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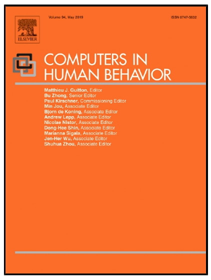

Examining shared monitoring in collaborative learning: A case of a Recurrence Quantification Analysis Approach

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Abstract

The aim of this study is to investigate the relationship between shared monitoring of collaborative learning processes and physiological synchrony between the collaborating group members. Shared monitoring fuels collaborative learning in groups. Video and electrodermal activity data were collected from a group of high school students (two male, one female) during two sessions of collaborative learning. Shared monitoring of learning progress among the group members, in terms of frequency and duration, were coded and calculated in video data. Physiological synchrony in electrodermal activity among the collaborating students was calculated with Multidimensional Recurrence Quantification Analysis (MdRQA). Results revealed that the relationship between physiological synchrony and shared monitoring might be dependent on task type. That is, a significant relationship was observed between MdRQA indices and shared monitoring in one session, whereas no significant relationship was observed in the other session. The current study contributes to the literature on computer-supported collaborative learning through demonstrating the utility of MdRQA to investigate the temporal dynamicity of collaborative learning processes. In conclusion, the chosen methods contribute to research on collaborative learning, as capturing invisible physiological signals and matching them with visible instances of monitoring processes facilitates identification of critical moments in collaboration.

Keywords: Collaborative learning; socially-shared regulation of learning; physiological data; Multidimensional Recurrence Quantification Analysis.

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Keywords: Computer-supported collaborative learning; socially-shared regulation of learning; multimodal data; Multidimensional Recurrence Quantification Analysis.

1. Introduction

Collaborative learning is a joint activity that requires multiple individuals to develop shared understanding, and temporally sequence and synchronize their actions to a certain extend in order to achieve a shared goal (Dillenbourg & Traum, 2006; Klein, 2001; Van den Bossche, Segers, & Kirschner, 2006). During collaborative learning, students engage in a variety of activities to complete a group task (Chi, 2009). These activities might be either related with development of a content space or a relational space (Barron, 2003). Activities related to content space include interacting with team members to develop a shared understanding of the knowledge domain (Slof, Erkens, Kirschner, Janssen, & Phielix, 2010). For example, asking questions, exchanging information, elaboration of concepts and procedures, discussion of different views, justification and revision of answers and decisions are examples of activities that occur in the content space (Chi, 2009; Jehn & Shah, 1997; Slof et al., 2010). On the other hand, relational space includes communicative activities among the group members in order to tackle identity issues and interactional challenges that might hinder development of productive discussions in the content space (Barron, 2003; Kirschner, Paas, & Kirschner, 2009). Challenges in relational space can be due to various within or between individual factors such as competition, differential efforts, self-focused contribution, or explication of negative emotions (Barron, 2003; Hobman, Bordia, Irmer, & Chang, 2002; Wilson, Straus, & McEvily, 2006). Student interactions in relational space are regulative in nature (Järvelä & Hadwin, 2013; Kirschner et al., 2009). That is, the student interactions are aimed at establishing and maintaining a shared understanding of the content space (Kirschner et al., 2009); students need to interact with each other to make their own knowledge and ideas explicit to other group members. Therefore, the student interaction in relational space includes information such as how group members come to share and negotiate the meaning of the collaborative tasks, and which group members participate in this process.

To succeed in collaboration there is a need for socially-shared regulation of learning (SSRL) (Järvelä & Hadwin, 2013). That is, learners should form a common ground on their collective perceptions about the collaborative learning processes and take control of task completion through shared and negotiated regulation of cognitive, behavioral, motivational, and emotional processes

(Hadwin, Järvelä, & Miller, 2017). SSRL acknowledges that challenges in the content and relational space of collaborative learning can be overcome by developing joint responsibility and shared understanding among the collaborating partners (Roschelle & Teasley, 1995). Monitoring, a core meta-cognitive activity in SSRL (Lee, O'Donnell, & Rogat, 2015), seems to be an especially important contributor to successful performance in collaborative learning (Goos, Galbraith, Renshaw, 2002; Hurme, Palonen, & Järvelä, 2006; Iiskala, Vauras, Lehtinen, & Salonen, 2011).

1.1. Monitoring of Collaborative Learning Processes

Establishing shared perceptions and standards through monitoring of learning progress is an essential dimension of SSRL (Järvelä & Hadwin, 2013). Shared monitoring in SSRL occurs through active questioning, prompting and restating of collaborative progress at the content space and relational space (Järvelä & Hadwin, 2013). Monitoring fuels progress in collaborative learning in two ways. First, it facilitates collaborative learning through inviting learners to reflect upon their metacognitive thoughts and feelings about the group's joint progress (de Bruin & van Gog, 2012; Ucan & Webb, 2015). Second, if monitoring is shared, it involves joint attention and mutual efforts of group members to keep track of the collective work and update regulatory strategies (Barron, 2003).

The positive influence of monitoring on regulation of learning and academic achievement has been demonstrated in several studies (Hmelo-Silver & Barrows, 2008; Lee et al., 2015; Malmberg, Järvelä, & Järvenoja, 2017; Molenaar & Chiu, 2014; Rogat & Linnenbrink-Garcia, 2011).

For example, shared monitoring has been identified as an essential pre-requisite for high quality collaboration (Lee et al., 2015). Shared monitoring in collaborative learning has been demonstrated to facilitate knowledge-building discourses, promote update of regulatory strategies, and set the stage for effective task execution (Hmelo-Silver & Barrows, 2008). The importance of shared monitoring in order to maintain collaborative interactions during knowledge building has been documented (Rogat & Linnenbrink-Garcia, 2011), along with a positive relationship between shared monitoring and successful collaboration (Molenaar & Chiu, 2014). Further, shared monitoring was identified as having a key role on facilitating task execution in collaborative learning (Malmberg et al., 2017). Moreover, joint monitoring of content space progress has yielded high quality SSRL (Volet, Summers, & Thurman, 2009).

