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Monitoring in collaborative learning: Co-occurrence of observed behavior and physiological
synchrony explored

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Abstract

Although research on collaborative learning suggests that monitoring plays an important role in successful regulation of the collaborative learning process, little is known about how students attend to it together. This study explores monitoring in collaborative learning. Specifically, it studies how students in a group monitor their cognitive, affective and behavioral processes during their collaboration, as well as how observed monitoring co-occurs with their physiological synchrony during the collaborative learning session. Data was collected from 48 Finnish highschool students who were learning about nutrition in groups of three. The session was videotaped and coded in terms of monitoring of cognition, behavior and affect. Students' arousal was measured as electrodermal activity with wearable sensors and used to calculate physiological synchrony between the students. Three case groups, with priority on the quality of the data, were chosen for detailed analysis. The results indicate that the main targets of monitoring for these case groups were cognition and behavior, while monitoring of affect occurred the least. Most of the student pairs inside the groups showed significant amounts of physiological synchrony. High values of physiological synchrony occurred when monitoring was frequent. Time series analysis showed a weak positive connection between monitoring and physiological synchrony for two groups out of three. These results indicate that physiological synchrony could potentially shine a light on the joint regulation processes of collaborative learning groups.

Keywords: Collaborative learning, Monitoring, Self-regulated learning, Physiological synchrony, Video data

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Collaborative learning has become increasingly popular in learning and education, and research on the subject has also increased (Hmelo-Silver & Chinn, 2015). It is known that keeping track of the progress of collaboration increases student success (Rogat & Linnenbrink-Garcia, 2011), but such a feat is not easy. Progress in collaboration requires deliberate monitoring and regulation of cognition, behavior and affect at the individual and group level (Authors, 2017b). Monitoring is a primitive cognitive operation during which the student compares the current state of the target being monitored (i.e., understanding of the topic) into standards that he or she holds (Winne, 2011). Despite the fact that monitoring can be viewed as individual metacognitive activity (Flavell, 1979; Nelson, 1996), in the context of collaborative learning, it can become partly “visible” in social interaction. When monitoring becomes visible (such as being externalized via interacting partners, for example), it can contribute to joint knowledge construction and progress in collaboration (Malmberg, Järvelä, Järvenoja, & Panadero, 2015; Rogat & Linnenbrink-Garcia, 2011).

Much is known about interaction processes (Webb, 1989), knowledge building (Scardamalia & Bereiter, 2014) and, more recently, group level regulation processes (Authors, 2017b), but little is understood about monitoring in groups. Since monitoring group progress is essential in collaborative learning, it is important to understand how individual contributions are related to monitoring groups’ progress (Volet, Vauras, Salo, & Khosa, 2017). Still, there has been little progress in developing methods that make invisible mental monitoring processes and their accompanying social interactions visible and, thus, measurable (Authors, 2017a). “Making visible” here means that even though monitoring is a psychological phenomenon it has

psychophysiological indicators, such as autonomic arousal (Hajcak, McDonald, & Simons, 2003), which can be tracked from physiological signals. Therefore, this study explores how students monitor cognition, affect and behavior during collaborative learning and the co-occurrence of monitoring with physiological synchrony. This exploration intends to not only capture visible contributions related to monitoring but also reveal sharing as joint psychophysiological reactions.

1.1. Regulation and role of monitoring in collaborative learning

Self-regulated learning (SRL) has been in the interest of researchers and teachers in recent years, most likely because it has been shown to affect students' academic achievement (Dignath & Büttner, 2008). Self-regulated learners are often described as active and pro-active: They take part in their learning by setting reasonable learning goals, making plans, and using various learning strategies to ensure that goals set for learning are met. In order to accomplish the goals set for learning, students need to monitor their cognition, behavior, motivation and emotion. If learners monitor a need to change cognition, behavior, motivation or emotions, they are aware of various strategies they can use to ensure that learning goals will be met (Zimmerman & Schunk, 2011).

Traditionally, monitoring is considered as a metacognitive activity (Flavell, 1979) that facilitates the flow of information from the object-level (i.e., cognition) to the meta-level (metacognition) (Nelson, 1996). During a learning process, students engage in monitoring, for example, when they become aware of their cognition and affect through judgement of learning (Nelson, 1996) or feelings of difficulty (Efklides, Samara, & Petropoulou, 1999). Monitoring makes it possible for a learner to notice problems at the object level and to control them in terms

of the goals assigned (Veenman, Van Hout-Wolters, & Afflerbach, 2006). This constant interplay can also be seen in the SRL process when learners create self-oriented feedback loops through which they monitor effectiveness of their learning and adapt according to their goals (Winne & Hadwin, 1998; Zimmerman & Schunk, 2011).

Traditionally, monitoring as a concept has been used in information processing models to explain student learning (Pintrich, 2004; Winne & Hadwin, 1998), and therefore, most of the research on metacognition has considered cognition as a main object of monitoring. Theories of SRL state that in addition to metacognition and cognition, behavior and affect are also central components in the regulation process (Pintrich, 2004; Zimmerman, 2000). This means students first need to become aware of these aspects via monitoring to then be able to use their strategies to control and regulate them effectively towards the set goals (Efklides, 2011; Wolters & Benzon, 2013). However, it cannot be assumed that students will, can or should monitor their cognition, behavior or affect consciously at all times or in all contexts (Pintrich, 2004). Monitoring can also take counterproductive forms, and, being a form of cognition, it also uses the same resources as other cognitive operations (Winne, 2011).

