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ORIGINAL RESEARCH

Exploring Adaptation in Socially-Shared Regulation of Learning Using Video and Heart Rate Data

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Abstracts
In socially shared regulation of learning, adaptation is a key process for overcoming collaborative learning challenges. Monitoring the learning process allows learners to recognize the situations that require a need to change, revise, or optimize the current learning process. This can be done through adapting their strategies, task perception, goals, or standards for monitoring their progress. This process is called small-scale adaptation. It is not yet clear how shared monitoring in groups activates small-scale adaptation "on the fly" or how this phenomenon can be detected using multimodal data. The aim of this study is to explore how small-scale adaptation emerges during collaboration. Video and heart rate data were collected from four groups of three high-school students (age 16–17) who worked together during six 75-min advanced physics lessons. The results show small-scale adaptation occurs most often when groups switch from enacting tasks to defining them. Physiological synchrony occurred throughout the collaboration and was not significantly more prevalent before or after adaptation occurred. The opportunities and challenges of combining video observation to identify monitoring and adaptation events, and physiological synchrony as a possible indicator of "sharedness," are discussed, contributing to the literature about using multimodal data to study learning processes.

Keywords Collaborative learning · Socially shared regulation · Monitoring · Adaptation · Physiological synchrony

1 Introduction

There is increasing interest in understanding what makes collaborative learning successful (Kwon et al., 2014; Volet et al., 2017). Socially shared regulation of learning (SSRL) has been identified as an important prerequisite for successful collaborative learning in terms of joint task achievements (Khosa & Volet, 2014) and the quality of productive collaborative interaction (Barron, 2003; Isohätälä et al., 2017; Näykki et al., 2017). Socially shared regulation of learning deals with a group's strategic planning, task enactment, reflection,

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and adaptation. During these phases, the group negotiates adjustment of cognitive, emotional, motivational, and behavioral states as needed (Hadwin et al., 2018). The need for regulation is recognized through metacognitive monitoring. When monitoring reveals that learners face a challenge, they must use this information to strategically control their learning processes to ensure progress toward their learning goals (Winne & Hadwin, 1998). Learners can exercise metacognitive control in various ways: through making minor adjustments to enacted strategies and through strategically *adapting* their task perceptions and plans (Miller, 2015).

Adaptation has long been recognized as a core mechanism of regulated learning (Winne & Hadwin, 1998), because adaptation reflects how learners exert strategic control of their thoughts and actions when the need arises (Järvelä & Hadwin, 2013). Adaptation is described as small-scale when it happens "on the fly" and is aimed at optimizing the current learning process (Hadwin et al., 2018). For example, small-scale adaptation can occur when learners update the task understanding they initially formulated when they faced a challenge while solving the task (Miller, 2015).Large-scale adaptation on the other hand refers to transferring regulatory knowledge gained in the current task to future situations (Hadwin, 2013; Winne & Hadwin, 1998). An example of large-scale adaptation is when at the end of the learning sessions, learners reflect back on their experiences and update their task perceptions which then affects what strategies they use for a similar task in the future (Winne, 2010). In this study, the term adaptation refers to adaptation that occurs during one learning session (small-scale adaptation).

However, although a core mechanism of self-regulated learning, adaptation has scarcely been studied empirically (Pieschl et al., 2012). Adaptation is temporally situated (it occurs at certain moments during the learning process), and only under certain conditions (is the group facing challenges, are they aware of it, do they take the necessary steps to overcome it). For this reason, to examine adaptation, it must be empirically conceptualized and defined, and then process-oriented methods are needed to capture it. This methodological challenge of evidencing temporality has only recently been addressed in the field of learning sciences. Pieschl et al. (2012) examined how university students adapt to different task complexities in a hypermedia environment and found that students adapted their learning processes significantly to the task complexity, for example, by accessing more hypertext pages. In addition, in a study of the temporal progress of regulatory processes and socioemotional interaction, Bakhtiar et al. (2017) found that adaptation is often preceded by monitoring and discovered that negative emotions act as a constraint on shared adaptation. However, how socially shared, group-level monitoring activates small-scale adaptation in an authentic collaborative learning setting remains unclear.

Understanding adaptation in collaboration is important, because through adaptation learners change their self-regulated learning strategies (or conditions, standards, or goals) during and across learning situations (Winne et al., 2013), when metacognitive monitoring reveals a need to do so. Without adaptation, group members may work toward goals that are misaligned with one another, select, and enact ineffective strategies for the task, and monitor progress against misaligned goals. Ultimately, the group's learning and performance may suffer (Hadwin et al., 2018; Winne & Hadwin, 1998). Better understanding of how and when learners adapt their learning processes would help provide targeted support for this regulatory process. Previous empirical findings for collaborative learning clearly point out a need to support the collaborative learning process either by the teacher (Fischer et al. 2013) or prompts by technological tools (Azevedo et al., 2009; Järvelä et al.,2016b; Laru et al., 2012; Malmberg et al., 2010). As learning sciences moves toward using big data to study and support learning, there is an increased need to understand cognitive, behavioral, social, and emotional processes as they unfold in an actual learning situation to make sense of the collected data (Gibson, 2017). Therefore, using multiple types of data (including physiological and video data), we explore how monitoring activates small-scale adaptation to emerge in authentic collaborative learning.