1.2. Capturing Monitoring Processes in Collaborative Learning

When learning collaboratively, regulation unfolds over time in relation to both individual and contextual factors (Azevedo, 2014; Järvelä, Volet, & Järvenoja, 2010; Malmberg, Järvelä, & Kirschner, 2014; McCardle & Hadwin, 2015; Winne, 2014). Thus, the recent understanding on SSRL suggests that in order to improve quality in collaborative learning, research should focus on identifying a means to better understand the temporal dynamics of coordination among the group members during their joint work on a shared task (Klein, Feltovich, Bradshaw, & Woods, 2005). In this regard, process-oriented methods such as think-aloud protocols (Azevedo, Moos, Johnson, & Chauncey, 2010), digital traces (Hadwin, Nesbit, Jamieson-Noel, Code, & Winne, 2007), and online measures (Kirschner, Kreijns, Phielix, & Fransen, 2015), have become popular instruments for investigating joint perceptions and strategies in SSRL research. There is also a growing interest in utilizing physiological measures to investigate temporal sequences in collaborative learning (e.g. authors). Physiological measures can reflect emotional or cognitive arousal of individuals and serve as a complement to conventional measures (e.g. self-reports, video observations) by providing unobtrusive, objective, and real time information (Elkins, Muth, Hoover, Walker, Carpenter, & Switzer, 2009; Montague, Xu, & Chiou, 2014; Trimmel, Wright, & Backs, 2003). A promising approach for utilizing physiological measures in group learning processes, specifically in SSRL research, involves the investigation of synchrony among the learners (Pijeira-Díaz, Drachsler, Järvelä, & Kirschner, 2016).

1.3. Physiological Synchrony in Collaborative Learning

Physiological synchrony (PS) refers to the relation between physiological responses of interacting individuals as they perform a collaborative task (Henning, Armstead, & Ferris, 2009). PS develops spontaneously and unintentionally, and thus, can be indexed by measuring responses of the autonomic nervous system (ANS) (Ellamil, Berson, & Margulies, 2016; Palumbo, Marraccini, Weyandt, Wilder-Smith, McGee, Liu, & Goodwin, 2016; Strang, Funke, Russell, Dukes, & Middendorf, 2014). Electrodermal activity (EDA) and heart rate (HR) activity are considered popular measures derived from the ANS. Numerous studies on a variety of social interaction and group situations have documented positive relationships between PS and emotional engagement (Konvalinka, Xygalatas, Bulbulia, Schjødt, Jegindø, Wallot, Orden, & Roepstorff, 2011; Slovák, Tennent, Reeves, & Fitzpatrick, 2014), empathy (Gates, Gatzke-Kopp, Sandsten, & Blandon, 2015; Marci, Ham, Moran, & Orr, 2007), understanding (Järvelä, Kivikangas, Kätsyri, & Ravaja, 2014), marital satisfaction (Chanel, Kivikangas, & Ravaja, 2012; Levenson & Gottman, 1983), and trust between individuals (Mitkidis, McGraw, Roepstorff, & Wallot, 2015).

Several studies have addressed the development of PS in collaborative teamwork situations as well. For example, an investigation of the relationship between PS and perceived team cohesion showed that higher team cohesion was related to higher levels of PS (Mønster, Håkonsson, Eskildsen, & Wallot, 2016). PS was related with the trust building process among collaborating partners in a mental economics game (Mitkidis et al., 2015). In addition, higher PS was associated with lower errors in team performance (Henning & Korbelak, 2005), and could differentiate between more and less successful groups in military training (Elkins et al., 2009). PS between collaborating video game players has also been associated with higher empathy and understanding(Järvelä et al., 2014).

Contradictory results regarding the relationships among PS, teamwork outcomes, and team attributes have also been documented. In a comparison of PS among collaborating dyads in competitive, shared understanding, and get to know conditions, no significant differences were observed (Guastello, Pincus, & Gunderson, 2006). Examination of the relationships between PS, cognitive load, and team performance revealed a significant association between PS and team performance, however, no relationship was observed between PS and subjective cognitive load (Montague et al., 2014). A negative relationship between PS and team performance was documented among team members who had differentiated roles on a joint task (Strang et al., 2014). Finally, in a joint construction task, PS was negatively related with product quality, and the relationship between PS and individual satisfaction varied by interaction with types of task conditions(Wallot, Mitkidis, McGraw, & Roepstorff, 2016).

1.4. Measuring PS: Recurrence Quantification Analysis (RQA)

RQA was developed to assess recurrent activity over time in a non-linear dynamic system (Eckmann, Kamphorst, & Ruelle, 1987). This method characterizes the dynamic systems that are too complex to be described by time series analysis (Anderson, Bischof, Laidlaw, Risko, & Kingstone, 2013). (Webber Jr. & Zbilut, 2005) illustrated the concept of recurrence from the fluctuation of sea waves. They found aperiodic dynamics on sea wave heights over time. This variation can be represented by a squared N×N distance matrix, in which every element is the distance between a specific signal sample and all the other signal samples of the time series using a predefined distance metric. The recurrence plot is a visualization of the distance matrix elements, which surpass a threshold indicating frequently recurring signal samples. Figure 1 illustrates how a periodic time series (a sinusoidal signal plus random noise) is reflected in the recurrence plot. Given that there are four cycles in the time series, every sample has close amplitude values with the other three samples in the time series. In order to quantitatively represent a recurrence plot and be able to assess recurrence in the time series, a set of descriptive features are extracted.