Despite the fact that the regulation process and underlying monitoring have a strong effect at the individual level, accumulating research shows that during collaborative learning it also manifests at the group level (Authors., 2017b). Because collaborative learning involves synchronously engaging in a shared problem space with joint goals and attention (Baker, 2015; Roschelle & Teasley, 1995), it also sets its own demands for students' monitoring and regulation theories advanced in the collaboration context (Hadwin et al., 2011; Winne & Hadwin, 1998).

Monitoring is critical in collaboration, since in successful collaboration students accurately perceive the task conditions and mental states of others in the group, assemble a set of

joint standards and then accurately examine the differences between the features and standards (Winne, Hadwin, & Perry, 2013). This sets the stage for successful control and regulation in the collaborative process (Järvelä & Hadwin, 2015).

Few studies have investigated how monitoring occurs in regulation during collaborative learning, and even fewer studies have concentrated on how monitoring of behavior and affect occurs in these situations. What these studies have shown, however, is that monitoring is often, but not always, shared with the group members in the practice of collaboration, and its quality varies. For example, Rogat and Linnenbrink-Garcia (2011) have found that on the one hand, high quality monitoring provided students with opportunities for support and explanation, which encouraged elaboration and revision to task responses. This also seemed to lead to deeper understanding of the content. On the other hand, if the quality of the monitoring was low, it seemed to block the opportunities for deep level task understanding in the group. Studies have also recognized the importance of monitoring in the development of shared understanding and learning in the group (Lee, O'Donnell, & Rogat, 2014; Näykki, Järvenoja, Järvelä, & Kirschner, 2017).

When monitoring is shared during collaborative learning, it builds communal awareness of group processes and facilitates adaptation to the challenges through shared regulation (Winne et al., 2013). Socially shared regulation of learning (SSRL) refers to a process by which groups of students share the regulation in terms of the goals, planning, monitoring and controlling (Hadwin et al., 2011). The most salient features of SSRL have been identified in terms of joint cognitive and metacognitive regulatory strategies (Iiskala, Vauras, Lehtinen, & Salonen, 2011; Panadero & Järvelä, 2015), as well as group motivational efforts and emotion regulation (Järvelä, Järvenoja, & Veermans, 2008; Järvenoja & Järvelä, 2009). Sharing or lack of sharing monitoring

is difficult to find evidence of in studies, since many current methods (e.g., think aloud or self-reports) are incapable of revealing these processes at the group level.

1.2. How can monitoring in regulation be studied?

Empirical evidence of monitoring in self-regulated learning research relies strongly on self-report measures (e.g., Pintrich, Smith, Garcia, & McKeachie, 1993) and, more recently, online protocols (Veenman, 2011) used with individual students. For example, in Pintrich et al.'s (1993) Motivated Strategies for Learning Questionnaire (MSLQ), the students are presented with a Likert scale and asked whether they agree that, during their studies, they try to determine which concepts they do not understand well. Self-report questionnaires have been criticized about their accuracy (Tobias & Everson, 2000; Winne & Jamieson-Noel, 2002), and they usually lack the ability to capture the temporally unfolding dynamics of the regulation process. Thus, online measures, such as think-aloud protocol (TAP), were developed to better capture the temporal aspects of cognition (Ericsson & Simon, 1980). Azevedo (2005), among others, has used TAP online protocols to capture the temporal aspects of SRL. He coded monitoring events that occurred when students were told to think aloud as they engaged with a hypermedia learning task and found that successful students use significantly more metacognitive monitoring processes and strategies during their learning process. However, TAPs are also not well suited for studies in collaborative contexts, because they disturb the normal flow of interactions in the group.

Recently, some studies in have combined the support and measurement of regulation in the form of tools that frequently gather information from students' answers (e.g., Likert-scale or open-ended questions), analyze the information and present them back to students in order to support the regulation process (Panadero, Klug, & Järvelä, 2016). These tools aim to raise the

awareness of the group through activation of monitoring and regulation by offering students the opportunity to reflect on the cognitive and affective status of the group and to plan and evaluate how to deal with the task (Järvelä et al., 2015). Other studies have combined the data gathered from the tools with observational video analysis to further reveal the temporality of the regulation process (Sobocinski, Malmberg, & Järvelä, 2017).

Observational video analysis has been the common approach of studying regulation and monitoring in collaborative learning. This approach relies on students' elaborated utterances. In earlier research, monitoring was coded from the video data in terms of its quality (Rogat & Linnenbrink-Garcia, 2011) and target (Näykki et al., 2017). This type of analysis provides results in the form of durations and frequencies, which can, for example, be compared between successful and unsuccessful groups. It also offers possibilities for further temporal analysis of monitoring and regulation through techniques like statistical discourse analysis (Molenaar & Chiu, 2014) and process mining (Malmberg et al., 2015). The restriction with this method, however, is that only the interactions that students elaborate on in their group can be analyzed.

