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Exploring temporal sequences of regulatory phases and associated interactions in low- and high-challenge collaborative learning sessions

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Abstract Investigating the temporal order of regulatory processes can explain in more detail the mechanisms behind success or lack of success during collaborative learning. The aim of this study is to explore the differences between high- and low-challenge collaborative learning sessions. This is achieved through examining how the three phases of self-regulated learning occur in a collaborative setting and the types of interaction associated with these phases. The participants were teacher training students ($N = 44$), who worked in groups on a complex task related to didactics of mathematics during 6 weeks. The participants were instructed to use an application that was designed to increase awareness of the cognitive, motivational and emotional challenges the group might face. Based on the application's log files, the sessions were categorized into low- and high-challenge sessions. The video data from each session were coded based on the self-regulation phases and the types of interaction. The frequencies of the phases and the types of interaction were calculated for each session, and process discovery methods were applied using the heuristic miner algorithm. The results show no significant differences between the sessions in the frequency of phases. However, the process models of the two sessions were different: in the high-challenge sessions, the groups switched between the forethought and performance phases more. In conclusion, the regulation phases and types of interaction that contribute to successful collaboration differ in high- and low challenge sessions and support for regulated learning is needed especially at the middle of the learning process.

Keywords Self-regulated learning · Temporal patterns · Process mining · Video data · Collaborative learning · Interaction types

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Introduction

Self-regulated learning (SRL) can be viewed as an aptitude: developing skills and beliefs that affect learning or as a string of events consisting of specific actions that learners perform (Winne 2010). Self-regulated learning as an event does not happen automatically; it can instead be viewed as intentional activity that is used when a need arises (Hadwin et al. 2011).

Metacognitive monitoring is the process by which learners become aware of the need for regulation, and monitoring can occur in each phase of SRL, such as orientation, performance and evaluation (Wolters et al. 2011). The phases build into each other, and they can occur multiple times within and across learning sessions (Cleary and Zimmerman 2012). Although much is known about SRL phases and the accompanying regulation processes (e.g., Zimmerman 2008), it is not yet clear how SRL phases actually occur throughout the learning session and how learners' perceptions of a learning situation impact the learning activities.

Viewing self-regulated learning as a series of events, accompanied by learners' perceptions of a learning situation, provides an opportunity to study the order in which SRL processes occur, when they happen in the learning process and how situational interpretations affect the self-regulated learning process (Molenaar and Järvelä 2014). This information is important because looking at how and when the different SRL phases occur during challenging and unchallenging learning situations in a real-life setting can be useful for supporting self-regulated learning in a targeted way when it is needed the most. This is especially the case in collaborative learning, in which regulation of the collaboration contributes to better learning results (Järvelä et al. 2016a, b, c).

In recent years, several studies focused on discovering patterns in students' learning activities (Bannert et al. 2014; Malmberg et al. 2015a, b; Molenaar and Järvelä 2014; Sonnenberg and Bannert 2015); however, as Bannert et al. (2014) pointed out, comparing these studies is problematic as they use different learning settings (individual or collaborative) and focus on different microlevel learning processes. Microlevel SRL processes can be grouped under macrolevel processes (Greene and Azevedo 2009). For example, microlevel SRL processes such as content evaluation, monitoring the use of strategies or progress and self-questioning can be grouped under monitoring, which is a macrolevel SRL process. Greene and Azevedo (2009) used think-aloud data from high school and middle school students and identified several macro- and microlevel SRL processes, showing out that the macrolevel process related to monitoring was associated with more sophisticated mental models. This finding indicates that not only microlevel SRL processes but also certain macrolevel SRL processes can be central for learning.

When it comes to understanding the temporality of regulation processes, studies have focused on the SRL process and the performance SRL leads to, for example, by comparing the patterns of high- and low-performing groups (Bannert et al. 2014; Malmberg et al. 2015a; Schoor and Bannert 2012) or by comparing the effects of different prompts on the process and the learning outcome (Bannert et al. 2015; Sonnenberg and Bannert 2015). During a long-term collaboration, students can face challenging learning situations, and if the students are successful in regulating their learning and overcoming these challenges, the students' final learning outcome will improve (Malmberg et al. 2015a, b).

In this study, we take a macrolevel approach to explore when challenging learning sessions occur within a long-term collaboration and how these sessions differ from unchallenging ones in terms of the learning process, focusing on SRL phases and types of interaction. The type of interaction that students use during learning can provide insight into the targets that are being regulated (cognition, emotions, motivation) and how that regulation is achieved.

Cyclical phases of regulated learning

Self-regulated learning is an active, constructive and cyclical process consisting of forethought, performance and evaluation phases. During each phase, by engaging in metacognitive monitoring, learners have opportunities to regulate their cognition, motivation, emotion and behavior guided and constrained by the learners' goals and their environment (Pintrich 2000; Zimmerman 2000). Depending on the theories, there are differences in how phases of regulated learning are portrayed (Pintrich 2000; Winne and Hadwin 1998; Zimmerman 2011), but in general, three phases in the SRL process can be identified (in addition to monitoring and control): preparation, execution and reflection. In the following, the three phases are referred to as forethought, performance and self-reflection (Zimmerman 2000). Zimmerman (2013) pointed out that how learners engage in regulated learning during each phase has the potential to explain major qualitative differences in self-regulated learning.