PLEASE INSERT FIGURE 1 AROUND HERE

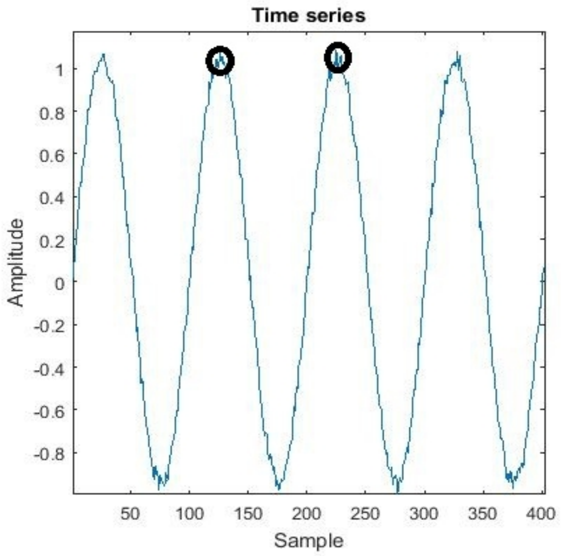

Fig. 1. A Sample Recurrence Plot.

A variety of RQA measures exist in the literature. Among those, Multidimensional RQA (MdRQA), an extension to the RQA family, is related to the repetition of values over time in a synchronously measured set of signals. MdRQA allows researchers to investigate how groups differ from one another in terms of their dynamics (Knight, Kennedy, & Mccomb, 2016). One significant advantage of MdRQA is that it allows investigation of group dynamics for groups with more than two members. Figure 2 illustrates an example recurrence plot computed by feeding two time series into the MdRQA method. It considers the pattern of repetitions among the variables of the dynamic system. In MdRQA, group dynamics are determined according to several features of the recurrence plot. These features are summarized at Table 1.

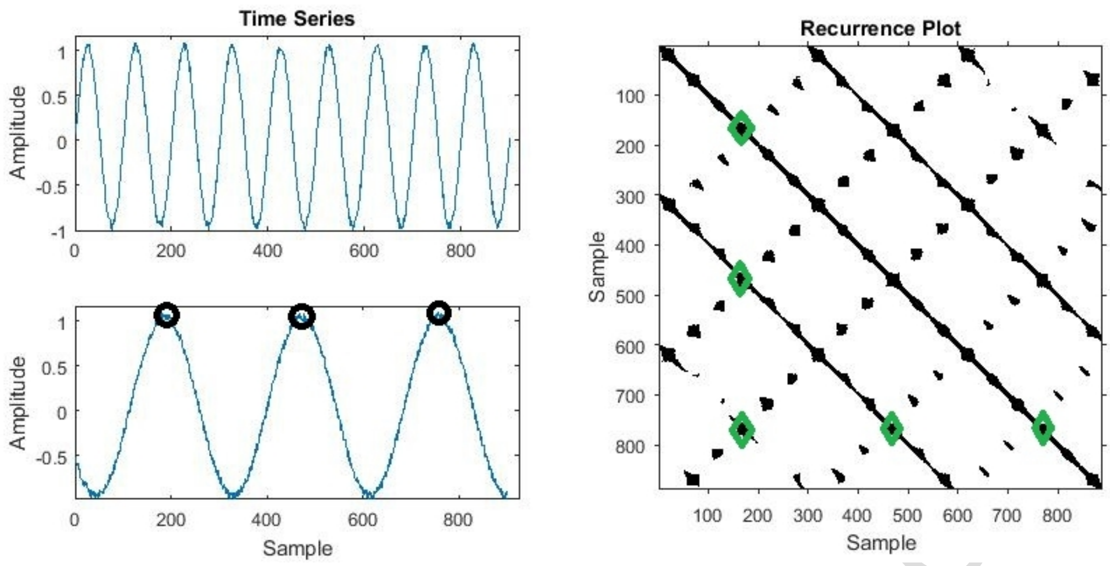

Fig. 2. MdRQA is an extended version of RQA, which enables users to feed multiple signals for recurrence quantification analysis.

Table 1
MDRQA feature descriptors.

Abbreviation	Feature	Definition
%REC	Recurrence rate	Percentage of recurrent points in the recurrence plot.
%DET	Determinism	Proportion of recurrent points constructing diagonal lines.
%LAM	Laminarity	Proportion of recurrent points constructing vertical lines.
DENT	Diagonal entropy	Shannon entropy of diagonal line's lengths in a histogram.
VENT	Vertical entropy	Shannon entropy of vertical line's lengths in a histogram.
DMax	Diagonal max	Maximum length of diagonal lines.
VMax	Vertical max	Maximum length of vertical lines.
LMean	Mean length	Average length of adjacent recurrent points.
DMean	Diagonal mean	Average length of adjacent diagonal recurrent points.

PLEASE INSERT FIGURE 2 AROUND HERE

PLEASE INSERT TABLE 1 AROUND HERE

The vertical lines in the recurrence plot show that the group state remained stable for some time. The diagonal lines in the plot suggest that the electrodermal activity fluctuations of the group members are similar to each other, and thus more deterministic. On the other hand, single isolated points suggest chaotic and random characteristics of the signals in those time instants.