Thus, even providing a strong methodological grounding for SRL research, these methods alone are not capable of revealing the socially shared regulation process and the internal and external conditions in between the individual and group level (Authors, 2017b) as well as temporal progress of regulation in collaboration (Azevedo, 2014). Therefore, it has been proposed (Azevedo, Taub, Mudrick, Farnsworth, & Martin, 2016; D'Mello, Dieterle, & Duckworth, 2017; Authors, 2017a) that combinations of different forms of process data—called multimodal data—enabled by new technologies might reveal more about the temporal characteristics of the learning process.

1.3. Physiological synchrony revealing process of regulation in collaboration

Years of research in the field of psychophysiology has confirmed that human cognition isn't separate from the body (Critchley, Eccles, & Garfinkel, 2013). This connection is bidirectional since, on the one hand, many of the mental states are reflected in the body's physiological signals (Pecchinenda & Smith, 1996), and, on the other hand, physiology of the body influences human consciousness and cognition (Garfinkel et al., 2015). The field of learning sciences has just recently become interested in these methods despite its fundamental interest in these same mental states. The transition towards these measures is supported by development of the technology, which has made it easier to measure these signals. Specifically, measures reflecting arousal and activity of the autonomic nervous system (ANS) like electrodermal activity (EDA) can be applied rather unobtrusively (Garbarino, Lai, Tognetti, Picard, & Bender, 2014).

As such, ANS measures like EDA (electrical characteristics of the skin, reflecting sympathetic nervous system activity) only tell of students' general level of arousal and therefore cannot be easily linked to any specific mental state (Kreibig, 2010). Thus, they still need other forms of contextual data for accurate interpretation. In prior research (e.g., Harley, Bouchet, Hussain, Azevedo, & Calvo, 2015) physiological arousal has often been linked to the arousal dimension of the emotion in the traditional circumplex model (Russell, 1980). This does not relay any information regarding pleasantness (valence) of the learning situation, but instead it reflects how physiologically activating the emotion is (Pekrun, 2006). Recently, however, it has been argued that through interoception, physiological arousal can be straightly linked to cognition as well as emotion (Barrett, 2017; Critchley & Garfinkel, 2018).

In practice, physiological data (e.g., measured heartrate or skin conductance) can serve as a single modality of data in multimodal data sets, which may additionally include, for example, log-data and video data. Although some early studies (Kaplan, 1967) combined physiological measures with observational data to study student interaction, most of the prior research utilized it in strictly controlled experiments during which the individuals' reactions to specific stimuli had been measured.

Although ANS activity doesn't directly tell how a student is monitoring learning, it seems to react when an individual consciously monitors the feeling of knowing (Morris, Cleary, & Still, 2008) or errors made during a task (Hajcak et al., 2003). It has also been associated with many of the conditions (Greene & Azevedo, 2007; Winne & Hadwin, 1998), setting a stage for the regulation process. Autonomic arousal measured from heartrate or electrodermal activity can reflect, for example, engagement and perceived coping potential (Pecchinenda & Smith, 1996), self-efficacy (Bandura, Cioffi, Ban-Taylor, & Brouillard, 1988; Bandura, Reese, & Adams, 1982), cognitive appraisals (Tomaka, Blascovich, Kelsey, & Leitten, 1993) and goal relevance (Kreibig, Gendolla, & Scherer, 2012), which in many of the SRL models are considered to be part of the regulation process (Boekaerts, 1997; Efklides, 2011; Winne & Hadwin, 1998; Zimmerman, 1989).

Autonomic nervous system activity, despite pertaining to an individual, can also be analyzed at the social level through synchrony. Palumbo et al. (2017) define physiological synchrony as "any interdependent or associated activity identified in the physiological processes of two or more individuals" (p.2). Plenty of research findings to date indicate that physiological synchrony—seen, for example, as simultaneous changes in students' EDA signals—can be informative of social interactions. Evidence suggests that synchrony contributes to construction

and maintenance of common social and affective space (Cornejo, Cuadros, Morales, & Paredes, 2017), and has been linked to shared mental processes relevant to monitoring in efficient collaboration like joint understanding (Järvelä, Kivikangas, Kätsyri, & Ravaja, 2014) and empathy (Marci, Ham, Moran, & Orr, 2007). It has also been suggested that physiological synchrony plays an important role in the development of self-regulation and social adaptation (Feldman, 2007; Feldman & Greenbaum, 1997), which are essential in the context of collaborative learning (Järvenoja & Järvelä, 2009).

Interest in the subject is still increasing, so there are only a few studies that have measured physiological synchrony in educational settings (Ahonen, Cowley, Hellas & Puolamäki, 2018; Ahonen, Cowley, Tornainen, Ukkonen, & Vihavainen, 2016; Gillies et al., 2016; Authors, 2017c; Authors, 2017d). For example, Authors et al. (2017c) investigated how physiological arousal, types of interaction and emotional valence occur in the context of collaboration. Results indicated that learners expressed the highest frequency of negative emotions in specific situations where they were confused and aroused (Authors et al., 2017c). Those situations also involved markers of metacognitive monitoring. Similar results were obtained in a study that explored how physiological synchrony occurred during collaborative task execution (Mønster Håkonsson, Eskildsen, & Wallot, 2016); physiological synchrony was correlated with group tension and negative affect. Further, other work examined how physiological synchrony was related to learners' beliefs of their cognition, motivation, emotions and behavior, and found that students who shared their reflected views on the groups' cognition, motivation or behavior also showed higher physiological synchrony (Authors et al., 2017d). In light of these studies, it can be argued that physiological synchrony may be informative in terms of exploring monitoring during collaborative learning. This is to say physiological synchrony can

reflect joint cognitive and affective states that are important for group success; however, the measures alone are not able to tell of the progress of learning.

