## RESULTS

### Research question 1: What types of socio-emotional interaction episodes can be identified during collaborative learning?

The socio-emotional interaction episodes were clustered on the basis of sequential patterns of valence, activation and regulation of learning, and four clusters were identified: *positive, negative, occasional regulation* and *frequent regulation*. Positive cluster was characterized by dominant positive affective states throughout the episodes while unfavourable states predominated in negative cluster. Affective states did not seem to afford regulation of learning in these episodes. On the other hand, episodes in occasional regulation and frequent regulation clusters were characterized by occasional or frequent regulation of learning to maintain or restore favourable affective states for collaboration. The four clusters are described in detail below.

#### Cluster 1: Positive

This cluster \( (f = 127) \) accounted for 28% of socio-emotional interaction episodes. Figure 2 shows the flow of positive cluster episodes for two affective states (i.e., hidden states): *positive* and *mixed-positive*. In these episodes, groups began from a positive state (100%) characterized by positive valence and low

![Flow of positive cluster episodes through positive and mixed-positive states](image)

**Figure 2** Flow of positive cluster episodes through positive and mixed-positive states. The clusters are viewed as dynamic, and each cluster has two states. Numbers below the pie charts indicate the proportion of episodes starting in that state; arrows between the charts indicate transition probabilities (i.e., how frequently the transitions may occur between the states)
or divergent activation. This positive state remained stable throughout the episode, with only minor positive-mixed instances.

Figure 3 disassembles the two affective states into observed states of valence, regulation and activation. This shows that positive valence predominated in the positive state while activation fluctuated between divergent and low. During the positive state, group members were either positively activated or deactivated, and no major socio-emotional challenges were observed. Groups did not engage in regulation and maintained the positive state through recurring positive socio-emotional interactions.

Cluster 2: Negative

Of socio-emotional interaction episodes, 26% were assigned to the negative cluster \( f = 115 \). Figure 4 shows the flow of negative cluster episodes through negative and mixed-negative affective states. Most of the negative cluster episodes (93%) began in the negative state, in which negative valence was accompanied mainly by low activation. Relatively few episodes began with mixed-negative state (7%). The starting state remained stable in most cases, with relatively few instances of fluctuation between the two states.

As shown by the observed states of the three data channels in Figure 5, negative valence predominated in the negative state, with few instances of positive valence. Regulation was rarely attempted, and the state shifted from negative to mixed-negative, but the change was insufficiently stable to restore the convergent positive or neutral state. In both affective states, activation fluctuated between low and divergent, with low more dominant. Recurrent negative interactions sustained the negative state (deactivated or activated), and occasional group efforts to engage in positive interaction and regulation were insufficient to overcome challenging socio-emotional situations.
FIGURE 4 Flow of negative cluster episodes through negative and mixed-negative affective states

FIGURE 5 Derivation of negative cluster and negative and mixed-negative states from observed states of the three data channels (valence, regulation, activation)
Cluster 3: Occasional regulation

The most common cluster type was occasional regulation ($f = 188$), which accounted for 42% of the socio-emotional interaction episodes. Figure 6 shows the flow of occasional regulation episodes through mixed-positive and positive affective states. In most cases (74%), the episode typically started in the positive state (involving positive valence and mostly low activation), which persisted throughout. However, some episodes (26%) started in the mixed-positive state, which often changed to the positive state during the episode.

Figure 7 illustrates the observed states of valence, regulation and activation from which the two affective states derive. When an episode started in the positive state, valence remained predominantly positive, and activation remained low throughout the episode, with relatively few instances of negative and mixed valence and divergent activation. In the mixed-positive state, valence fluctuated more between positive, mixed and negative, and activation fluctuated between low and divergent. Groups occasionally engaged in regulation; in general, despite the short-term mixed-positive states, groups managed to end the episode in the positive state by activating regulation when this state was temporarily jeopardized.