The need for regulation is recognized through active monitoring of the learning process: Regulation can potentially occur if the learner detects a discrepancy between the current state and the desired state for learning at any stage of the learning progress (Winne and Hadwin 1998). However, although one might monitor the need to self-regulate learning, it does not necessarily mean that SRL is activated (Hadwin et al. 2011). Instead, whether the regulated learning is activated depends on the contextual features that shape and constrain the quality of the students' learning and what individuals bring to the specific learning situation (Butler and Cartier 2004). From this perspective, the degree to which SRL is actualized is assumed to be determined by one's interpretations of the current learning situation (Zimmerman 1989, 2001). McCardle and Hadwin (2015) used self-report data collected over 11 weeks to study how SRL unfolds over time and context, and found that learners' perception of the learning situation can offer valuable insight into understanding the adaptation of SRL processes for specific conditions. To sum up, this is why it is relevant to consider learners' perceptions that guide their regulatory actions and decisions as learners engage in the forethought, performance and evaluation phases.

In the forethought phase, the learner activates beliefs and self-regulatory processes as preparation for the learning itself. According to Zimmerman (2000), there are two categories of forethought: task analysis (which includes goal-setting and strategic planning) and self-motivational beliefs (which include self-efficacy beliefs, outcome expectations, intrinsic interest and goal orientation). Previous research that examined the importance of the forethought phase in student learning identified that students who set specific goals for their studying and activate their prior knowledge carry out deep-level learning strategies during the performance phase (Malmberg et al. 2013).

The performance phase includes processes that occur during the learning efforts: self-control and self-observation. Self-control processes help students focus on the task and use the most efficient strategies to achieve their goals. The second type of process, self-observation, involves monitoring specific aspects of performance. The performance phase is guided by the decisions made during the forethought phase and situation-specific interpretations. Malmberg et al. (2013) identified that in learning situations in which students perceive no difficulties, high- and low achieving students use the same types of strategies. However, when the situation is perceived as difficult, there are qualitative differences between the strategies high- and low-achieving students use during the performance phase.

The third phase, self-reflection, involves processes that occur after the learning performance. During the self-reflection phase, learners self-evaluate the information they gathered through monitoring their behavior against the goals the students set during the forethought phase or the feedback they received and make causal attributions for the outcomes. The products of the reflection phase, the learner's reflections on experiences, affect the following forethought phase, supporting the cyclical nature of self-regulation (Zimmerman 2000). Cleary et al. (2014) found that following negative feedback about their performance, medical students' self-efficacy beliefs and strategic regulatory processes decreased, showing how the self-reflection phase can affect later performance.

When looking at SRL as an event, the temporal nature and the sequential nature of these phases become relevant. Although there is no typical cycle (Azevedo and Witherspoon 2009), in every type of learning situation there is a connection between the phases, as they influence each other. This means, for example, that learners' perception of the task and task-related goals in the forethought phase affect what types of strategies the learners employ and how much time and resources the learners are willing to invest in the task during the performance phase (Winne and Hadwin 1998).

Socioemotional and cognitive interaction in collaboration

Prior research has identified cognitive and socioemotional processes as important factors in collaborative learning (Phielix et al. 2011). Scholars contend that socioemotional interaction can set the stage for cognitive interactions (Kreijns et al. 2013) and thus fuel cognitive processes (Järvelä et al. 2016a). In a study that examined the quality of cognitive regulatory processes in small collaborative groups, Rogat and Linnenbrink-Garcia (2011) found that positive socioemotional interactions facilitated higher-quality regulation.

Despite the importance of socioemotional interaction that can provide grounding for regulation to occur, the temporality of cognitive and socioemotional interactions within collaborations has not been studied, and it is not clear how different types of interaction within the different phases of regulated learning occur. Kapur (2011) argued that there is a need to study how interactions change in collaborative learning and what contextual features influence these changes.

The temporality of the different types of interaction is relevant, because in a collaborative learning situation group members need to react to situated challenges as they arise during the process of collaboration. Challenges trigger the need to regulate cognitive and socioemotional aspects of the collaboration (Hadwin et al. 2011). Järvelä and Hadwin (2013) pointed out that in order to recognize challenges, groups need to be aware of their own and shared socioemotional states and actions. To solve the recognized challenges (cognitive, motivational, emotional and social) in collaboration, the group members are required to regulate their learning (Kreijns et al. 2013). Successful regulation of the cognitive and socioemotional aspects of collaboration provides space for cognitive processes to occur in interactions, such as grounding, critical thinking and joint knowledge construction. These cognitive processes in particular can enhance knowledge construction, deep-level learning and critical thinking (Roschelle and Teasley 1995).

When considering how regulated learning appears in social interactions, Molenaar and Järvelä (2014) argued that the same phases of regulated learning (forethought, performance and reflection) can apply to a collaborative situation. In a similar way, cognitive and socioemotional interactions are intertwined with the three phases of regulated learning. Cleary and Zimmerman (2012) used the term “sequential feedback loop” to describe the cyclical nature of these phases and encouraged researchers to use novel methods to capture the dynamic changes in the cyclical phases.