This study explores the complex situational nature of monitoring and physiological synchrony in collaborative learning through in-depth multimodal analysis of three case groups. It especially investigated how individuals' recognized reactions, such as what they say, could be linked to invisible indices—physiological indicators—in such ways that could provide evidence of how and when students in the group engage in monitoring processes.

1.4. Aims

The aim of this study is to explore how monitoring processes emerge in the context of collaborative learning. This will be investigated through observational and physiological data. The research questions are 1) How do students in a group monitor their cognitive, affective and behavioral processes during their collaboration?; and 2) How does observed monitoring co-occur with physiological synchrony during the collaborative learning session?

2. Methods

2.1. Participants and task

Participants ($N = 48$) were Finnish high school students (M age = 17.4, $SD = .67$, 27 females). Participation in the experiment was voluntary for the students. During the experiment, the students collaborated in groups of three, comprising 16 groups in total, and the students' collaborative task was to design a "healthy breakfast" by using the weSPOT learning environment.

2.1. Experiment

The experiment lasted 75 minutes in total. At the beginning of the experiment, the students were assigned to groups on the basis of their previous knowledge of the topics and on the basis of their individual scores in the Motivated Strategies for Learning Questionnaire (MSLQ) (Pintrich, Smith, Garcia, & Mckeachie, 1993). MSLQ is a 7-point Likert-scale instrument designed to measure students' understanding of their SRL. It constitutes 81 items in two sections with a total of 15 scales (see Appendix for Cronbach alpha values). In order to ensure possible comparisons, the groups were made as homogenous as possible in terms of the individual scores on the MSLQ instrument ($M = 357$, $SD = 53.4$, Range 245–467) and previous knowledge of the topics ($M = 75$, $SD = 10.65$, Range 50–95).

After grouping the students, they were introduced to the experiment, and Empatica (E3) sensors were placed on the students to measure their EDA. Each student was provided with a tablet device for the task execution. At the beginning of the task, the students were given instructions on what they were supposed to do, along with the instructions on how to use the weSPOT learning environment collaboratively.

WeSPOT is a cloud-based approach for collaborative inquiry learning that allows learners to perform scientific investigations (Mikroyannidis et al., 2013). It also gives instructors a flexible tool to arrange and script collaborative inquiry learning. The collaborative task was to plan a healthy breakfast for a case subject. The weSPOT learning environment (see Figure 1.) included the task instructions, along with informative descriptions of what a healthy breakfast should include. In addition to the instructions and information, the learning environment included a script that guided the students' collaboration. The script consisted of five phases: 1) use your prior knowledge; 2) plan your collaborative working and set the criteria for the task's

completion; 3) search for information; 4) evaluate, discuss and complement the findings in the learning environment; and 5) check your answer and communicate the results. The students' collaborative task outcome was a detailed list that included a description of nutrients needed for the breakfast. The current study focuses specifically on three case groups ($n = 9$, M age = 17.33 years, $SD = 0.66$, 4 females) and explores those groups in further depth. The three case groups were selected due to holding the most artifact-free sets of physiological data.

The screenshot shows the 'Breakfast Athlete' inquiry space. At the top, there are buttons for 'Leave inquiry' and 'Export inquiry'. The main content area is divided into sections:

- Case description:** A circular icon representing the case.
- Owner:** Inquiry members: 4. Status: Closed membership.
- Description:** Three paragraphs of text describing the case, followed by a list of resources: 'Kuvaus tyypillisestä ravinnosta' (Word document - Ravinto) and 'Excel dokumentti ravintoaineiden laskemista varten' (Excel spreadsheet - Ravintoainemäärät).
- Language:** English.
- Inquiry phase navigation:** A horizontal flow of five steps: 1. Task instruction (Tehtävän anto ja tieto tehtävästä), 2. Planning (Suunnitteluvaihe), 3. Knowledge acquisition (Tiedonkeruu), 4. Evaluate and discuss (Arvioi ja keskustele), and 5. Check your answer (Tarkista tietosi).
- Inquiry phase navigation:** Two main sections: '1. Mistä tässä tehtävässä on kysymys' (0 votes, 2 answers) and '2. Käsitteiden määrittelyä' (Kalium, Proteiini, Ravintorasva).
- Activation of prior knowledge:** A section for activating prior knowledge, with a 'More questions | Add question' link.

Fig. 1. Screenshot of the weSPOT inquiry space

2.2. Data collection

The data collection involved two different data modalities, observational data and physiological data. The data was collected during the experiment in a classroom-like research space with modern equipment. The observational data consisted of video recordings of three groups (3 hours 45 minutes in total) during the students' collaborative learning task. The video was recorded with

the MORE video system (Keskinarkaus et al., 2015), which can simultaneously record 30 speech tracks and three video tracks through spherical, 360° point-of-view cameras.