1.1 Monitoring in SSRL

When learning in collaborative groups, learners face cognitive, emotional, motivational, and social challenges (Van den Bossche et al., 2006). To succeed, learners need to recognize these challenges and activate appropriate modes of regulation (self-, co-, and socially shared regulation) to progress; that is, regulatory activities are critical for the outcome of collaborative work (Barron, 2003).

In this study, we build on Winne and Hadwin's (1998) model, which describes self-regulated learning as unfolding in four phases: task understanding, goal setting and planning, task enactment, and adaptation. The phases are described as weakly sequenced (learners can shift among phases) and recursive (learners can repeat phases, and information generated during a particular phase can provide input to the same or subsequent phases). In each phase, learners monitor their progress against a set of standards they had set and change their strategies or update the standards when they detect a discrepancy (Winne, 2010). Standards are generated by learners based on their beliefs, motivational state, task knowledge, as well as current task conditions (Winne, 2014). Thus, metacognitive monitoring is the process by which learners become aware of the need for regulation. It is an effort to observe one's learning process and evaluate information about specific processes or actions that affect learning (Pintrich, 2002) and to detect ineffective performance (Winne et al., 2011). In each phase, learners monitor different targets: their cognition, motivation, emotion, as well as behavior. The monitoring process may be active unconsciously in the background until a problem is encountered (Wolters et al., 2011).

Hadwin et al., (2018) extended this model of self-regulated learning to group learning situations, describing how the same four phases also apply in socially shared regulation of learning. Through socially shared monitoring, learners recognize how the learning is progressing and are able to respond to the new situations and challenges by optimizing the group's shared strategies used or updating the standards for monitoring group progress (Hadwin et al. 2018).

Metacognitive monitoring is always an internal mental process, but in collaborative situations, it can be externalized via interaction with other group members. When externalized, monitoring has also been found to help maintain shared mental models and to support effective group work (Fransen et al. 2011). If monitoring is shared, it can promote other group members to engage in monitoring a group-level cognitive, emotional, motivational, or collaborative learning process to achieve a common goal (Iiskala et al. 2011).

Shared monitoring is the mechanism that invites other group members to participate in socially shared regulation of learning. As a result of monitoring, learners have an opportunity to jointly negotiate how to overcome the challenges detected and control their learning process: either by making minor adjustments to enacted strategies or through strategically *adapting* their task perceptions and plans (Miller, 2015). However, monitoring does not always lead to regulation: In a study exploring individuals' contribution to socially shared metacognitive regulation, Volet et al. (2017) found that in lower-performing groups, individuals' regulation attempts were not followed up by peers, as opposed to higher-performing groups in which several members jointly contributed to regulatory efforts. Koivuniemi et al. (2018) found similar results: Ignoring recognized challenges during collaboration can adversely affect the collaborative process, causing unequal participation and lower satisfaction levels with group learning.

As monitoring activates adaptive regulation, the temporality of monitoring and regulation processes has been recently the focus of empirical research. Binbasaran Tuysuzoglu and Greene (2014) examined the relationship between metacognitive monitoring and control in a hypermedia learning environment. They differentiated between adaptive use of strategy (change in the use of strategies) and static use of strategy (no change in the strategy used) after verbalized monitoring. They found that learners' adaptive use of strategy is positively related to learning and concluded that learners rely on monitoring to regulate subsequent learning activities. When examining the temporal sequences of regulated learning events in collaborative learning, Malmberg et al. (2017) found that metacognitive monitoring has a facilitative role throughout the task execution phase and pointed out that investigating monitoring in more detail could potentially reveal more about adaptation.

1.2 Adaptation in SSRL

Adaptation that aims to optimize the current learning process is defined as small-scale adaptation, whereas large-scale adaptation refers to changes that contribute to future tasks. Small-scale adaptation can be considered exercising metacognition in the moment, for example, when a monitoring activity leads learners to adapt their tactics, adjust environmental factors, or revise standards (Winne et al., 2013).