Cluster 4: Frequent regulation

The smallest cluster was frequent regulation, which accounted for only 4% ($f = 17$) of the socio-emotional interaction episodes. Figure 8 shows the flow of frequent regulation cluster episodes through positive and negative affective states. As compared with the other clusters, episodes of frequent regulation included more fluctuation between the two states, which themselves differed more from each other. About half of the episodes (52%) began in the positive state (positive valence combined with low or divergent activation) while the remaining episodes (48%) began in the negative state (negative valence combined with low or divergent activation). Interestingly, fluctuation between these two states was observed in every episode.
Figure 7 represents this fluctuation in terms of observed states of valence, regulation, and activation, showing that positive states were frequently jeopardized by negative states. However, almost every episode included frequent regulation attempts, and the positive state was eventually restored. While

Figure 8 Flow of frequent regulation episodes through positive and negative states

Figure 9 represents this fluctuation in terms of observed states of valence, regulation, and activation, showing that positive states were frequently jeopardized by negative states. However, almost every episode included frequent regulation attempts, and the positive state was eventually restored. While
collaboration was challenged by recurring negative and mixed states, groups were able to overcome this issue through persistent positive interaction and frequent strategic regulation.

Research question 2: How do group emotional valence and activation fluctuate with regulation of learning during socio-emotional interaction episodes?

The next stage of the analysis disclosed the extent of valence and activation fluctuations in each cluster in terms of proportions of positive valence and divergent activation and Shannon’s entropy during clustered episodes. Descriptive statistics are presented in Table 3. KW testing and pairwise comparisons were used to identify differences between the clusters. The pairwise comparisons results are visualized in Figures S1–S4 provided in Appendix S1.

Emotional valence

KW testing revealed significant differences between the clusters in terms of proportion of positive valence ($\chi^2[3] = 220.82, p < .001$). Positive valence predominated in positive cluster ($\mu = .87$), followed by occasional regulation ($\mu = .64$) and frequent regulation ($\mu = .43$). The lowest proportion of positive valence was found in negative cluster ($\mu = .23$). Pairwise comparisons revealed significant differences between clusters, with the exception of frequent regulation and negative clusters (Appendix S1, Figure S1). These results confirm the implications of the cluster visualizations (Figures 2–9); the positive valence predominates in positive episodes while other episodes included more mixed and negative valences.

KW testing revealed significant between-cluster differences in valence entropy ($\chi^2[3] = 84.63, p < .001$). The highest entropy values related to frequent regulation cluster ($\mu = .78$), followed by negative ($\mu = .49$), occasional regulation ($\mu = .40$) and positive clusters ($\mu = .13$). The pairwise comparisons also reveal significant differences between each paired cluster (Appendix S1, Figure S2), confirming the interplay
between regulation of learning and emotional valence fluctuation. When emotional valence fluctuated frequently, regulation was also more frequently activated.

**Emotional activation**

KW testing revealed significant between-cluster differences in terms of proportion of divergent activation ($\chi^2[3] = 50.54, p < .001$). Additionally, the pairwise comparisons (Appendix S1, Figure S3) indicate significantly more divergent activation in positive ($\bar{\mu} = .58$) and frequent regulation clusters ($\bar{\mu} = .50$) than in negative ($\bar{\mu} = .46$) and occasional regulation clusters ($\bar{\mu} = .35$). In other words, groups exhibited more divergent activation in episodes with consistent positive states or recurring negative and mixed affective states, which they tried to overcome through frequent regulation. In turn, when affective states were consistently negative or when positive states were maintained through occasional regulation, the groups exhibited little divergent activation.

KW testing revealed significant between-cluster differences in activation entropy ($\chi^2[3] = 60.69, p < .001$). The pairwise comparisons (Appendix S1, Figure S4) show that activation fluctuated significantly more in frequent regulation ($\bar{\mu} = .68$) and positive clusters ($\bar{\mu} = .56$) than in negative ($\bar{\mu} = .37$) and occasional regulation clusters ($\bar{\mu} = .36$). That is, when groups needed to restore positive states through frequent regulation, activation also fluctuated more. Interestingly, while emotional valence remained

**Table 3** Descriptive statistics for proportions of positive valence, divergent activation and valence and activation entropy in the four clusters