Physiological data was collected using Empatica (E3) sensors (Garbarino et al., 2014). Empatica E3 is a wireless multisensor device which can be used to gather data in real life situations in a comfortable and non-distracting way. It measures electrodermal activity from the user's wrist through silver-coated electrodes with small alternating current. Its EDA sensor provides values with 4hz frequency and range of 0-100 μ S.

3. Analysis

3.1 Qualitative video analysis

Monitoring was identified from the video data based on student utterances (See Table 1). The analysis focused on groups' monitoring of cognition, behavior, emotion and motivation (Winne & Hadwin, 1998; Pintrich, 2004; Wolters, 2013). At the first phase of the analysis, general principles based on the data and theory (Rogat & Linnenbrink-Garcia 2011; Greene & Azevedo, 2007) were negotiated in order to capture all the instances when monitoring occurs followed by careful coding of two videos. At the second phase, the coding category was refined based on the joint negotiations. This iteration resulted in a more accurate coding scheme. The Cohen's kappa of inter-rater reliability between the two raters was calculated for categories, and it was .76, which can be considered as good agreement. Given that the reliability was acceptable, the team decided to use the most experienced researchers' original category codings to establish final agreement of the data. The categories of emotion and motivation were combined into a single category called affect due to low frequency of coded utterances.

The utterances focusing on monitoring cognition included phrases such as students vocalizing their prior knowledge, and focusing on content monitoring (e.g. quality of a task,

content knowledge) and monitoring the task (e.g. task understanding and progress in a task; see Lee, O'Donnell, & Rogat, 2015). The utterances focusing on monitoring are explained in more detail in Table 1.

Table 1

Coding scheme for observing monitoring

Code description	Examples
<i>Monitoring cognition</i>	
- task understanding	<i>"What are we supposed to do here? Write opinions?"</i>
- prior knowledge	<i>"Hey, we did really know more than that!"</i>
- progress of the task	<i>"No wait, we passed this phase on which we should have set the criteria together"</i>
- quality of the task product	<i>"Okay, this answer of yours is quite good already"</i>
- content knowledge/understanding	<i>"Avocado, doesn't it have quite a lot of vegetable fat?"</i>
<i>Monitoring affect</i>	
- motivation	<i>"My interest dropped"</i> <i>"I really would like to go home already"</i>
- emotion	<i>"My feelings are great currently"</i> <i>"This is exciting!"</i>
<i>Monitoring behavior</i>	
- concrete task actions	<i>"Has everyone read the book chapter?"</i>
- resources needed	<i>"Does anyone have a calculator?"</i>

3.2. Analysis of physiological synchrony

This study adopted physiological concordance (PC) as a method to indicate physiological synchrony between the students. In practice, physiological synchrony was analyzed at the level of pairs inside the group (see Figure 2 for steps), which means that three pairs inside each three member group were analyzed. PC has been applied this way in other research contexts (Karvonen, Kykyri, Kaartinen, Penttonen, & Seikkula, 2016; Marci, Ham, Moran, & Orr, 2007; Slovák, Tennent, Reeves, & Fitzpatrick, 2014), and it offers a potential tool to measure interpersonal autonomic activity through EDA in social settings (Palumbo et al., 2017) such as collaborative learning. To our knowledge, this is the first study to adopt this approach in learning research.

The first part of the analysis follows the approach of Marci et al. (2007) with the only exception being that the students' signals were standardized in order to make them more comparable (Ben-Shakhar, 1985). Verification of the significance of synchrony through Monte Carlo shuffling was adopted from Karvonen et al., (2016), and the temporal analysis of changes in the concordance followed the approach introduced by Slovák et al. (2014).

Physiological concordance was calculated from the learners' EDA and was based on moment-by-moment comparison of the slopes in students' EDA signals (Marci, Ham, Moran, & Orr, 2007). Therefore, baseline measures of EDA level weren't relevant for this analysis. However, because there are individual differences in the amount of variation in EDA values, the first step was to standardize the signals in order to make them more comparable across participants (Ben-Shakhar, 1985; Dawson, Schell, & Fillion, 2017).

In the second step, physiological concordance (PC) was calculated to index physiological synchrony (Marci et al., 2007). The average slope of skin conductance (SC) was determined for

each student within a moving 5-second window. Pearson correlations were then calculated over successive, running 15-second windows between two students' SC slope values. A single session index (SSI) was then calculated from the ratio of the sum of the positive correlations across the entire learning session divided by the sum of the absolute value of negative correlations across the session. Because of the skew inherent in ratios, a natural logarithmic transformation of the resulting index was calculated. Thus, an index value of zero reflects equal positive and negative correlations or neutral concordance for the given period of time.