Studying sequential characteristics of regulated learning with the assistance of technological tools

Previous studies that used novel methods were concerned with microlevel analysis, focusing on the detailed self-regulatory processes learners use (Bannert et al. 2014; Johnson et al. 2011; Malmberg et al. 2015a, b; Molenaar and Chiu 2014; Molenaar and Järvelä 2014; Sonnenberg and Bannert 2015). In a study that examined the temporal and dynamic nature of students’ self-regulatory processes using think-aloud data, Johnson et al. (2011) found that learners use a higher amount of planning in the later part of the learning session, not right at the beginning. The authors argued that this might be due to the lack of prior knowledge in the subject: as learners become more familiar with the topic, they are able to use planning activities, such as prior knowledge activation. Molenaar and Chiu (2014) used statistical discourse analysis to statistically test significant microlevel relationships among sequences of cognition, metacognition and relation activities during collaborative learning. The results showed that planning facilitates the transition between low and high cognition.

Bannert et al. (2014) found that successful students show more learning and regulation events compared to less successful students. Furthermore, using process mining the authors discovered that the two groups also differed in the temporal pattern of their learning steps: The successful students’ process model included monitoring and evaluation activities and showed activities related to the forethought phase occurred before information processing. These studies provide empirical evidence of how different regulatory activities are linked to each other, and the methods used in the studies offer an opportunity to capture the dynamic changes in the cyclical phases (forethought, performance, reflection) that these regulatory activities can be grouped under.

Today, many technological tools have been successfully used to trace self-regulatory processes, while simultaneously supporting them. Sonnenberg and Bannert (2015) used a hypermedia learning environment, where they integrated metacognitive prompts. They found that in groups that received these prompts, orientation, planning and goal-setting activities (i.e., forethought phase activities) were better integrated in the process model, and these groups engaged in a higher number of regulation loops.

Other technological tools aim to prompt students’ awareness of emotional, motivational and cognitive challenges (Azevedo et al. 2009; Järvelä et al. 2013; Järvenoja and Järvelä 2009; Malmberg et al. 2010), especially to assist computer-supported collaborative learning (Järvelä et al. 2014). The feedback the groups get from the awareness tools might influence the strategies the groups use later during collaboration (Kreijns et al. 2003). These tools have a dual purpose in regulated learning research. They provide support for the students’ regulation and collaboration, but the tools can also be used as a methodological tool to identify, for example, learning situations that might call for activation of regulation (Järvelä et al. 2014).

Previous studies adopted a microlevel perspective and focused on identifying in what context and in what order specific metacognitive processes occur (Bannert et al. 2014, 2015; Reimann et al. 2009; Schoor and Bannert 2012; Sonnenberg and Bannert 2015). In the present study, we took a macrolevel perspective to investigate how SRL phases (forethought, performance and reflection) occur in collaborative learning and what types of interaction are associated with these phases in the learning process. Studying how types of interaction are associated with SRL phases can provide insight into the areas that are regulated (cognition, emotions, motivation) and how that regulation is achieved.

Aim of the study

The aim of this study is to explore the differences between high- and low-challenge collaborative learning sessions from the point of view of phases of regulation and the types of interaction associated with these phases. The research questions are the following:

1) When do high-challenge sessions occur during long-term collaboration?
2) How do SRL phases and the associated types of interaction occur in low- and high-challenge sessions?
3) What types of patterns of learning activities correspond to low- and high-challenge sessions?

Method

Participants and context

The participants ($n = 44$; mean age = 24.9, 36 female) were teacher training students attending a mathematics didactics course that lasted for 6 weeks. The participants were divided into 11 groups of four, and one student dropped out before the course started. The students worked in the same groups throughout the course. All analyzed group work sessions took place in a learning laboratory that had a flexible space suitable for group work and was equipped with 360° cameras.

The course requirements included collaborating on a mathematics term plan for elementary school students. The students were expected to continuously work on their term plans with their groups during the 6-week period. There were five assigned time slots of 90 min for working face-to-face on the term plan in the learning laboratory; however, the students had the option of choosing how to organize their work. Attending the face-to-face meeting occasions was not compulsory. The groups attended the offered face-to-face sessions two to five times ($M = 3.7$; $SD = 1$; mean duration: 1 h 5 min, SD: 18 min 48 s).

Procedure and data collection

The term plan group sessions were entirely student led. The students were given the general task and had to decide for themselves how to organize their work. Designing a term plan is considered a complex task for students, as it requires them to review theory and different materials, choose teaching and assessment methods and design individual lessons for a larger given topic. Designing a term plan can be considered an ill-structured task, and thus, it provides students with more challenges but also more opportunities to regulate their learning compared to a well-structured task (Malmberg et al. 2014; Molenaar and Chiu 2014).

Before each group work session, the students were required to use an application (S-REG) that was developed to support socially shared regulation of learning by helping students become aware of their cognition, motivation and emotions and to serve as the basis for discussing possible problems in the groups (Järvelä et al. 2016b). The S-REG tool was available for students as an HTML5 mobile application. First, the students were asked to think collaboratively about what their task was and what they were supposed to do during their group work session. Second, they had to rate statements related to cognition (e.g., I know what I am doing), motivation (e.g., I feel motivated) and emotions (e.g., I feel comfortable) individually. Based on these answers, the application gave a rating of the whole group's state as a traffic light indicator: green (everything is good), yellow (there might be some problems) and red (there are serious problems). A screenshot of a traffic light indicator is presented in Fig. 1. The rating was given separately for the groups' cognition, motivation and emotions, and there was a different traffic light for all three areas. Third, after the groups had the opportunity to discuss these ratings, the groups had to explain in writing why they thought they received these specific traffic light indicators. In this study, traffic light indicator data were used.