Recently, in social sciences, RQA has become a popular approach to understand dynamics of groups (Knight et al., 2016). Specifically, RQA has become common when investigating coordination and synchrony between individuals on collaborative tasks (Fusaroli & Tylén, 2016; Shockley, Santana, & Fowler, 2003; Strang et al., 2014; Wallot et al., 2016). For instance, to investigate dyadic conversational dynamics in a joint decision making task, RQA was used to demonstrate the positive relationship between patterns of synergistic conversation (e.g. complementarity) and performance (Fusaroli & Tylén, 2016). Consideration of postural fluctuations of dyads when solving a puzzle, results showed that postural fluctuations exhibited greater recurrence when participants conversed within their dyads compared to others (Shockley et al., 2003). Another RQA study investigating whether working on a joint task was related to behavioral (i.e. postural sway) and physiological coupling (i.e., heart beat intervals) among the co-actors demonstrated that both behavioral and physiological coupling occurred between the co-actors during the collaborative work (Strang et al., 2014). Finally, RQA was used to examine the relationship between hand movement synchrony in a hands-on collaborative task and performance; the relationship between synchrony and performance was dependent on the nature of the task (Wallot et al., 2016). In complex tasks, complementarity rather than synchronicity might be more influential on task performance.

1.5. The Current Study

Overall, research on collaborative learning has revealed that SSRL processes are dynamic and cyclical in nature (Hadwin et al., 2017). Thus, it is necessary to apply process-oriented measures in order to investigate how SSRL unfolds over time (Butler, 2011; Samuelstuen & Bråten, 2007; Schellings & van Hout-Wolters, 2011). Research also showed that PS can be indicative of cognitive, affective, and behavioral alignment among the individuals during collaboration (Cacioppo, 2007; Critchley & Garfinkel, 2018; Patterson, 2002). In this regard, utilization of PS in collaborative learning can provide situated and time sensitive information when investigating the

SSRL processes. This is important because there is a need for methods that can provide objective measures of joint processes during collaboration (Barron, 2000). Specifically, it is worth investigating how PS alters in relation to shared monitoring considering that monitoring requires a certain extend of joint attention and collective efforts among the collaborators, as argued by Hadwin et al., (2017). Nevertheless, the role of shared monitoring of collaborative learning progress on PS of group members has been neglected in past research, mostly because of lack of methodological ways. Drawing on this, the current case study incorporated video data with electrodermal activity data to investigate the association between PS and monitoring of group progress when engaging in collaborative learning. The following research questions were addressed:

RQ1: Is there a relationship between group monitoring duration and PS among group members?

H1. Increased duration of shared monitoring would be relate with higher PS among the learners.

RQ2: Is there a difference in PS between collaborative learning situations with and without monitoring?

H2. Monitoring of the group progress would yield higher PS among the learners compared to non-monitoring.

2. Methodology

2.1. Participants and context

In total, 12 groups (N = 31) of students enrolled to Advanced Physics course held in the spring of 2016 at a secondary school in Finland. The course was part of the Finnish high school curriculum and enrollment in the course was voluntary. At the beginning of the course, students were split into groups of three to four students and asked to work with the same group throughout the duration of the course. Due to practical reasons and feasibility of the data analysis process, the current study focuses to investigate one group of three students over two collaborative learning sessions. There were two male and one female students in the chosen group. Their ages varied between 15 and 16 years. The group was selected based on the consultation of the classroom teacher to reflect the average the classroom profile.

The study occurred in the Learning and Interaction Observation Forum (Leaforum), which is a classroom-like collaborative learning space that can accommodate up to 30 students. The advanced infrastructure of the LeaForum allows researchers to collect a variety of data (e.g. video, audio, physiological) without interfering with the learning process. The course in the LeaForum had technology-enhanced learning activities; each student was given a tablet computer with internet access to use during the collaborative learning sessions to search for information, access collaborative task guidelines, and report about their collaborative task assignments.

2.2. Collaborative learning sessions

The topic of the first collaborative learning session was the speed and intensity of light. In the session, students listened to a teacher's short introduction about the space and slides were including information about the speed of light were presented. Then, they were asked to work collaboratively to write a group essay related to the speed of light. Students were encouraged to browse the Web when developing their essay. The group was asked to report about the following tasks and questions in their essay: 1) Design an experimental setting on which you could possibly measure the speed of light; 2) Draw a picture about the setting with argumentation; 3) Investigate how the historical understanding about the speed of light fits with your experimental setting.

The topic of the second session was interference and diffraction. In this session, students were given equipment to do experiments with light. There were two collaborative tasks with sub parts. The first task as refraction in double split: 1) Set a laser beamer above the holder and direct light into the double split. Investigate the light pattern on the wall and answer the questions: a) Briefly describe the parts you can find from the pattern; b) How do you think it has been formed?; c) Read the background of the phenomenon from the book, p. 106-108, and explain again with your own words what the phenomenon is all about. The second task was determining the thickness of a hair. Students were to: 2) a) put a hair ahead of the light instead of the double split, determine the thickness of the hair by using the theory learned in the session, and present your calculations to the teacher when you are ready; b) Write an experiment report about the task.

2.3. Data Collection

The data in the current study was comprised of video, audio, and electrodermal activity recordings for the three participants. Video data was gathered through a camera that could capture participants in a 360-degree point of view. The audio of the participants was recorded in separate channels with mobile microphones that were installed on each of them. The MORE software system in the LeaForum synchronized audio and video of the participants in real time during the learning sessions. EDA activity was captured with Empatica 4 wristbands. Researchers distributed wristbands to the students at the beginning of each session and ensured that they were worn properly until the end of the session. EDA signals were recorded at a sampling rate of 4 Hz.

2.4. Data Analysis

For each session, only the episode of the collaborative task was included in the data set. Classroom activities before or after the collaborative task were not included in the analysis. The video data in the first session included 45 minutes of collaborative task performance. For the second session, it was 37 minutes. Prior to the analysis, data for each session was split into 1-minute chunks. This allowed to investigate the durations and frequencies of monitoring in each 1-minute chunk and the occurrence of PS during the same 1-minute chunk. The duration of monitoring in each minute was calculated through subtracting the end time of a monitoring instance from its beginning with the help of Observer XT software. Figure 3 displays the chunking procedure.