Although a PC index allows the calculation of PS during the session, it includes explanatory shortcomings because of the possible autocorrelation. Therefore, Monte Carlo shuffling—also earlier utilized with a PC index (Karvonen et al., 2016)—was used to estimate the significance of the synchrony for the pairs. This could be done with repeated random concordance calculation by keeping the slope values of the first person in the pair stable but randomly picking up the 15-second Pearson correlation window values from the signal of the other person for each moment. Concordances were then sorted in ascending order to determine the 95% point of the sequence. In addition, to see if there existed some general flow of the lesson that could be mistaken for synchrony, hypothetical pairs (see eq. Marci et al., 2007; Richardson & Dale, 2005) were formed by making all the possible combinations of pairs from 9 participants so that the students were not drawn from the same group. As a result, there were 27 SSI values for hypothetical pairs made up of people who were not actually working in the same group.

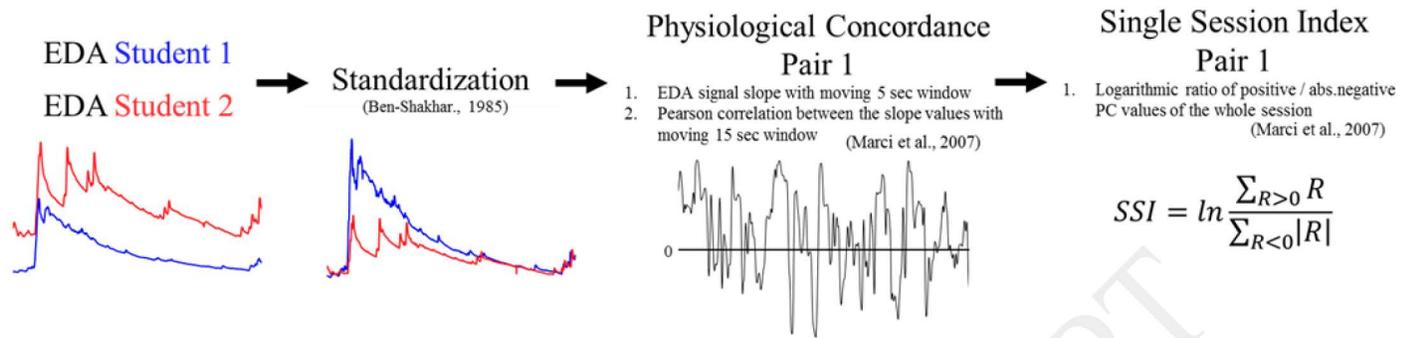


Fig. 2. Calculation process of Physiological Concordance and Single Session Index

3.3. Combination of physiological data with observational data

Finally, the physiological data was combined with the video codings into a multimodal time series. For temporal inspection of the amount of monitoring, a 120-second moving window was applied. This was done by counting the duration of coded monitoring for the first 120-second time window and then sliding this window second by second through the session. The result was a 1Hz time series with changing values. This made it possible to see the temporal changes in the amount of monitoring despite the varying duration of monitoring codes. To investigate the temporal changes in the synchrony and to be able to see the possible co-occurrence with students' monitoring activity, a moving 120-second SSI window was applied (Slovák et al., 2014). Calculations followed the principle of the Single Session Index (Marci et al., 2007) described above, only this time it was applied for each 120-second window of time instead of the whole session. The mean value of the groups' moving SSI was calculated using the values of three pairs inside each group. After this, the timestamps of each data format were synchronized accordingly, and a line graph was formed for visual analysis of the session.

To explore the connections between groups' monitoring processes and physiological synchrony (group mean) time series, a detrending moving-average cross-correlation (DMCA)

coefficient was used. The DMCA coefficient was chosen for this purpose because it has been shown to lower the risk of type 1 error with non-stationary data like those being used in this study (Kristoufek, 2014). Block bootstrapping (window length 30) was used to determine the significance level of each coefficient value (Chernick & LaBudde, 2011).

4. Results

4.1. How do students in a group monitor their cognitive, affective and behavioral processes during their collaboration?

In order to find how students monitor their learning process, different targets of monitoring were examined. The duration of the codes varied from seconds to 1min 20 sec. Overall, there were 323 coded monitoring events for three groups. The three case groups engaged the most in monitoring their cognition (relative $f = 56,35\%$) and behavior (relative $f = 35,91\%$). Affect (relative $f = 7,74\%$) was least often the target for monitoring. Individual groups differed from the average in terms of proportions of monitoring targets (Table 2). Most of the monitoring in Group 1 had behavior (relative $f = 52,31\%$) as a target, and the group monitored affect less than other groups. It also monitored less than half the total duration of other groups. In Group 2, the proportion of monitoring cognition was high (relative $f = 70,37\%$) when compared to the average. Group 3 monitored affect (relative frequency 8,94%) more often when compared to average. It also monitored learning the most in terms of total duration.