Adaptation is manifested in the fourth phase in Winne and Hadwin's (1998) model, when learners pause to reflect on the features of the previous phases (reflection) and consider modifications at the end of the learning process. This phase is considered optional. In recent publications, this phase has been referred to as "large- and small-scale adaptation" (Bakhtiar et al., 2017; Hadwin et al., 2018), detailing that it encompasses not only large-scale modifications but also updates standards, task perceptions, or goals aimed to improve the current learning process. Winne (2010) also specified that the fourth phase might occur mid-task. These instances of small-scale adaptation are a result of ongoing metacognitive monitoring throughout the learning process, which can cause learners to revisit a previous phase of regulated learning. For example, when a strategy used in the task enactment phase does not bring the desired results, monitoring might reveal that the task is more difficult than initially evaluated in the task understanding phase, which leads learners to update the products of the task understanding phase. For instance, learners can update their assessment of the current task's difficulty level. This example also illustrates how traces of small-scale adaptation can be observed in learners' behavior and interaction, although they do not verbalize that they are adapting. This is also an example of how self-regulated learning (SRL) phases are weakly sequenced and recursive (Winne & Perry, 2000).

In empirical studies, adapting has been defined as a change in different processes in the face of a challenge. Bakhtiar et al. (2017) empirically defined adapting as making a purposeful change in task perceptions, goals, or strategies to overcome a challenge, stated that adapting is often preceded by monitoring, and discovered that negative emotions act as a constraint on shared adaptation. Zheng and Yu (2016) also defined the code "adapting metacognition" as making changes in goals, plans, or strategies. In their study, a sequential-lag analysis revealed adaptation is a characteristic of high-achieving groups, suggesting that high-achieving groups are able to update their task understanding and plans sufficiently to progress, while low-achieving groups indicate comprehension failure after planning.

1.3 Use of Multimodal Data to Examine Monitoring and Adaptation

Individual monitoring has been investigated previously using think-aloud protocols and log data from computer-supported learning environments (Azevedo et al., 2009; Winne et al., 2017), Monitoring in group situations has been examined through analysis of interactions in video data (Järvelä et al., 2016a; Malmberg et al., 2017). Studies showed that higher frequency of monitoring events has been linked to better performance (Iiskala et al., 2011; Järvelä et al., 2016a; Näykki et al. 2017). McCardle and Hadwin (2015) used students' weekly reflections to capture the dynamic adaptations learners make during and between study sessions, and found that learners adapt their SRL processes to the varying conditions across study episodes.

In SSRL, collective monitoring is needed to achieve joint decisions and make adaptations to progress in collaborative learning. To capture this collective, shared nature of monitoring in collaboration, in this study we combined group members' physiological synchrony with video data analysis. Multimodal data (e.g., physiological measures) can provide a new way to capture critical phases of regulated learning as they occur in collaborative learning situations (Harley et al., 2015). Researchers have shown that the physiological responses of people interacting with each other can show relatedness, a phenomenon called physiological synchrony (see also coupling and compliance; Elkins et al., 2009). Specifically, physiological synchrony refers to "any interdependent or associated activity identified in the physiological processes of two or more individuals" (Palumbo et al., 2016, p. 2). Physiological synchrony was found to be a useful tool for examining group processes in a study that aimed at understanding the shared experiences of users in a computer-supported environment, where physiological synchrony was related to group performance and perceptions of trust (Montague et al., 2014). For example, when individuals were asked to solve a video game with a partner, Strang et al., (2014) found that physiological synchrony did not occur by chance but was influenced by task demands and pair dynamics. When studying physiological synchrony in the context of an improvised performance group, researchers found that synchrony was higher when participants reported a higher sense of togetherness, enhanced engagement, and enjoyment (Noy et al., 2015). Physiological synchrony, however, has rarely been investigated in the context of collaborative learning in general (Pijeira-Díaz et al., 2016), and SSRL in particular, although in recent years interest in using psychophysiological measures to investigate learning processes in collaborative learning has increased (Ahonen et al., 2018; Haataja et al., 2018; Pijeira-Díaz et al., 2018). For example, Haataja et al. (2018) found a connection between monitoring frequency and physiological synchrony of high school students solving a task related to nutrition and concluded that physiological synchrony has the potential to reveal shared regulation processes.

SSRL can occur when learners share their task perceptions, goals, and strategies. Therefore, physiological synchrony can potentially be used as a measure of this "sharedness" based on previous findings, while the specific regulatory processes can be identified during video data analysis of the interaction. This regulatory process is small-scale adaptation. Empirical studies provided evidence that small-scale adaptation occurs when learners jointly and purposefully update their task perceptions, goals, or plans when monitoring detects a need (Bakhtiar et al. 2017; Zheng & Yu, 2016). However, it is still not clear how often small-scale adaptation occurs and what kind of monitoring (phase, target of monitoring) activates it in a collaborative learning situation.

1.4 Aim of the Study and Research Questions

The present study aimed to explore how small-scale adaptation emerges through monitoring in a collaborative learning setting. The following questions guided the research: (1) How often do learners react to monitoring in different regulated learning phases? (2) How often do learners adapt their learning by shifting to a previous regulated learning phase, and what are these phases? (3) What does physiological synchrony tell about small-scale adaptation?