PLEASE INSERT FIGURE 3 AROUND HERE

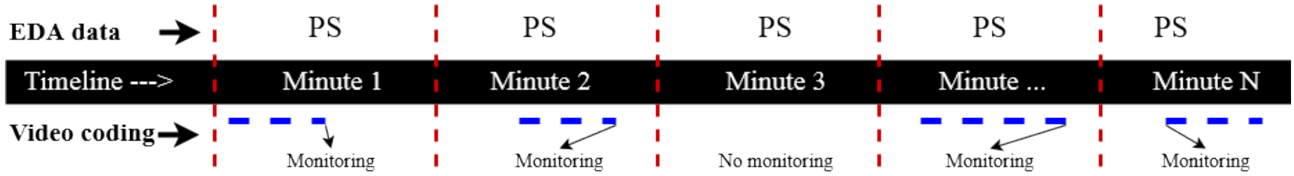

Fig. 3. Analyzing sessions in 1-minute intervals.

2.4.1. Identifying monitoring of SSRL during collaboration

To identify monitoring events from a video data, a coding scheme was developed and tested based on the earlier studies (Azevedo & Witherspoon, 2009; Rogat & Linnenbrink-Garcia, 2011) (see Appendix). At the first stage of the analysis, all of the individual student utterances focusing on monitoring the groups' collaborative learning progress were identified from the videotaped learning sessions. At this point, monitoring was defined as the monitoring of one's own or one's group's cognition, behaviour, motivation or emotions (Winne & Hadwin, 1998). The individual who engaged in each monitoring utterance was identified. At this phase of the analysis, based on earlier studies (Azevedo & Witherspoon, 2009; Schunk, 1991; Wolters, 2011), it was decided to elaborate the three areas of monitoring in more detail. Thus, the coding was done at the individual student level, and each utterance related to monitoring cognition, motivation, emotion and motivation of the group was coded.

During the second phase of the analysis, a single video was coded. The coding was negotiated in terms of a) what is monitoring, b) what is not monitoring and c) empirical examples of the data. After the coding scheme was negotiated, agreed upon and fine-tuned, another round was conducted in which two researchers coded the same video again using the created coding scheme to ensure that the coding was clear, understandable and valid for use in the final coding. Observer XT software was used to code video data under mutually exclusive categories for monitoring of cognition, behavior, motivation, and emotion. In order to check the reliability of the coding, an independent rater coded 20% of the data. Inter-rater reliability of video coding was checked by calculating Cohen's kappa value. The Cohen's kappa was calculated as .73.

2.4.2. Calculation of PS with MdRQA

In the current study, MdRQA method was applied to reveal the dynamics of EDA signals for the group members in a recurrence plot and quantitatively describe their relations. There are a number of parameters for the MdRQA method, including the dimensionality of signals (DIM), number of embedding dimensions (EMB) by the time delay surrogates, delay parameters (DEL), distance norms (NORM), and radius size (RAD) of the phase space window that is taken for recurrence evaluation (Wallot et al., 2016). Some of the parameters are determined by the system in question, while others should be tuned. We used the cross recurrence plot (CRP) toolbox (Marwan, Wessel, Meyerfeldt, Schirdewan, & Kurths, 2002) in our analysis to tune the parameters of the MdRQA. We found the optimal EMB by means of false nearest neighbors in the CRP toolbox, and calculated MdRQA for every one minute interval, as illustrated in Figure 2. Table 2 shows the settings for the MdRQA function. The feature set was constructed from each recurrence plot and concatenated for further analysis.

PLEASE INSERT TABLE 2 AROUND HERE

Table 2
Parameter settings.

Parameter	Value	Definition
DIM	3	signal dimension (three participants)
EMB	5	every dimension is embedded by five time-delayed version
DEL	4	samples of delay between each embedded dimension
NORM	Euclidean	distance metric
RAD	0.3	recurrent points analysis radius

Figure 4. A and B illustrate the recurrent plots of all 1-minute intervals for both sessions. Both sessions are represented by a feature vector, constructed by concatenation of the computed MdRQA based features described in Table 1 for all intervals, in proper time order.

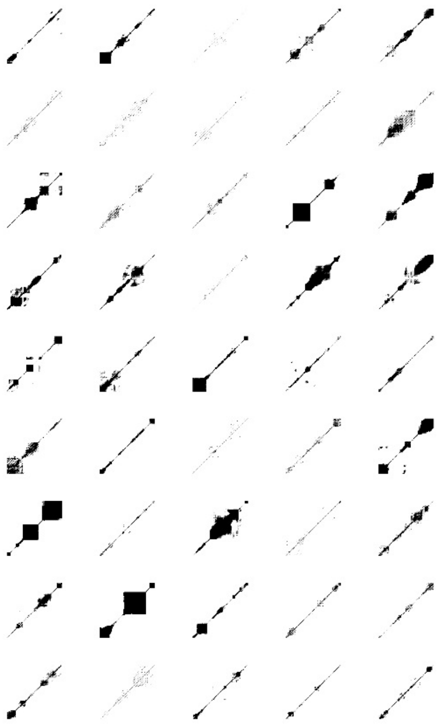

Fig. 4a. Recurrence plots for all 1-minute intervals in Session 1.