<table>
<thead>
<tr>
<th>Descriptives</th>
<th>Cluster</th>
<th>N</th>
<th>Mean</th>
<th>95% confidence interval</th>
<th>95% confidence interval</th>
<th>Median</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proportion of positive valence</td>
<td>Positive</td>
<td>127</td>
<td>.866</td>
<td>.832 - .900</td>
<td>.832 - .900</td>
<td>1.000</td>
<td>.196</td>
</tr>
<tr>
<td></td>
<td>Negative</td>
<td>115</td>
<td>.225</td>
<td>.185 - .265</td>
<td>.225 - .265</td>
<td>.222</td>
<td>.218</td>
</tr>
<tr>
<td></td>
<td>Occasional regulation</td>
<td>188</td>
<td>.636</td>
<td>.592 - .679</td>
<td>.592 - .679</td>
<td>.600</td>
<td>.305</td>
</tr>
<tr>
<td></td>
<td>Frequent regulation</td>
<td>17</td>
<td>.433</td>
<td>.387 - .478</td>
<td>.387 - .478</td>
<td>.438</td>
<td>.096</td>
</tr>
<tr>
<td>Valence entropy</td>
<td>Positive</td>
<td>127</td>
<td>.127</td>
<td>.091 - .163</td>
<td>.091 - .163</td>
<td>.000</td>
<td>.207</td>
</tr>
<tr>
<td></td>
<td>Occasional regulation</td>
<td>188</td>
<td>.400</td>
<td>.345 - .456</td>
<td>.345 - .456</td>
<td>.402</td>
<td>.392</td>
</tr>
<tr>
<td></td>
<td>Frequent regulation</td>
<td>17</td>
<td>.785</td>
<td>.686 - .884</td>
<td>.686 - .884</td>
<td>.778</td>
<td>.208</td>
</tr>
<tr>
<td>Proportion of divergent activation</td>
<td>Positive</td>
<td>127</td>
<td>.581</td>
<td>.543 - .620</td>
<td>.543 - .620</td>
<td>.500</td>
<td>.221</td>
</tr>
<tr>
<td></td>
<td>Negative</td>
<td>115</td>
<td>.465</td>
<td>.405 - .524</td>
<td>.405 - .524</td>
<td>.500</td>
<td>.324</td>
</tr>
<tr>
<td></td>
<td>Occasional regulation</td>
<td>188</td>
<td>.348</td>
<td>.307 - .388</td>
<td>.307 - .388</td>
<td>.429</td>
<td>.282</td>
</tr>
<tr>
<td></td>
<td>Frequent regulation</td>
<td>17</td>
<td>.496</td>
<td>.456 - .535</td>
<td>.456 - .535</td>
<td>.500</td>
<td>.082</td>
</tr>
<tr>
<td>Activation entropy</td>
<td>Positive</td>
<td>127</td>
<td>.560</td>
<td>.508 - .612</td>
<td>.508 - .612</td>
<td>.666</td>
<td>.299</td>
</tr>
<tr>
<td></td>
<td>Negative</td>
<td>115</td>
<td>.372</td>
<td>.314 - .430</td>
<td>.314 - .430</td>
<td>.562</td>
<td>.316</td>
</tr>
<tr>
<td></td>
<td>Occasional regulation</td>
<td>188</td>
<td>.357</td>
<td>.314 - .399</td>
<td>.314 - .399</td>
<td>.500</td>
<td>.298</td>
</tr>
<tr>
<td></td>
<td>Frequent regulation</td>
<td>17</td>
<td>.681</td>
<td>.630 - .732</td>
<td>.630 - .732</td>
<td>.662</td>
<td>.108</td>
</tr>
</tbody>
</table>
stable in positive cluster (i.e., valence entropy was small), emotional activation fluctuated more than in negative and occasional regulation clusters, which exhibited higher valence entropy.

**DISCUSSION**

This study examined the affective states of collaborative groups and how they fluctuate with regulation of learning. The results align with the COPES framework (Winne & Hadwin, 1998) view of affect as influencing collaborative interactions among group members, as well as being constantly reset by socio-emotional interactions and regulation of learning (Bakhtiar et al., 2018; Winne & Hadwin, 2008). Multichannel sequence mining identified four clusters of socio-emotional interaction episodes, helping to clarify how emotional valence and activation fluctuate in each cluster and how these fluctuations go together with group-level regulation.

These results show that while the need for regulation is highly situation-specific, affective states that afford regulation of learning do not always lead to its activation (Järvenoja, Järvelä, et al., 2020), as it was detected in only two of the four clusters. In occasional regulation episodes, regulation was linked to temporal endangerment of positive affective states, and frequent regulation was needed to restore positive states in episodes where negative conditions recurred. Since positive states were dominant in the occasional regulation episodes, the need for regulation may not have been frequent and occasional regulation was enough to keep up the positive state when it was temporally jeopardized. During frequent regulation episodes, in turn, both emotional valence and activation were more ambiguous than in other episodes, and thus, regulation was needed more frequently. Li et al. (2021) studied the relationship between emotion variability, phase of self-regulated learning and task performance among individual medical students when solving patient cases using an intelligent tutoring system and reported that emotional variability was higher during difficult tasks. This may also have been the case in the frequent regulation episodes of the present study, as negative affective states and the need for regulation may reflect task-related cognitive challenges. Indeed, the present results suggest that regulation of learning was used strategically to alter group affective states during the learning process (Hadwin et al., 2018).