2 Method

2.1 Participants and Measures

The participants ($n = 12$, age 16–17 years, 3 female and 9 male) were high school students enrolled in an advanced high school physics course. The course was an elective, and it required students to have completed two other physics courses. All participants were informed about the details of the data collection and were told that participation would not affect their grade in any way, and that they could revoke their consent at any time during the data collection. All 12 students gave written consent to participate in the study, and their guardians were informed in writing about the study.

The course consisted of 18 lessons with a duration of 75 min each, which the researchers designed with the teacher. Each of the 18 lessons included a short introduction to the topic presented by the teacher followed by collaborative group work related to the lesson topic. The students collaborated in the same groups throughout the course. The collaborating groups were formulated based on the heterogeneity of learning regulation profiles for the sake of between-team comparability. Students were asked to fill out the cognitive and metacognitive strategies part of the Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich et al., 1993) as a measure of their self-regulation profile. Based on the questionnaire scores, students were categorized into three self-regulation groups: low, middle, and high. Each group included one student from each category.

Six lessons (lessons 8–13) took place in a learning environment located a short walking distance from the school, which was designed for observing collaborative work and where video data can be collected unobtrusively. The tasks during these six lessons included designing an experiment for measuring the speed of light and one for measuring the thickness of hair, as well as conducting hands-on experiments using lasers, mirrors, lenses, prisms, and a double-slit to study reflection, refraction, dispersion, and interference. The present study used the data collected during these six lessons from groups in which all members were present. For this reason, from the 24 possible group working sessions (four groups, six lessons), 18 were included in this study.

Physiological data were collected using Empatica E4 bracelets. Students were fitted with the bracelets at the beginning of each lesson and were informed that they could be taken off if they were uncomfortable; however, none of the students felt the need to do so.

A total of 18 h 53 min of video data were collected during the 18 sessions. The video data were coded for general classroom activities: evaluation (students were asked to assess their previous performance at the beginning of each lesson), homework-related activities, instruction (explaining the task), lecturing (theoretical introduction to the topic), collaborative work, and individual tasks. In the data analysis, only parts coded as collaborative work are included, which involves the time students were asked to work collaboratively on the tasks, resulting in a total of 10 h 19 min of data (54.63% of the total time of the learning sessions). The instruction, the teacher's theoretical introduction to the topic, and homework-related activities were not included in the data analysis.

2.2 Data Analysis

Video data Monitoring episodes were identified, including the monitoring target (cognition, behavior, motivation, and emotion), according to the criteria described in Table 1.

Each monitoring code had an additional modifier consisting of the regulation phase (task definition, goal setting, task enactment, and reflection) based on Winne and Hadwin's (1998) model (see Table 2). For the purpose of the empirical coding, we use the term "reflection" instead of adaptation for the fourth phase, as this term better portrays what was visible in the data to the external coder (evaluation of strategies and ways of working).

Next, the group's reaction (or lack of) was coded. Verbal utterances, as well as actions and gestures related to monitoring, were coded as reactions. Gestures or utterances were considered reactions if they were directly linked to the preceding monitoring episode. Gestures (or actions, such as moving equipment) were included in the reactions because of the hands-on nature of the tasks. The monitoring episode was coded "no reaction" if none of the group members reacted.

During the 18 sessions, the four groups engaged in 815 instances of monitoring. Table 3 presents the detailed distribution of the monitoring events for each monitoring target and the phases in which the monitoring occurred. Monitoring behavior was the most common event ($n=421$), followed by monitoring cognition ($n=350$). Monitoring motivation and monitoring emotion ($n=44$) were scarce in the data.

To ensure reliability of the coding process, 20% of the identified monitoring episodes were coded by two independent coders, resulting in a moderate level of agreement (Cohen's $\kappa=0.68$; McHugh, 2012). The discrepancies were discussed, and the definitions of the coding categories were negotiated until consensus was reached. Then, the data were recoded to reflect complete agreement.

Based on theory and previous empirical studies (Bakhtiar et al., 2017; Hadwin et al., 2018; Zheng & Yu, 2016), the code "adaptation" was added when monitoring was followed by a group reaction, which was followed by monitoring of a previous phase (e.g., monitoring cognition in the task enactment phase followed by a reaction followed by monitoring behavior in the task definition phase). Following this method, 82 traces of adaptation were captured. An example of coded data is presented in Table 4.

Cardiovascular data In the first step for processing the cardiovascular data, 1 Hz mean heart rate values were downloaded from the Empatica E4 bracelets the students wore during each lesson. Next, the data were synchronized between the group members. Then the heart rate values were standardized for each participant and session, and signal matching scores were calculated (Elkins et al., 2009) for each pair of students in a group by subtracting the absolute standardized values from each other. A group-level signal matching value was then calculated for the whole group for each second by calculating the mean of the signal matching scores. Additionally, directional agreement scores were calculated for the whole group for each second. The directional agreement value was 1 if all three participants' signals were increasing or all were decreasing.