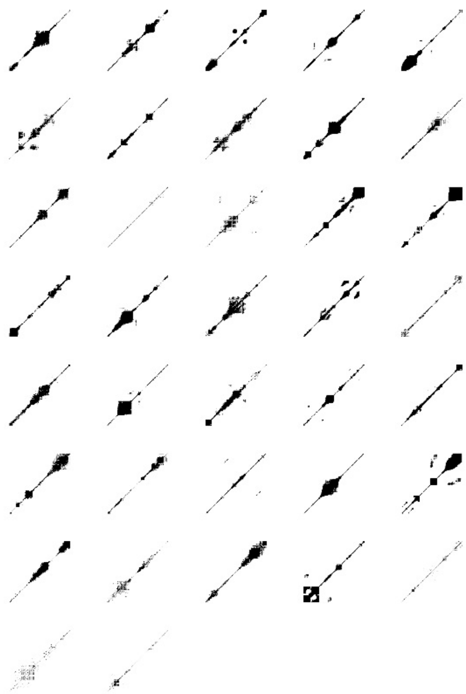

Fig. 4b. Recurrence plots for all 1-minute intervals in Session 2.

Figure 4 shows recurrence plots for session 1 and session 2. Each subplot shows MdRQA visualization for several one-minute segments of the EDA signals. The more dots there are in a plot, the more similar the EDA signals of the group members were at those time instants.

PLEASE INSERT FIGURE 4 AROUND HERE

3. Results

Descriptive statistics revealed that in both sessions, monitoring events occurred at the cognitive and behavioral dimensions, whereas monitoring of motivation and emotion rarely occurred (see Table 3). Considering the descriptive findings and sample size assumptions for the parametric tests, all monitoring categories were collapsed into a single category and monitoring was analyzed as a whole.

PLEASE INSERT TABLE 3 AROUND HERE

Table 3

Frequency of minutes with and without monitoring.

	Session 1		Session 2	
	f (No monitoring)	f (monitoring)	f (No monitoring)	f (monitoring)
Cognition	31	14	24	11
Motivation	43	2	35	2
Emotion	45	0	35	2
Behavior	34	11	24	11
Total	22	23	18	17

Is there a relationship between monitoring durations and MdRQA indices?

A Pearson's correlation analysis with SPSS21 software was conducted to answer the research question. The results are displayed in Tables 4 and 5.

PLEASE INSERT TABLE 4 HERE

PLEASE INSERT TABLE 5 HERE

Table 4

Session 1- Correlations between monitoring durations and MdRQA indices.

	%REC	*%DET*	*MeanL*	*MaxL*	*EntrL*	*%LAM*	*MeanV*	*MaxV*	*EntrV*
Monitoring duration	.418**	.551**	.409*	.494**	.510**	.556**	.363*	.445**	.505**
%REC		.820**	.898**	.892**	.868**	.781**	.943**	.957**	.722**
%DET			.830**	.829**	.958**	.987**	.796**	.895**	.923**
MeanL				.809**	.842**	.773**	.905**	.931**	.723**
MaxL					.816**	.825**	.754**	.876**	.789**
EntrL						.927**	.907**	.904**	.849**
%LAM							.729**	.865**	.956**
MeanV								.916**	.646**
MaxV									.823**

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

Table 5

Session 2- correlations between monitoring duration and MdRQA indices.

	%REC	*%DET*	*MeanL*	*MaxL*	*EntrL*	*%LAM*	*MeanV*	*MaxV*	*EntrV*
Monitoring duration	-.214	-.017	-.187	-.051	.021	-.031	-.077	-.173	-.075
%REC		.772**	.523**	.700**	.760**	.812**	.733**	.897**	.817**
%DET			.740**	.784**	.959**	.983**	.773**	.815**	.933**
MeanL				.610**	.600**	.686**	.774**	.651**	.640**
MaxL					.708**	.802**	.520**	.612**	.787**
EntrL						.939**	.780**	.811**	.922**
%LAM							.714**	.823**	.967**
MeanV								.873**	.638**
MaxV									.801**

**. Correlation is significant at the 0.01 level (2-tailed).

As seen in Table 4, all MdRQA indices were correlated with monitoring duration in Session 1 at small to moderate levels. On the other hand, none of the MdRQA indices was correlated with monitoring duration in Session 2 (see Table 5). The current findings partially support H1.

Is there a difference in PS between collaborative learning situations with and without monitoring?

To address this research question, separate independent samples t-tests were conducted for sessions 1 and 2. In Session 1, all MdRQA indices were higher for 1 minute intervals of collaboration when monitoring occurred compared with the 1-minute intervals in which monitoring did not occur (see Table 6). On the other hand, in Session 2, no difference was observed between monitoring and non-monitoring situations of collaboration (see Table 7). These findings partially support H2.

PLEASE INSERT TABLE 6 HERE

PLEASE INSERT TABLE 7 HERE

Table 6

Session 1- Comparison of MdRQA indices for episodes with monitoring and non-monitoring.

MdRQA indices	Monitoring	M	SD	t	df	p	partial eta-squared
%REC	0	4.07	4.98	-2.756	43	0.009	0.15
	1	8.38	5.48				
%DET	0	28.71	31.62	-4.758	43	<.001	0.35

	1	68.50	24.15				
MeanL	0	15.19	7.14	-3.459	36	0.001	0.25
	1	24.55	8.94				
MaxL	0	40.23	48.48	-3.318	43	0.002	0.2
	1	87.26	46.61				
EntrL	0	1.78	1.43	-3.67	43	0.001	0.24
	1	3.26	1.28				
%LAM	0	33.05	34.54	-4.986	43	<.001	0.37
	1	76.18	22.49				
MeanV	0	13.33	12.58	-2.105	35	0.043	0.11
	1	22.27	12.75				
MaxV	0	21.36	22.02	-3.612	43	0.001	0.23
	1	46.74	24.93				
EntrV	0	2.04	1.49	-4.476	43	<.001	0.32
	1	3.69	0.94				

Monitoring: 0=non-monitoring; 1=monitoring

Table 7
Session 2- Comparison of MdRQA indices for episodes with monitoring and non-monitoring.