In the other two clusters, regulation of learning was not activated. In the positive episodes, group affective states remained positive throughout. Previous research has indicated that positive affect and positive socio-emotional interactions can facilitate group level regulation (Linnenbrink-Garcia et al., 2011; Rogat & Adams-Wiggins, 2015). Interestingly, stable positive learning conditions did not seem to invite regulation of learning in the present study, but this is not necessarily at odds with previous findings, as the focus here was on in-situ regulation within short episodes rather than, for example, at learning-session level. The groups may have made smooth progress without facing any severe challenges requiring regulation (Järvenoja et al., 2019). Regulation was not detected either in episodes where negative affective states occurred. Theoretically, these socio-emotionally critical situations would invite regulation to restore more positive conditions for collaboration (Linnenbrink-Garcia et al., 2011; Mänty et al., 2020). However, previous studies have also shown that when negative interactions are recurring, they can hinder the group’s ability to engage in regulation (Bakhtiar et al., 2018; Rogat & Adams-Wiggins, 2015), which might have been the case in this study. In sum, these findings may indicate that socio-emotional interaction can be enough to maintain positive affective states, but strategic regulation of learning may be needed to address socio-emotional challenges before the negative states start accumulating (Bakhtiar et al., 2018; Näykki et al., 2014).

These results also invite methodological discussion regarding the use of biophysiological measures in emotion regulation research—in particular, whether sympathetic arousal can be considered an indicator of emotional activation in learning situations. Previous studies have reported that students experience quite low levels of arousal in learning situations, with only occasional simultaneous high arousal among group members (Harley et al., 2019; Malmberg et al., 2019; Pijeira-Díaz, Drachsler, Kirschner, et al., 2018; Törmänen et al., 2021b). When it occurs, high arousal has been linked, for instance, to student negative affect (Ahonen...
The present study was built on the assumption that EDA data could reveal such temporal and changing markers of the physiological component of affect that cannot be captured with other process measures. In line with this assumption, the present study was able to show indications of the physiological emotional activation. First, it was found that all group members were rarely in high arousal simultaneously, and group-level activation typically remained low or divergent. In light of previous findings, it was interesting that divergent group-level activation (i.e., one or two group members in a state of high arousal) was most often observed during positive episodes. However, it should be noted that these findings are also determined by the researchers' preconditions for data processing. In the present case, limit values for individual high arousal varied between 5 and 9 peaks/30-s, which could theoretically be considered as medium arousal optimal for performance (Boucsein, 2012; Dawson et al., 2007; Yerkes & Dodson, 1908). The positive episodes also returned the second largest fluctuation in emotional activation (i.e., changes in groups' aggregated sympathetic arousal state) even though valence remained very stable. Sobocinski et al. (2020) suggested that changes in groups' physiological state during a learning process may relate to cognitive aspects of collaboration such as smooth task progress and related changes in action. In other words, both the emergence of divergent activation and fluctuations in activation level may indicate that groups were progressing smoothly during positive episodes. In contrast, the frequent regulation cluster included the second largest proportion of divergent activation, as well as the largest fluctuation. One possible explanation is that groups are more likely to engage in regulation when the emotional or cognitive challenges they face are also experienced as more physiologically intense. This is also supported by the finding that in the negative episodes, which were dominated by low activation, regulation did not occur despite the negative and mixed states. Alternatively, joint regulation efforts and subsequent changes in affective states or learning actions may be reflected in the group's activation level (Matejka et al., 2013; Pizzie & Kraemer, 2018).

The methods employed in this study represent a novel way of harnessing multichannel process data to explore socio-emotional processes during collaboration. This study showcased the significance of biophysiological data for understanding affect in learning as multifaceted and dimensional. It showed that by adding activation, captured with EDA data, as a component of affect it is possible to increase the level of explanation regarding the interplay between affect and regulation of learning in groups' socio-emotional interactions. Given the abundance of learning-related data from multiple sources, methods like multi-channel sequence mining can make a valuable contribution to our understanding of the multi-componential and dynamic nature of learning. In the present case, MHMM facilitated the exploration of heterogeneity in the data by differentiating socio-emotional interaction episode clusters and trajectories. Recent implementations confirm the potential of MHMM for early prediction of such trajectories or behavioural profiles (Helske & Helske, 2019), including for example which groups are likely to follow e.g., a certain regulation of learning profile. This information could be used to give appropriate and proactive support for the groups.