Table 1 Video coding categories for monitoring episodes

Code	Description	Examples
Monitoring cognition	Monitoring task understanding, previous knowledge, task product, content understanding, or procedural knowledge	I'm not sure how we are supposed to do this We at least know from previous lessons that the speed of light won't change I have no idea what I'm now doing How we are supposed to use the formula here? Is this result in a reasonable range? Are we still adding something, or do you think this is ready? I'm not sure what critical angle means? This should work according to the same principle as earlier
Monitoring motivation	Student monitors the current trend in motivation, includes monitoring volition and self-efficacy	Who is willing to draw this? Our motivation is on a good track I really would not want to do this I'm so bad at drawing. Who can do this?
Monitoring emotion	Monitoring emotional state	My feelings are good! Let's start! These microphones make me annoyed… This is exciting!
Monitoring behavior	Monitoring task-related behavior, resources needed for the task and task progression	Have you all now read the whole paragraph? I wonder if this is a good place for this laser Is someone writing up our results? Do we have all the equipment needed? How much time we have left? We still have three tasks to do

Table 2 Video coding categories for the regulation phases of monitoring episodes, based on Winne and Hadwin's (1998) model

Code	Description	Examples
Task definition	Forming or redefining task understanding	So what are we supposed to do? So is it asking for the refraction rate? Do we just have to find the value or explain the process?
Goal setting and planning	Defining an acceptable level of achievement Making concrete plans	Let's just start with the playing with the laser The goal here is to come up with something original How should we proceed with this?
Task enactment	Evaluating the progress against the standards set while working on the task	Should we check if this is correct? We already know that value So what are we seeing?
Reflection	Strategies and ways of working evaluated	Well, we didn't manage to finish everything This went easier than we expected!

Table 3 Frequencies of monitoring events by monitoring targets

Monitoring target	Monitoring phase	*f*	Mean duration (in sec)	SD (in sec)
Monitoring behavior	Task definition	65	3.49	3.00
	Goals and planning	24	4.17	1.97
	Task enactment	324	3.34	1.80
	Reflection	8	3.50	1.69
	Total	421	3.41	2.04
Monitoring cognition	Task definition	57	4.26	2.92
	Goals and planning	4	3.25	1.26
	Task enactment	286	4.36	2.89
	Reflection	3	4.00	3.46
	Total	350	4.33	2.88
Monitoring motivation and emotion	Task definition	7	2.29	0.76
	Goals and planning	5	4.00	1.22
	Task enactment	28	2.54	1.04
	Reflection	4	2.75	0.96
	Total	44	2.68	1.09

In the second step, both synchrony scores were aggregated to define synchronous episodes: If the group's mean signal matching score was < 1, and the directional agreement score was 1 for the whole group, the episode was marked as in synchrony. Episodes shorter than 5 s were not considered, and when the time between two episodes was shorter than 5 s, the episodes were merged. Thus, 335 episodes were identified, with a total duration of 1 h 30 min and a mean duration of 16.00 s, with a standard deviation of 14.26 s. Finally, the episodes of physiological synchrony were integrated with the video data coding using Observer XT software. Thus, the cardiovascular data was triangulated with the video data, which allowed it to be contextualized within the learning process.

3 Results

3.1 How Often do Learners React to Monitoring in Different Regulated Learning Phases?

Small-scale adaptation requires learners to recognize the challenge that they are facing and react to the challenge. Monitoring events were followed by a reaction from the group in 83.33% of the cases across the phases. Monitoring adaptation was the least often followed by a reaction from the group (60%), as opposed to monitoring task definition, which was followed by a reaction in 88.37% of the cases. Table 5 presents the frequencies of the monitoring events by the regulation phase. When looking at the reactions by the monitoring target, monitoring cognition was most likely to be followed by a reaction (88%), closely followed by monitoring behavior (83.14%). Monitoring motivation and emotion were most often followed by the lack of a reaction from the group (52.27%).