MdRQA Indices	Monitoring	Mean	Std. Deviation	t	df	p	partial eta-squared
%REC	0	6.28	2.38	1.222	33	>.05	0.043
	1	5.33	2.22				
%DET	0	69.24	26.58	0.554	33	>.05	0.009
	1	64.37	25.37				
MeanL	0	23.79	7.09	0.864	33	>.05	0.024
	1	21.67	7.03				
MaxL	0	90.44	42.14	0.002	33	>.05	0.000
	1	90.41	49.31				
EntrL	0	3.13	1.09	0.505	33	>.05	0.008
	1	2.96	0.86				
%LAM	0	75.73	25.74	0.538	33	>.05	0.009
	1	71.14	24.61				
MeanV	0	17.60	4.83	1.245	32	>.05	0.046
	1	15.01	7.10				
MaxV	0	40.22	14.59	1.164	33	>.05	0.039
	1	34.53	14.33				
EntrV	0	3.73	1.13	0.507	33	>.05	0.008
	1	3.56	0.79				

Monitoring: 0=non-monitoring; 1=monitoring

4. Discussion

Performance in collaborative learning is dependent on iterative regulation of cognitive, behavioral, motivational, and emotional processes within and between the group members (Hadwin et al., 2017; Roschelle & Teasley, 1995). Considering that collaboration is situated and affected by contextual features (Kapur, 2011), process-oriented measures are necessary to unpack the temporal emergence of regulatory processes in SSRL research (Panadero & Järvelä, 2015). Drawing on this, the current case study combined MdRQA with video data to investigate the possible associations between PS and monitoring of group learning progress.

In the current study, a group of three students worked on collaborative tasks for two sessions. In the first session, students' PS was significantly correlated with their monitoring duration. In addition, MdRQA indices were higher in instances with monitoring compared to instances without monitoring. On the other hand, no relationship was observed between PS and group monitoring events in the second session, nor there was a difference between instances of monitoring and non-monitoring in terms of PS derived from MdRQA indices. Previous studies showed that performing collaborative tasks often leads to similar physiological responses among the collaborators (Strang et al., 2014; Wallot et al., 2016), and PS can be a result of interactions that reflect shared goals and strategies during collaboration (Knoblich, Butterfill, & Sebanz, 2011). The current study partially supported these findings. Our results revealed that shared monitoring of learning progress might be reflected as PS, though only in some collaborative task situations. This corresponds with Wallot and colleagues (2016), who found that in some task situations, collaboration could occur as the complementarity of actions rather than their synchronicity. In line with their findings, Lazer and Bernstein (2012) also noted that some collaborative tasks require synchronicity of actions among the group members whereas some require coordination. Thus, it can be expected that not all collaborative task processes might be reflected as PS among the collaborators. In addition, Wallot and colleagues (2016) stated that PS could also be a function of task difficulty. Thus, it is possible to assert that in complex task situations, duration of monitoring group progress might be more evident in PS. Further, past studies have shown that motivational dispositions such as task interest might influence the amount of involvement in a collaborative task (Järvelä & Järvenoja, 2011). However, students' perceptions of task complexity, and task interest were not measured in the current study. Thus, future studies are necessary to identify the relationship between task complexity, task interest, PS, and SSRL processes.

The video analysis showed that collaborative tasks triggered monitoring of behavior and cognition. This can be considered SSRL processes that occur in the content space of collaboration. On the other hand, monitoring of motivation and emotion, which are the regulatory processes related to the socio-emotional space of collaboration, rarely occurred during the collaborative tasks in the current study. Thus, the results demonstrate the possible relationship between PS and monitoring events in the content space of collaboration rather than the socio-emotional space. Our findings revealed that intense motivational or emotional arousal is not necessary in collaborative work in order to experience PS among individuals. On the other hand, several studies reported that PS would be more evident in intense affective arousal situations (Butler, 2011; Elkins et al., 2009; Henning et al., 2009; Karvonen, Kykyri, Kaartinen, Penttonen, & Seikkula, 2016; Konvalinka et al., 2011; Mitkidis et al., 2015; Mønster et al., 2016; Wallot et al., 2016). Therefore, future studies should investigate how collaborative tasks that elicit higher frequencies of motivational and emotional regulation affect PS among the collaborators.

In the existing study, recurrence of PS was calculated at the group level. That is, if EDA scores of the three participants fell into a specific radius at a specific time, it was regarded as a recurrence. Similarly, durations of monitoring the group progress were calculated at the whole group level. However, in collaborative learning research it is common to observe that not all members of a group participate effectively in a collaborative task. Issues such as the “free rider effect”, benefiting from collaboration without contribution, and the “sucker effect”, contributing less to avoid negative feelings of others, might happen during collaboration (Schneider & Pea, 2013). Therefore, investigation of PS and monitoring of SSRL at the dyadic level in a group and comparing it with PS at the whole group level might help to detect group members who are not committed to the group work.

The current study contributes to the contemporary perspective in SSRL that regard regulation as a highly dynamic and sequential series of events during learning (Greeno, 2006). Investigating the temporal development of regulation over time can facilitate identification of critical moments that promote or hinder effective learning, and provide just-in- time support to learners during those moments (Winne, 2015). However, the tools that can capture or support the regulatory processes as they unfold during learning is yet to be developed. This is because empirical research has shown that investigating mental processes during group learning is challenging due to methodological limitations (Järvelä, Hadwin, Malmberg, Miller, 2017). For example, widespread self-reports tools inform about the dispositions of learners towards regulation rather than capturing the dynamic transitions among the regulatory processes towards task completion. Considering such limitations, the current study utilized EDA and video data to identify the physiological markers of shared monitoring processes identified in the video data. Although the current study cannot claim any direct relationship between PS and shared monitoring, it can serve as a springboard for future studies to understand whether and/or how regulatory processes are reflected in physiological signals. This is important to investigate because the advent of mobile devices allow recording of several bodily signals (e.g. EDA and heart rate) unobtrusively during learning. The real-time metrics developed from these signals might open a new path in supporting teachers and learners through making so-far invisible SSRL processes visible to them. The future practical implications can be dealing, for example, with "on the fly" support during the learning process, especially in group learning contexts.