The data used in this study consisted of 46 h of video recordings collected from all group work sessions. Log data resulting from the S-REG tool, containing the traffic light the group was assigned, were also collected. In two sessions, the tool malfunctioned, leaving 39 term plan sessions for which there were video data and log data.

Analysis

Types of interaction and phases of regulation The first step of the analysis was coding the videos based, using NVivo video analysis software. The coding was done in two stages. In the first stage, the types of interaction were identified, while the second round focused on the regulation phases. In both stages, the coding categories and criteria were negotiated and agreed on with the researchers involved. Clear definitions and examples were provided to ensure the consistency of the coding process. The detailed coding criteria are presented in Table 1. Thirty percent of all the data was coded by two independent coders, resulting in a good inter-rater agreement (Cohen's kappa = .89, Std = .24).

In the first stage, the data were coded under socioemotional and cognitive-focused interactions. The criteria for identifying the types of interaction were based on research on collaborative learning

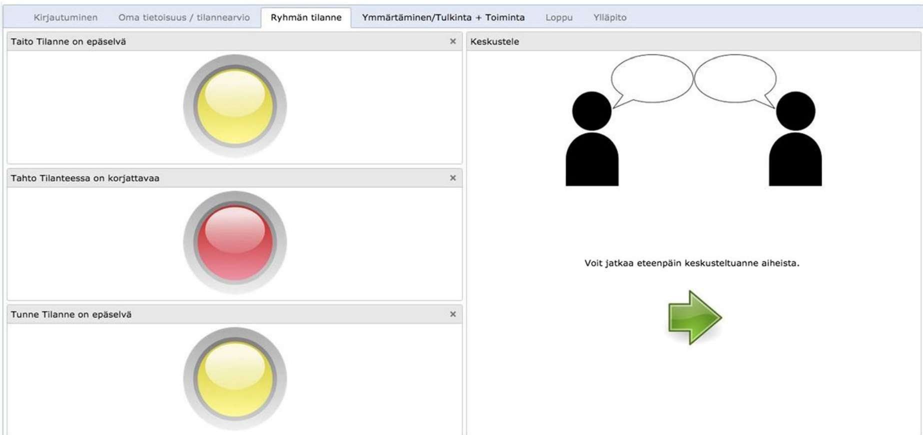

Fig. 1 Screenshot from the S-REG tool showing the traffic light indicator: *yellow* for cognition and emotions and *red* for motivation. The image on the right instructs students to discuss the traffic light results

Table 1 Definitions of coding categories used for the video data

	Category	Indicators
Types of interaction	Cognitive-focused collaborative interaction	Interaction between two or more group members who were sharing task-related ideas, developing each other's ideas; working toward a shared goal; joint task solving
	Socioemotional interaction	Interaction between two or more group members about emotions or motivation or expressing emotions
	Irrelevant interaction	Off-topic interactions that are not socioemotional
	No interaction	Lack of interaction
Regulation phases	Forethought phase	Expressing beliefs about task outcome or expressing interest Activities related to task understanding, planning and setting goals
	Performance phase	Using task strategies Monitoring whether the strategies used were appropriate Time and environment management
	Reflection phase	Evaluating whether the goals were achieved, explaining the cause of the success or failure

and group regulation (Dillenbourg et al. 1995; Rogat and Linnenbrink-Garcia 2011). Interactions were considered cognitively focused when they included discussions that were task focused or related to group members' metacognition. Interactions were coded as socioemotional if they were about emotions or motivations, or included expressions of emotion (e.g., laughter, frustration). Because of the assumption that cognitive and socioemotional processes can coexist, and a socioemotional interaction creates a space for learning (Kreijns et al. 2013), these two codes were not considered mutually exclusive. Parts could be coded as both cognitive-focused and socioemotional interactions. For further analysis, parts coded under both types of interaction (cognitive-focused and socioemotional) were considered a separate category. Examples of mixed cognitive and socioemotional interactions included interactions between two or more group members who were sharing task-related ideas, intertwined with the expression of emotions or including brief comments about emotions or motivation. Parts without interactions were marked no interaction. Examples of segments of the interactions can be found in the Appendix.

In the second stage, data were coded under self-regulation phases. The criteria for these codes were derived from self-regulated learning theory (Zimmerman 2000). Data coded under the phases included on-task collaborative learning situations, which potentially provided opportunities for activating regulation. For example, episodes coded under the forethought phase included planning, goal-setting, task-understanding; the performance phase included using task strategies and the reflection phase included discussions about the outcomes and what the group could have done differently. The three phases were considered mutually exclusive.

Episodes that were not coded under any phase were considered off task and were not included in this analysis (e.g., arriving, off-topic discussions). After the two rounds of coding, on-task segments had two codes (the self-regulated learning phase and the type of interaction) resulting in six codes, such as a cognitive-focused interaction in the forethought phase. Examples of the activities coded under the overlapping categories can be found in Table 2.