Table 4 Example from the coded data includes monitoring and reaction coding, as well as an example of a series of utterances considered small-scale adaptation

Group 1, 37:19–38:12	Code types	
Student 1: (reading the task again) Like what does refraction rate even mean?	Monitoring cognition, task definition phase	
Student 2: Let's see… (starts playing with the laser)	Reaction	
Student 3: Look, it looks like the reflection depends on which angle the laser goes to other substance	Monitoring cognition, task enactment phase	Small-scale adaptation
Student 2: Aha	Reaction	
Student 1: But which formula are we going to use to calculate it?	Monitoring cognition, goals and planning phase	
Student 2: If we use this one… (points out the formula from the book, starts calculating)	Reaction, monitoring cognition, task enactment phase	

Table 5 Distribution of monitoring events by the regulation phases and the reactions from the group

Monitoring phase	Monitoring target	*f*	Followed by	
			Reaction (%)	No reaction (%)
Task definition	Monitoring behavior	65	59 (90.77)	6 (9.23)
	Monitoring cognition	57	51 (89.47)	6 (10.53)
	Monitoring motivation or emotion	7	4 (57.14)	3 (42.86)
	Total	129	114 (88.37)	15 (11.63)
Goals and planning	Monitoring behavior	24	20 (83.33)	4 (16.67)
	Monitoring cognition	4	3 (75)	1 (25)
	Monitoring motivation or emotion	5	1 (20)	4 (80)
	Total	33	24 (72.73)	9 (27.27)
Task enactment	Monitoring behavior	324	266 (82.1)	58 (17.9)
	Monitoring cognition	286	252 (88.11)	34 (11.89)
	Monitoring motivation or emotion	28	14 (50)	14 (50)
	Total	638	532 (83.39)	106 (16.61)
Reflection	Monitoring behavior	8	5 (62.5)	3 (37.5)
	Monitoring cognition	3	2 (66.67)	1 (33.33)
	Monitoring motivation or emotion	4	2 (50)	2 (50)
	Total	15	9 (60)	6 (40)

3.2 How Often Do Learners Adapt Their Learning Learners Shifting to a Previous Regulated Learning Phase, and What Are These Phases?

During SSRL, learners move through four loosely sequenced phases as in self-regulated learning: task definition, goals and planning, task enactment, and reflection (Hadwin et al., 2018). In this study, small-scale adaptation was recognized by identifying episodes where learners switched after a shared monitoring event to monitoring a previous SSRL phase. Table 6 shows which phase preceded and followed the instances of recognized small-scale adaptations. In 75.56% of the cases, adaptation events occurred when learners switched from enacting a task to defining it.

Table 6 Phases of coded monitoring events before and after small-scale adaptation

Before small-scale adaptation	After small-scale adaptation	Total number (%)
Task enactment	Task definition	61 (74.39)
	Goals and planning	12 (14.63)
Reflection	Task definition	2 (2.44)
	Goals and planning	2 (2.44)
	Task enactment	1 (1.22)
Goals and planning	Task definition	4 (4.88)
Total		82 (100.00)

Monitoring that occurs before the small-scale adaptation (column 1) activates groups to adapt their task perceptions, goals, plans, or strategies, which can be recognized through the phase that follows the small-scale adaptation (column 2)

The most common type of monitoring found before small-scale adaptation was monitoring behavior (60 cases, 66.67%), followed by monitoring cognition (29 cases, 32.22%). After small-scale adaptation, there was monitoring behavior in 52.22% ($n=47$) and monitoring cognition in 46.67% ($n=42$) of the cases. There was only one instance of small-scale adaptation that was preceded by monitoring motivation or emotion, and one instance that was followed by it.

A partial correlation was run to determine the relationship between monitoring events and small-scale adaptation in different sessions, while controlling for the different lengths of the sessions. Data were screened for normality, and the data that were not normally distributed were transformed with a natural logarithm. After normalization, it was found that there was a strong, positive correlation between monitoring cognition and adaptation ($r=0.789$, $n=17$, $p<0.005$), and monitoring cognition and reaction ($r=0.872$, $n=18$, $p<0.005$), while controlling for the length of the session.

3.3 What Does Physiological Synchrony Tell About Small-Scale Adaptation?

Small-scale adaptation in collaboration requires learners to jointly monitor their learning process, as well as make a coordinated effort to update their strategies, task perception, goals, or standards for monitoring their progress. With this research question we examine if this shared regulatory process is reflected as heart rate synchrony. Episodes of synchrony were found in all the sessions ($M=18.61$, $SD=10.787$). The total duration of the synchrony episodes was 1 h 31 min 30 s, mean duration 16.08 s ($SD=14.26$), accounted for 14.44% of the duration of the sessions. To see at what point during the collaboration physiological synchrony occurred the most, we divided the sessions into three parts of equal length, and a Friedman's test showed that the distribution of the frequency of the synchrony episodes was the same across the three parts ($\chi^2(2)=3.49$, $p=0.17$).

To examine whether the level of physiological synchrony changed with adaptation, 1-min windows before and after an adaptation were created. For each window, the amount of physiological synchrony was calculated (in seconds). The times not included in these windows were considered times without adaptation, and the amount of synchrony was calculated for these times as well. As the three types of windows (before adaptation, after adaptation, and no adaptation) were not the same length, the ratio of synchrony to the duration of the window was calculated (see Table 7). Using these ratios, the three types of windows were compared using a Kruskal–Wallis test, which showed that the physiological synchrony was distributed equally between the categories (χ^2 (2) $=2.46$, $p=0.29$).