Limitations

The present study has some limitations. First, video data coding was performed to capture group-level affective states and regulation of learning, which meant aggregating individual sympathetic arousal data. While this enabled systematic integration of valence and activation data, individual-level changes were not captured. Second, the use of 30-s segmentation to integrate video and sympathetic arousal data of differing granularity levels may have obscured more subtle changes in affective states. Third, while video coding addressed the chosen variables of valence and regulation, ongoing learning activities related to the socio-emotional interaction episodes were not explored; that is, group task progress during the episodes could only be assumed. In practice, the focus of the study was group-level processes at episode level, especially the interplay between affective states and regulation, and the methodological choices reflect this emphasis. The present study serves as a starting point for future research, which is needed for both more in-depth exploration of the identified socio-emotional interaction episodes in...
relation to the learning activities and the role of these socio-emotional processes for the groups' learning outcomes and experiences of collaboration.

Implications for educational practice

For the collaborative groups in this study, maintaining positive affective states seemed easier than engaging in strategic regulation of learning to overcome the accumulating negative states. This highlights the importance of increasing group members' awareness of affective states, especially at the beginning of the collaborative learning process, before socio-emotional issues begin to accumulate (Järvenoja, Järvelä, et al., 2020). This could be done for example by different types of awareness tools (Järvelä, Kirschner, et al., 2016; Kwon, 2020; Lavoué et al., 2020). Furthermore, the groups could benefit from more knowledge and support on how to apply appropriate regulation strategies to overcome the socio-emotional challenges (for emotion regulation strategies, see e.g., Bakhtiar et al., 2018; Järvenoja et al., 2019; Mänty et al., 2022). However, the challenge for both teachers and students is to recognize these socio-emotionally critical episodes in situ and to provide learning groups with timely information and support. This is especially the case when novel learning technologies offer alternative contexts for collaboration, some of which do not enable face-to-face interaction between students and teachers. Thus, it can be argued that this type of research provides a more direct benefit for educational technology developers who can utilize the results in designing more appropriate support for learners and teachers, and as a result promote timely regulation. Future research should explore how the full potential of multichannel data and advanced technologies can be harnessed to provide collaborative groups with well-timed personalized support (Järvelä & Bannert, 2021).

CONCLUSION

It seems clear that comprehending how affect influences learning depends on understanding how affective states interact with both individual and group learning processes. Moreover, it is not enough to measure affect and its effects on outcomes (Taub et al., 2019); to extend our understanding of learning processes, we need novel methods that can capture the interplay between different components and multiple levels (Azevedo & Gašević, 2019; Järvelä, Malmberg, et al., 2021). The present study augments the empirical evidence on how the changing affective states and regulation of learning are intertwined with socio-emotional interactions during collaboration. The study also makes a methodological contribution to collaborative learning research by employing multiple data channels, including biophysiological measures, to explore the various dimensions of socio-emotional processes in groups. The results support the view that measuring emotional activation as a separate component can help to clarify the affective and related cognitive processes involved in collaboration (Malmberg et al., 2019; Monster et al., 2016). The use of complementary data sources helps to clarify when emotional activation is beneficial for learning and collaboration and when regulation may need to be supported (Järvelä, Malmberg, et al., 2021).

AUTHOR CONTRIBUTIONS

Tiina Törmänen: Conceptualization; formal analysis; funding acquisition; investigation; methodology; writing – original draft; writing – review and editing. Hanna Järvenoja: Conceptualization; funding acquisition; methodology; project administration; supervision; writing – original draft; writing – review and editing. Mohammed Saqr: Formal analysis; visualization; writing – original draft; writing – review and editing. Jonna Malmberg: Conceptualization; funding acquisition; methodology; project administration; supervision; writing – original draft. Sanna Järvelä: Conceptualization; funding acquisition; methodology; project administration; supervision; writing – original draft.
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CONFLICT OF INTEREST
All authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT
Research data are not shared.

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REFERENCES


GROUP AFFECTIVE STATES AND REGULATION


SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.