Table 2 Examples of activities coded under overlapping types of interaction and regulation phases

	Forethought phase	Performance phase	Reflection phase
Cognitive-focused collaborative interaction	Planning the group activities Reading and commenting on the task instructions	Writing together in a shared document Discussing concepts or other content-related issues	Discussing what the group has achieved Discussing what the group could have done differently
Socioemotional interaction	Expressing excitement about the task or feeling unmotivated	Talking about emotions while solving the task, expressing current tiredness, frustration anger, joy or other emotions	Reflecting on motivation or the emotions experienced during the task Expressing emotions while reflecting on how the task went

Level of challenge Using the log file data from the S-REG tool, each session of each group was marked as either low challenge or high challenge. The challenge level was determined based on the three traffic light indicators the S-REG tool gave the groups at the beginning of each session. The color of the traffic lights was dependent on the groups' answers to questions regarding their current motivation, emotion and cognition. If the traffic light indicated at least two green lights and no red lights, it was considered that at that moment the group did not recognize any considerable challenges that would require them to actively regulate their motivation, cognition or emotion. If the traffic lights had at most one green light (i.e., two or three yellow and/or red) or at least one red light, the group was considered high challenge, because they indicated they had challenges in particular areas. Thus, the high- and low-challenge categories reflect the group members' interpretations of the current situation as seen at the beginning of each session. Out of 39 sessions, 15 were marked as low challenge and 24 as high challenge. Details on the distribution of the traffic light indicators are presented in Table 3.

Process mining A log file was created based on the coded video data. The log file contained 1254 events and their duration, a selection of which are presented in Table 4. To analyze the relative arrangement of the learning activities, the process mining method was employed. Process mining provides tools for gaining insights into complex processes in a variety of fields, and it builds on data mining (van der Aalst 2011). Process mining methods discover process models inductively from activity sequences, taking the frequencies and sequences of events into account by examining dependencies between events (van der Aalst 2011). The result of process mining is a process model, which contains states and transitions, and provides a generalized representation of the sequences (Reimann et al. 2009).

Table 3 Distribution of traffic light indicators

Session type	Combination of traffic light colors	*f*
High-challenge sessions ($f = 24$)	One red, two yellow	4
	One red, one yellow, one green	3
	Two red, one yellow	6
	Three red	3
	One green, two yellow	8
Low-challenge sessions ($f = 15$)	Two green, one yellow	6
	Three green	9

Table 4 Section from the event log

Session nr	Start timestamp	End timestamp	Interaction	Phase	Challenge (1: high challenge; 2: low challenge)
14	21.03.2014 1:00:50.0	21.03.2014 1:02:49.0	COG	PERF	1
14	21.03.2014 1:02:49.0	21.03.2014 1:04:29.7	COG+SOC-EM	FORE	1
14	21.03.2014 1:04:29.7	21.03.2014 1:05:21.8	COG	FORE	1
14	21.03.2014 1:05:21.8	21.03.2014 1:06:26.7	COG	REF	1
14	21.03.2014 1:06:26.7	21.03.2014 1:07:53.6	COG+SOC-EM	FORE	1
14	21.03.2014 1:07:53.1	21.03.2014 1:09:27.4	COG	PERF	1

COG Cognitive-focused collaborative interaction, *SOC-EM* socioemotional interaction, *PERF* performance phase, *FORE* forethought phase, *REF* reflection phase

Bannert et al. (2014) argued that this method is suitable for SRL research because researchers can assume an event-based view of SRL processes, and this method is appropriate for investigating regulatory patterns. This method has been used successfully by several scholars in the field of learning sciences to explore the regulatory processes of groups and individual learners using log files from computer-supported learning contexts or think-aloud protocols (Bannert et al. 2014, 2015; Reimann et al. 2009; Schoor and Bannert 2012; Sonnenberg and Bannert 2015).

The analysis of the created log file was conducted using ProM 6.5.1 (2015). We first added start and end events for each session and then used the simple heuristics filter and removed the least frequent events (<10 occurrences). For the process discovery, we used the heuristic mining algorithm (Weijters et al. 2006), because in a review of state-of-the-art process discovery algorithms, De Weerdt et al. (2012) found that the heuristics miner algorithm was especially suitable in a real-life setting, and the algorithm was successfully used in the past for discovering SRL processes (Sonnenberg and Bannert 2015).

Results

Occurrence of high-challenge sessions during long-term collaboration

Attending the face-to-face meetings was not compulsory. Table 5 shows how many groups participated in each time slot offered (1: first, 5: last) and the distribution of low- and high-challenge sessions in each time slot. Sessions were categorized as high- or low-challenge sessions based on the S-REG tool data. The third (middle) session was considered challenging by 90% of the groups while the last session was seen as low challenge by all seven groups who participated.