Table 7 Duration of synchrony before adaptation, after adaptation, and no adaptation windows

Time windows	Total duration of synchrony in windows (in seconds)	Total duration of windows (in seconds)	% in synchrony (%)
Before adaptation	679	4920	13.80
After adaptation	834	4920	16.95
No adaptation	4025	28,309	14.22

4 Discussion

The aim of this study was to examine how shared small-scale adaptation emerged through monitoring during collaborative learning by combining video data and heart rate data. Small-scale adaptation was examined by focusing on monitoring events, and whether they were followed by a reaction from the group. SSRL is a deeply metacognitive process, and shared monitoring can reveal to learners when small-scale adaptation is needed to optimize the learning process (Hadwin et al., 2018). In this study, monitoring behavior and monitoring cognition were the most common type of monitoring events during student collaboration, and there was little evidence that learners engaged in monitoring motivation and monitoring emotion. These results are in line with previous research pointing out that although collaborating groups engage in intense socioemotional interaction (Isohätälä et al., 2019; Järvelä t al., 2016a; Järvelä et al., 2016b), the need for actual regulation of emotions or motivation occurs infrequently (Järvenoja et al., 2019).

The first research question revealed information about the progress of the learning process through examining what phase of the learning process learners were monitoring, what was the target of monitoring, and whether there was a reaction from the group members to the monitored event. According to Hadwin et al., (2018), one of the key characteristics of SSRL is that multiple perspectives come together and share metacognitive, cognitive, behavioral, and motivation states. In this study, monitoring events were most commonly found in the task enactment and task definition phases. During the task definition phase, learners construct task interpretations based on their cognitive conditions (Winne & Hadwin, 1998), which provide the background condition for the learners' planning processes, as well as the strategies learners use during task enactment. Taub and Azevedo (2018), who analyzed the eye fixations of learners studying with an intelligent tutoring system, found that all participants used SRL processes, indicating the learners were engaging in SRL phases, and the authors confirmed that the cognitive condition of prior knowledge continues to impact the use of SRL processes throughout the learning process.

The present results show that most monitoring attempts were followed by a reaction from the group members, which is in agreement with the findings of Isohätälä et al. (2017). In a study on higher education students' collaboration, Isohätälä et al. found that instances of SSRL (such as planning, monitoring, or evaluating) coincided with moments of high participation. Monitoring motivation and monitoring emotion stood out as the only monitoring attempts not followed by a reaction in more than half of the cases; however, as this type of monitoring is so scarce in the data, no conclusions can be drawn. The scarcity of monitoring emotion and motivation could be due to the participants of the present study, who all chose to participate in an advanced physics class, and thus, might be considered high achievers. Chen et al. (2020) studied high-school students' collaborative problem solving processes during an online science class and found that low achievers focus on social activities, while high achievers engage in cognitive activities.

Next, we focused on the instances of small-scale adaptation that we found in the data and examined what events preceded and followed these instances. The results show that three out of four small-scale adaptation events occurred when groups switched from enacting the task back to defining the task. This result might be due to the high prevalence of monitoring in these phases in the data compared to other phases. However, as learners progress with solving the task and face a challenge, they might need to update their task understanding, which would appear in the data as monitoring in the task definition phase. Rogat and Linnenbrink-Garcia (2011) also noted that planning activities occur at the beginning and toward the midpoint of the collaboration. Sobocinski et al. (2017) found that groups facing challenges switch between performance and planning more often compared to groups who do not report challenges. Zhou (2013) used traces from an online learning environment to analyze patterns of self-regulatory activities and found that mastery-approach-dominant learners revisit the task instructions after a series of actions related to task enactment (searching, selecting, and accessing information). In all, the results of this study are in line with those of previous studies indicating that as learners progress with a task, they also have better opportunities to change and adapt their task understanding and planning process (Malmberg et al., 2017). Considering the previous findings, it can be argued that possibilities for adaptation increase as learners become more familiar with the learning content.

The last research question focused on exploring when physiological synchrony occurs during collaboration. Our assumption was that the synchronization of heart rate signals among group members (i.e., physiological synchrony) might be associated with adaptation in SSRL, as this highly metacognitive process requires sharing of cognitive, emotional, and motivational states (Hadwin et al., 2018). Physiological synchrony was found to occur to the same degree at the beginning, middle, and end of the learning session. There was no statistically significant difference between the amount of synchrony before and after adaptation, and when there was no adaptation. As all the groups in the study completed the tasks assigned and engaged in socially shared monitoring, we hypothesize that the group members' engagement and "sense of togetherness" (Noy et al., 2015) were stable. Physiological synchrony is found to occur when people interact (Chanel & Muhl, 2015), and in this study, the group members were interacting throughout the session.