Table 2

Collaborative groups' targets of monitoring

Group	<i>Target of monitoring</i>	Duration of codes (sec)					Frequency of codes	
		<i>M</i>	<i>SD</i>	Total	Min	Max	Absolute	Relative (%)
Group 1	<i>Cognition</i>	5	3	131	2	13	28	43.08
	<i>Affect</i>	4	1	12	2	5	3	4.62
	<i>Behavior</i>	5	3	158	1	13	34	52.31
Group 2	<i>Cognition</i>	7	8	671	1	67	95	70.37
	<i>Affect</i>	5	4	50	2	14	10	7.41
	<i>Behavior</i>	4	3	127	1	14	30	22.22
Group 3	<i>Cognition</i>	11	9	633	2	47	59	47.97
	<i>Affect</i>	6	3	68	3	12	12	9.76
	<i>Behavior</i>	11	12	584	2	80	52	42.28
Overall	<i>Cognition</i>	8	8	1436	1	67	182	56.35
	<i>Affect</i>	7	3	130	2	14	25	7.74
	<i>Behavior</i>	7	9	869	1	80	116	35.91

4.2. How does observed monitoring co-occur with physiological synchrony during the collaborative learning session?

To answer for the second research question, it was first tested whether the physiological synchrony was significant by comparing the real SSI value with the one derived from the Monte Carlo shuffling procedure. Second, a visual representation from each group was composed by combining the 120-second moving window time series of the amount of monitoring and physiological synchrony. This is presented for each group in Figure 4. The amount of monitoring is presented within the gray color area. The value of the moving SSI window for each group is presented with black lines.

Table 3 displays the average SSI values for each group, along with the SSI values, confidence intervals, and *p*-values for each pair within the group. Eight out of nine pairs had an SSI value indicating statistically significant physiological synchrony. This means that physiological synchrony between the group members did not occur by chance. Group 1 had the highest mean value of SSI ($M = .44$), and Group 3 had the lowest ($M = .12$). The highest SSI value for pairs was 0.57, and the lowest was -0.08

Table 3

Student pairs' single session index values of concordance

Group	Pair	SSI value	95% CI Upper Bound	<i>p</i> (Two-tailed)
Group 1	Pair 1	0.13	0.08	.002
	Pair 2	0.38	0.13	<.001
	Pair 3	0.25	0.08	<.001
	Group mean	0.25		
Group 2	Pair 1	0.57	0.07	<.001
	Pair 2	0.41	0.08	<.001
	Pair 3	0.34	0.1	<.001
	Group mean	0.44		
Group 3	Pair 1	-0.08	0.09	.002
	Pair 2	0.17	0.09	<.001
	Pair 3	0.27	0.10	<.001
	Group mean	0.12		

To verify that the synchrony was not detected due to general similarity in the flow of the collaborative lesson, the mean of the real pairs (9) was compared with the hypothetical pairs (27) combined from different groups. Shapiro-Wilk and Kolmogorov-Smirnov tests indicated that the groups were normally distributed, and Levene's test supported the view of homogeneity of the variances. One-way ANOVA was used to compare the means of all the real pairs ($M = 0.27$, $SD = .19$) with hypothetical pairs ($M=0.01$, $SD=0.11$). Results of the analysis revealed that groups differed from each other significantly ($F = 25.11$, $p > 0.001$, $d = 1.48$, $\eta^2 = 0.43$), which supports the view that the synchrony was due to collaborative activity and not due to the general flow of

the lesson. Medians, first and third quartiles, as well as the outliers of the groups, are presented in Figure 3.

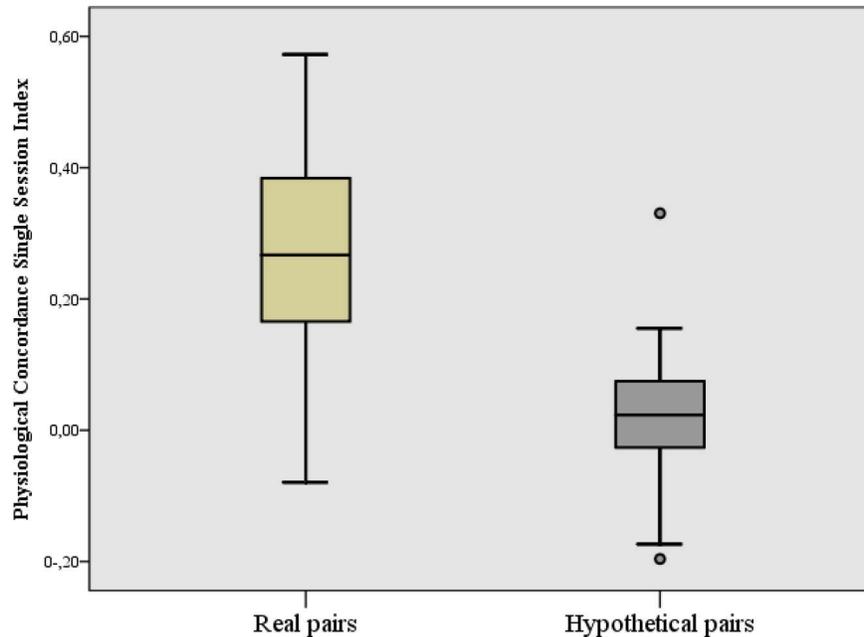


Fig. 3. Medians and first and third quartiles of physiological concordance scores for real pairs and hypothetical pairs. The bottom and top of the box present the first and third quartiles, and the band inside the box is the the second quartile (the median).