Distribution of SRL phases and the associated types of interaction in low- and high-challenge sessions

In the next step, the frequency and duration of the phases and the associated types of interaction were calculated based on the log file created for high- and low-challenge sessions. Table 6 presents the absolute and relative frequencies of learning events, as well as the minimum, maximum and mean occurrences of these events per session. In low- and high-challenge sessions,

Table 5 Distribution of high- and low-challenge sessions over time

Time slot	Number of participating groups	High-challenge sessions		Low-challenge sessions	
		f	%	*f*	%
1	7	5	71.4	2	28.6
2	9	6	66.7	3	33.3
3	10	9	90.0	1	10.0
4	6	4	66.7	2	33.3
5	7	0	0.0	7	100.0

the most frequent events were the performance and forethought phases associated with cognitive-focused interactions. Reflection phase events were scarcely present in the log files of both types of sessions. Although in high-challenge sessions the relative frequency of forethought phase events was higher than in low-challenge sessions, a Mann–Whitney *U*-test showed no statistically significant difference in any of the events between the two types of sessions.

Process analysis for low- and high-challenge sessions

The process mining results are presented in Fig. 2. The frequencies of the events are shown in the boxes. The arcs show the dependency between two events, and the number indicates the certainty of the dependency relation (the closer to 1, the higher the certainty). The model for the low-challenge sessions has a fitness value of 0.66, while the fitness score of the high-challenge session is 0.77. The fitness value can range from $-\infty$ to 1, with a number closer to 1 indicating a good fit between the model and the data. In a previous study that used the same process mining algorithm, the authors reported fitness values of 0.53 and 0.62, which were considered substantial (Sonnenberg and Bannert 2015).

Process model for low-challenge sessions For the low-challenge sessions, a common pattern or path of high certainty started with a socioemotional interaction in the forethought phase and then moved on to the performance phase expressed through a cognitive-focused interaction (START→FORE//soc-em →PERF//cog→END). The forethought phase cognitive-focused interaction creates a loop within itself, showing that this event occurred several times consecutively. There was a low certainty cycle comprising only performance phase events: From the cognitive-focused interactions, the groups moved to socioemotional interactions and then to combined cognitive and socioemotional interactions, which were followed by no interaction, which then cycles back to a cognitive-focused interaction.

Process model for high-challenge sessions In the high-challenge sessions, the probable path included switches between forethought and performance phase events. It started with a socioemotional interaction during the forethought phase, from which there was a transition to cognitive and socioemotional interactions combined in the performance phase, followed by a cognitive-focused interaction in the forethought phase, which was succeeded by a socioemotional interaction in the performance phase, and finally, a cognitive-focused interaction in the reflection phase (START→FORE//soc-em →PERF//cog+soc-em→FORE//cog→ PERF//soc-em →REF//cog→END). In this model, the forethought phase cognitive-focused interaction is connected to many different events, showing that it has a central role in the

Table 6 Frequencies of events in low- and high-challenge sessions

	Low challenge ($n = 15$)						High challenge ($n = 24$)					
	Absolute frequency	Relative frequency	Min.	Max.	Mean	Std. Deviation	Absolute frequency	Relative frequency	Min.	Max.	Mean	Std. Deviation
Forethought	**208**	**30.06%**	**2**	**36**	**13.87**	**9.81**	**397**	**37.85%**	**4**	**39**	**16.54**	**9.83**
FORE//SOC-EM	42	6.07%	1	7	2.80	1.86	63	6.01%	0	6	2.63	1.53
FORE//COG	125	18.06%	1	24	8.33	6.36	251	23.93%	2	28	10.46	7.85
FORE//COG+SOC-EM	41	5.92%	0	9	2.73	2.55	83	7.91%	0	9	3.46	2.32
Performance	**338**	**48.84%**	**0**	**56**	**22.53**	**17.39**	**443**	**42.23%**	**0**	**49**	**18.46**	**14.54**
PERF//SOC-EM	16	2.31%	0	6	1.07	1.62	26	2.48%	0	6	1.08	1.72
PERF//COG	234	33.82%	0	35	15.60	12.44	300	28.60%	0	33	12.50	9.78
PERF//COG+SOC-EM	72	10.40%	0	12	4.80	4.36	111	10.58%	0	20	4.63	5.51
PERF// NO	16	2.31%	0	11	1.07	2.84	6	0.57%	0	4	.25	.84
Reflection	**10**	**1.45%**	**0**	**2**	**.67**	**.72**	**17**	**1.62%**	**0**	**3**	**.71**	**.90**
REF//SOC-EM	1	0.14%	0	1	.07	.26	1	0.10%	0	1	.04	.20
REF//COG	5	0.72%	0	1	.33	.49	11	1.05%	0	1	.04	.20
REF// COG+SOC-EM	4	0.58%	0	1	.27	.46	5	0.48%	0	1	.04	.20
TOTAL	**692**						**1049**					

Values highlighted in bold correspond to the three regulation phases. These are the sums of the frequencies in the smaller categories. Bold was used to emphasize that these lines are different

COG Cognitive-focused collaborative interaction, *SOC-EM* socioemotional interaction, *IRR* irrelevant interaction, *PERF* performance phase, *FORE* forethought phase; REF: reflection phase