5 Limitations

The first limitation of this study is that the results are based on a small sample size (four groups of three students, 18 sessions in total), and the participants were those who chose to participate in an optional advanced physics course. This limitation of a sample size between 10 and 20 participants is commonplace in studies using neuroscience or psychophysiological techniques "owing to constraints of methods and expenses" (Ansari & Coch, 2006, p. 147). In addition, the aim of this study was to explore how small-scale adaptation emerges in collaborative learning, and this sample provides insights into how well-performing groups in terms of their learning outcome adapt their plans and goals when faced with challenges.

The second limitation of this study has to do with capturing monitoring and adaptation using video data analysis. Monitoring and small-scale adaptation are inherently metacognitive processes. In this study, we captured traces of these processes when they became shared through social interaction during collaboration. At the individual level, monitoring and adaptation can occur without it becoming visible to the group; if we had relied only on video data, these instances would have remained unaccounted for. However, the focus of this paper was on shared regulation processes. According to theory (Hadwin et al., 2018), to achieve shared regulation, groups need to jointly monitor their progress and negotiate learning strategies.

Although the findings of this study cannot be generalized, the study provided a transparent way to zoom into a phenomenon and a way to depict how small-scale adaptation can be conceptualized in light of theory.

6 Implications and Future Directions

Small-scale adaptation is a key process in self-regulation and socially shared regulation of learning, as this type of adaptation aims at optimizing the current learning process. The present study provides empirical evidence that small-scale adaptation is activated by monitoring that has been acknowledged by the group, and it most often leads to groups monitoring their definitions of the tasks. This study has implications for pedagogical practice, methodology, and theory. The study has implication for the design or implementation of learning modules. Based on the results of this study, it is important to consider that students re-examine their goals and plans for learning throughout a challenging task. Moreover, the implication of this study for pedagogical practice also concerns developing advanced learning technologies that can be used to support the learning process. When building adaptive support (see Azevedo et al., 2017), planning strategies might be needed throughout the learning process, not just at the beginning. Thus far, support for planning has been provided mostly at the beginning of a task (see Järvelä et al., 2016b), and currently, there are no systems that can detect "on the fly" when there is a need to revise plans. Support is static, not based on learners' needs. For example, when a group faces a challenge, a prompt might offer a suggestion to discuss collaboratively what action the students need to take: whether they should change the strategy they are currently using or whether they need to update their goals or plans.

The methodological implication of this study is that it showed how different multimodal data channels can be combined to study regulated learning processes and demonstrated what process-oriented analysis can reveal about adaptation. To gain a better understanding of what data channels can be used to capture certain aspects of the learning process, there is a need to gather more evidence and reflect on the results. We did not find a connection between adaptation and physiological synchrony of heart rates. Thus, considering the study findings, there is a need to collect multimodal data from different data channels (e.g., electro dermal activity, log data) to better understand adaptation. In addition, further studies are needed to explore what physiological synchrony can show about group-level learning processes, because previous studies focused on dyads (Ahonen et al., 2016; Montague et al., 2014; Noy et al., 2015) and in contexts other than learning (e.g., improvisation and pair programming). In the introduction to a special journal issue, Azevedo and Gašević (2019) pointed to the need for multiple data channels for analyzing SRL and SSRL processes to be able to provide automated targeted support, for example, for planning processes. This way, quantitative and situated perspectives can be added to recognize patterns of adaptation with the help of learning analytics or data mining.

The implications of this study regarding theory is it that we developed a transparent way to capture the process of adaptation in collaborative learning by taking into account the phases of monitoring events and groups reaction to them. According to SRL theories (Winne & Hadwin, 1998), adaptation is a key process in SRL, as adaptation allows learners to change the ways they learn. However, few studies have focused on examining how adaptation occurs in a collaborative learning situation. This study focused on small-scale adaptation, but further research is needed to explore how large-scale adaptation occurs. When engaging in large-scale adaptation, learners update their own beliefs and general dispositions of their own SRL that affect how they approach a new task in the future. Thus far, no studies have investigated how small-scale adaptation contributes to large-scale adaptation. Due to the rapid development of technological devices (e.g., physiological sensors), there are potentially more and perhaps new opportunities to "accurately" evaluate how learners choose to engage in regulation of learning (Järvelä et al., 2019). This type of research is still in its infancy, but it has the potential to advance the field.

We conclude that process-oriented video data analysis can reveal traces of small-scale adaptation in collaborative learning. However, in this study physiological synchrony was not found to directly relate to this process. Future research is needed to examine how, if, and under what conditions physiological data are a useful data source in SSRL research. As Järvelä et al. (2019) pointed out, physiological data as such do not solely tell anything about regulation, and the data must be triangulated with other data channels (e.g., video data). For this reason, triangulation of different data sources has the potential to provide a new approach with which to capture moments of regulation as they occur in the context of collaborative learning.

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Declarations

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

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