5. Conclusion

The current study investigated processes of monitoring group progress and temporal evolution of PS among group members in a natural, dynamic, and technology-enhanced collaborative learning context. The study utilized MdRQA and video analysis to investigate the dynamic nature of SSRL processes. MdRQA has been developed to reveal complex systems (Knight et al., 2016), and is a promising approach to investigate group dynamics in collaborative contexts. It can provide temporal insights regarding group interactions. Thus, MdRQA has the potential to complement SSRL research through adopting measures to reveal the temporal evolution of regulation in learning. Specifically, we studied the relationship between group monitoring of SSRL and PS among students during two sessions of a collaborative task. Our findings showed that the relationship between PS and group monitoring of SSRL might be dependent on the task type and group characteristics, and not all monitoring events in a collaborative tasks lead to PS. In addition, our findings revealed that interactions at the content space of collaboration could produce PS, even in the absence of the emotional or motivational regulation that takes place at the relational space. It should be noted that investigation of PS in team collaboration is still in its infancy and standard measures of PS are no yet developed (Ellamil et al., 2016). Thus, the current study is not conclusive and could be regarded as a preliminary attempt to unearth SSRL processes with PS. However, it is concluded that the methods chosen can contribute to collaborative learning research, especially given the lack of methods which can capture such invisible meta-level activities in collaborative learning (Reimann, Markauskaite, & Bannert, 2014). Capturing invisible physiological signals and matching them with visible instances of monitoring processes might facilitate identification of critical moments in collaboration that lead to success or failure in performance.

5.1. Limitations and future directions

The current study suffers from various limitations. First, the findings are highly situated within the chosen group and collaborative tasks. Second, performance outcomes of collaborative tasks were not measured in the current study. Thus, the findings are not capable of demonstrating how the relationship between PS and monitoring of SSRL produce learning outcomes in different collaborative task situations. Future studies should investigate the association between PS and SSRL processes in terms of their effect on learning outcomes. Generalization of these results is limited considering both the small sample size and lack of control for autocorrelation in repeated measurement of electrodermal activity. This limitation was partly due to the labor and time-intensive video coding process, and partly due to lack of standardized measures in PS. Also, a significant challenge in physiological data collection from a collaborative learning setting is that data collection devices attached to the students might get loose during the collaborative task and result in missing data. It is not possible to calculate PS for the group if data of a group member is missing. Unfortunately, this was the case in our study and we could not calculate PS for multiple sessions. Thus, we could only provide findings from two sessions, but believe that the results and reporting these restrictions will contribute to the increasing field of multimodal data us in SRL and CL. Future studies should aim to collect data from multiple groups in different collaborative task conditions in order to reach generalizable conclusions. Another limitation of the study was that monitoring types (i.e. cognition, behavior, motivation and emotion) coded from the video data were collapsed into a single category for statistical analyses. This was because only few instances of behavior, motivation and emotion categories were identified during the collaborative learning sessions. However, the proportion of monitoring categories other than cognition was not same in both learning sessions. This might have been a source of bias during the statistical analyses. Future studies should take this into consideration and aim to design the collaborative tasks in a way to trigger more instances of monitoring of behavior, cognition, motivation and emotion in order to investigate how variation in such instances affect PS. PS was investigated in terms of EDA in the current study. Future studies should implement other measures such as heart rate variability or accelerometer data to investigate whether different PS measures can provide a better understanding on the development of SSRL among group members. Another approach for future work would be investigation of high and low PS moments during collaboration with micro-analysis of video segments. Such an approach might provide valuable information whether and how PS responds to specific SSRL processes.

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Appendix

Coding scheme and data examples

Monitoring categories	*Empirical indicator*	*Data examples*
Behaviour	Monitoring task-related behaviour, such as the resources needed for the task. Monitoring task progression.	"Do we have all the equipment needed?" "I wonder if the laser is needed any more" "Does the book include a chapter about this?" "How much time do we have left?" "My network is down again." "We have done task number one. We can move to number two." "We still have three tasks to do."
Cognition	Monitoring task understanding and prior knowledge. Monitoring procedural knowledge and whether the study product is correct/in normal range. Monitoring content understanding	"I'm not sure how we are supposed to do this." "We at least know from previous lessons that speed of light won't change." "We know these values, but this we are missing." "I have no idea what I'm now doing." "I'm not sure what would be wise to do next." "How we are supposed to use the formula here?" "I think we should use the wave motion formula here." "Is this result in reasonable range?" "Are we still adding something, or do you think this is ready?"
Motivation and Emotions	Monitoring current trends in motivation. Monitoring volition and	"Who is willing to draw this?" "Our motivation is on a good track."

	efficacy. Monitoring emotional state.	"I really would not want to do this." "I'm so bad at drawing. Who can do this?" "My feelings are good! Let's start." "These microphones make me annoyed!" "This is exciting!"

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Highlights

- Regulation in collaborative learning is not a static aptitude but a dynamic process.
- Process-oriented methods can help to capture dynamicity of collaborative work.
- MdRQA is a promising method to capture physiological synchrony of collaborators.
- The level of physiological synchrony might be related with regulation of learning.