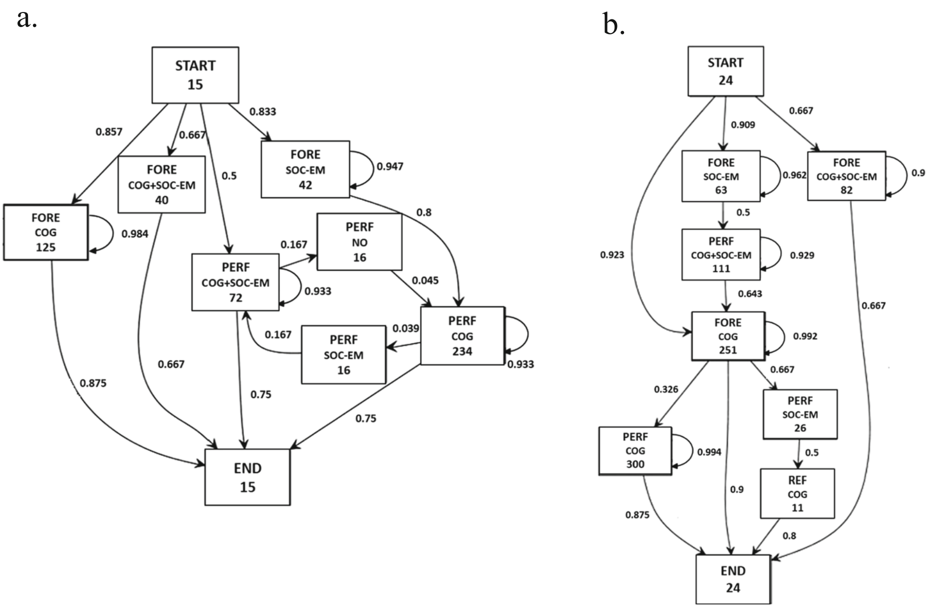

Fig. 2 Process model for the low-challenge sessions (**a**), $f=15$, and high-challenge sessions (**b**), $f=24$ created using the heuristic miner algorithm. COG: Cognitive-focused collaborative interaction; SOC-EM: socioemotional interaction; PERF: performance phase; FORE: forethought phase; REF: reflection phase

process. In these sessions, the performance phase cognitive-focused interaction was preceded by a cognitive-focused interaction in the forethought phase.

To summarize, the two process models mainly differed in the number of switches from forethought to performance phase events. In the low-challenge sessions process model, the forethought phase event was followed by a performance phase event once, while in the high-challenge sessions the switch between the forethought and performance phases happened several times (minimum of one time, maximum of three times). The models also differed in the event that was central to the model: In the low-challenge session, this event was a cognitive and socioemotional interaction in the performance phase, while in the high-challenge session, the central event was a cognitive-focused interaction in the forethought phase.

Discussion and conclusion

The purpose of this study was to explore the differences between high- and low-challenge collaborative learning sessions from the point of view of regulation phases and associated types of interaction. We presented the timing of high-challenge sessions during the collaboration process, the frequencies of learning events during the low- and high-challenge sessions and the process models of the learning events for both types of sessions. The results showed that during a long-term collaboration the highest occurrence of high-challenge learning sessions appeared toward the middle of the process, with the frequency decreasing toward the beginning and the end. A possible explanation for this result can be found in Zheng and Yu's (2016) study. When exploring the behavioral patterns of collaborating groups over several weeks, Zheng and Yu (2016) found that toward the middle of the collaboration the groups focused more on monitoring their progress. If through monitoring groups discovered that their progress was not going according to plan that could explain why most groups considered that session challenging.

Regarding the frequencies of different learning events in the high- and low-challenge sessions, no statistical significant difference was found; however, there was a difference in the process models of the two types of sessions. This finding is in line with those of previous studies, which showed no differences in the frequencies of different self-regulatory processes between the groups compared but identified a difference in the temporal order in which the processes appeared (Kapur 2011; Kuvalja et al. 2014; Zhou 2013).

The results showed high frequency and even distribution of the forethought phase among the high- and low-challenge sessions. In Schoor and Bannert's (2012) study, the frequency of the planning events was very low, and the authors recommended that this event should be supported specifically. The S-REG tool used in the present study was designed to support regulated learning by prompting students to reflect on their emotions, motivation and cognition thus raising students' awareness of the challenges they might be facing (Järvelä et al. 2016b). By design, the S-REG tool can be considered to trigger planning, a forethought phase process. Reflection was not prompted during the intervention, which can be seen in the low frequency of reflection phase events.

The process models presented in the present study provide evidence that in collaborative learning the regulation phases follow the same cyclical process as SRL (Molenaar and Järvelä 2014). According to the self-regulated learning cycle (Zimmerman 2000), the forethought phase is followed by the performance phase, which is followed by the reflection phase, and these phases repeat in a cycle. In the present study, the high-challenge session groups switched between the forethought and performance phases on several occasions. Although reflection phase events are scarce in the data, the reflection phase was positioned after the forethought and performance phases, just before the end of the session.

The cyclicality in the high-challenge sessions can be hypothesized as a sign of the students' awareness of the need for regulation, as regulation entails adaptation or change (Järvelä and Hadwin 2013); when confronted with challenges, groups adapt their strategies and explore different options in their collaboration by returning to the planning phase. The awareness of challenges and returning to the planning phase can be interpreted as a sign of metacognitive activation, as Sonnenberg and Bannert (2015) found that groups that receive metacognitive prompts engage in a higher number of regulation loops. Another explanation for this result suggests that in the high-challenge sessions the groups merely repeatedly performed the same behavior, which Zheng and Yu (2016) also found in a study when they examined how collaborating groups engage in regulation. Specifically, in Zheng and Yu's study (2016), the collaborating groups demonstrated an inability to adapt their regulation in the face of failure and reverted back to the same behavior.

In the low-challenge sessions, the process model did not present the same cyclicality; the groups moved on to the performance phase and stayed in that phase. Hadwin et al. (2011) argued that regulation arises only if there is a need; therefore, in the low-challenge sessions, the groups could focus on executing the task without a need for regulation.

When looking at the types of interaction associated with the different phases, the socioemotional and cognitive-focused interactions were equally integrated in the models. In a collaborative learning situation, the type of interaction can provide insight into the ongoing collaborative processes. Several studies have shown that socioemotional and cognitive processes are important for successful collaboration (Kreijns et al. 2013; Rogat and Linnenbrink-Garcia 2011). Cognitive and socioemotional interaction in the performance phase was the central event in the low-challenge sessions. Yang et al. (2015) found that collaborating groups with better learning outcomes talked about irrelevant topics during their collaboration, but the groups were able to switch back to the task and continue constructing knowledge. In the present study, similar results were obtained. Cognitive and socioemotional interactions in the performance phase had a central role in low-challenge sessions, indicating that learners switched between socioemotional and cognitive interactions frequently.

Limitations

Nevertheless, this study has several limitations. Regarding the first research question, the attendance of the groups in the different timeslots varied. The middle session, the one with the highest occurrence of high-challenge ratings, had the highest number of attending groups. This is due to the design of the study, in which the importance of capturing learning processes as they naturally occur in a real classroom was emphasized, instead of experimentally controlling all the variables. Nevertheless, a possible explanation is that more groups attended the meeting in the middle of the process because they were facing challenges, and thus, a face-to-face meeting was needed. Furthermore, the models created using process mining were descriptive. They depended on the coding scheme used and the level of granularity of the codes (Sonnenberg and Bannert 2015). In addition, in this study the macrolevel perspective was used to capture phases of regulated learning associated with different types of interaction. Using a macrolevel perspective can result in missing important microlevel processes of regulated learning. However, the macrolevel perspective examined cognitive and socioemotional interaction, when typically the focus is on cognitive microlevel processes (e.g., Johnson et al. 2011; Sonnenberg and Bannert 2015).

Implications and future directions

Regarding the implications of this study, the findings illustrate how self-regulatory phases occur in a collaborative learning setting. On the theoretical level, the macrolevel perspective used to capture the regulation phases and types of interaction provided a better understanding of the cyclicality of the phases as they occurred in collaboration and explored cognitive and socioemotional types of interaction that contribute to successful collaboration. On the empirical level, the results of this study can be used to develop and further study more targeted prompts for supporting regulation in collaborative learning, as the results provide insight into when challenging learning sessions might occur during long-term collaboration and how they differ from low-challenge sessions from the point of view of regulated learning. In addition, the results indicate that the S-REG tool has an effect on supporting the forethought phase and helping students become aware of the challenges they face, but further support is needed for triggering reflection.

We conclude that combining process-oriented video data on collaborative interactions and the coding of SRL phases provided new information about the temporal patterns of regulated learning and pointed out critical collaboration phases. In the future, it would be important to identify what exactly are the key regulatory phases and processes that contribute to successful collaboration.

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Compliance with ethical standards

Conflict of interest The authors (Márta Sobocinski, Jonna Malmberg, Sanna Järvelä) declare that there is no conflict of interest.

Appendix

Data examples of coded types of interaction. Students' names have been changed. All examples are from one group's term plan sessions.

Cognitive-oriented interaction

Mike: I want to discuss the part where we need to have a short introduction explaining how we narrowed down the topic. Although we didn't really narrow down the topic, did we? The topic is according to the textbook, no?

Sophie: Hmm..

Mike: Because we decided that the textbook is so good.

Sophie: Yes, and our topic is presented very well there. It's concrete. It's exactly our topic.

Mike: Yes, so narrowing down the topic means that we narrowed it down to the book. How should we argue that?

Anne: Well, we can't explain it. We were give that topic, and it cannot be narrowed further.

Mike: What was the topic?

Anne: Algeb..

Sophie: Algebra and functions.

Socioemotional interaction

Mike shows something to Sophie on the iPad. Sophie laughs.

Anne: Wonderful, Mike, you can really motivate us with that!

Mike: Exactly!

Anne: This is fun!

Dave: It's quarter to one already.

Cognitive-oriented and socioemotional interaction

Mike: Should we add something to that division lesson, something better? It's missing something a bit …maybe we should modify it. Sophie has planned it too poorly.

Mike and Sophie laugh.

Sophie: Don't start stressing out now.

Dave: Everyone is trying too hard to make all of these lessons into a special show.

Sophie: Yes, it's again like…

Mike: Although that wasn't my point.

Dave: No… It is also a bit stressful that we were taught didactics in first year, and now it's so hard to plan a basic mathematics class.

Anne: Yeah.

Dave: I was arguing with someone the other time, about whether such a thing as a basic lesson exists or not. She was saying that every lesson should be special. However, we weren't taught like that.

Mike: Well, it was kind of mentioned in the lessons somehow.

Dave: Maybe.

Mike: I checked those first-year didactics things.

Dave: They are on the slides. The instructions on how to plan a basic lesson. Quite clearly "basic."

Sophie: Yeah, I remember, too.

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