Figure 4 presents a line graph of temporally varying time series derived for monitoring and physiological synchrony through a 120-second moving window. Monitoring is indicated by a gray area. The moving SSI index (the mean value of three pairs inside the group) for each group are represented by black lines. Visual case analysis of the temporal changes in monitoring and physiological synchrony show that values above mean in terms of monitoring do co-occur with high physiological synchrony. This is especially the case for groups 1 and 2. Also, those groups do experience high values of synchrony when there is a lack of monitoring (e.g., Group 1 in time 2400 seconds and Group 2 in time 600 seconds). Group 3, with the lowest mean value of SSI and

highest duration of monitoring, had high values of monitoring with temporal variation. The group seemed to constantly monitor their learning throughout the session. However, their values of physiological synchrony stay rather low with a couple of exceptions.

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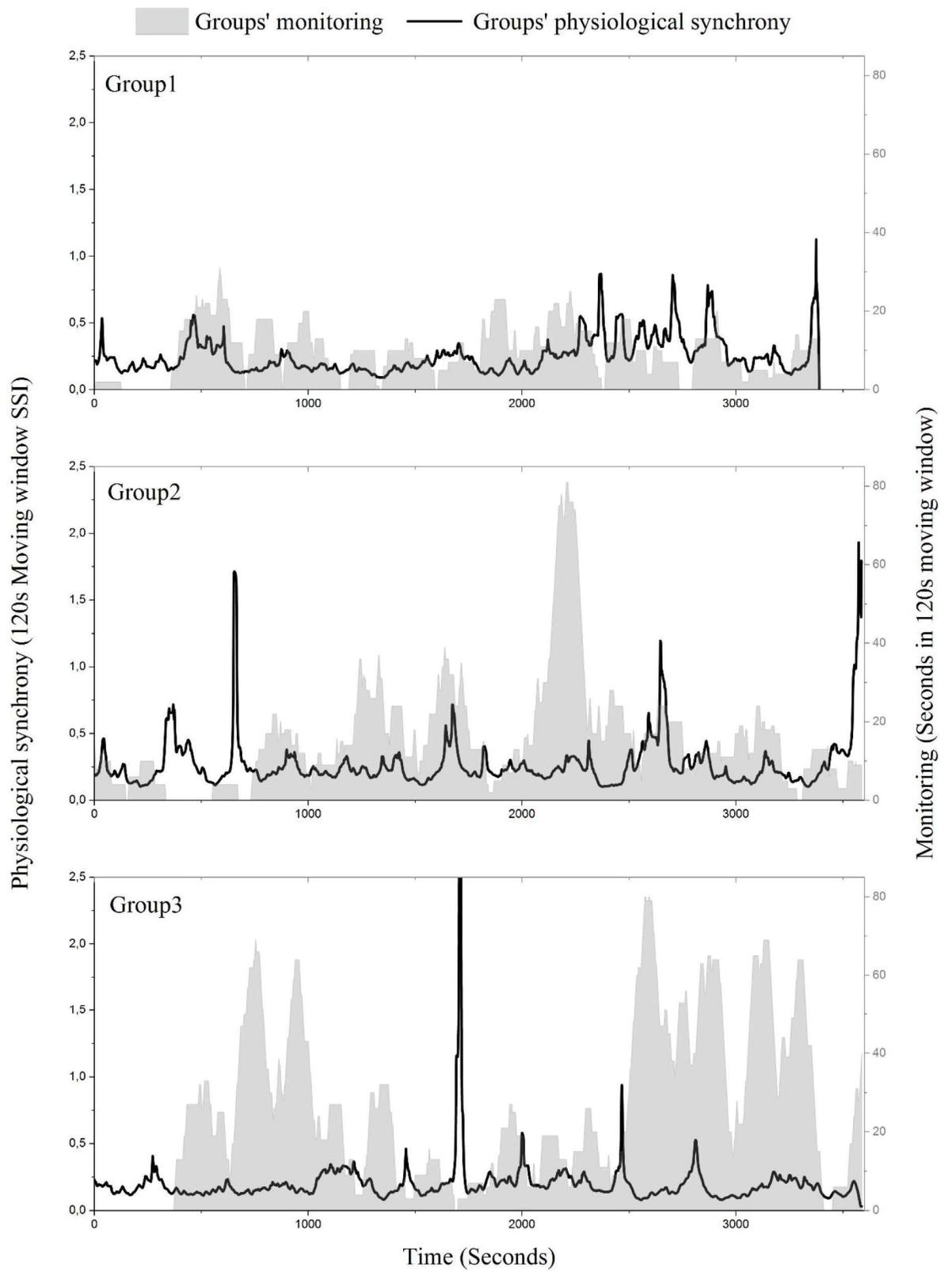


Fig. 4. Measured physiological synchrony and observed monitoring presented as a 120-second moving-window time series. Black lines represent temporally varying synchrony (mean of pairs) of each group. The dark gray area represents all coded monitoring.

The DMCA coefficient values for three groups are presented in Table 4. Affect was left out of this analysis due to an insufficient amount of variation. Weak but significant DMCA coefficient values were found between physiological synchrony and monitoring in Groups 1 and 2. The values were higher when all forms of monitoring were considered together in the analysis than when any one form was considered on its own. In Group 3, there were no significant relations between any form of monitoring and physiological synchrony.

Table 4. Detrending moving-average cross-correlation coefficients between groups temporal (120s moving-window) monitoring and groups' SSI mean

Group	Target of monitoring	Groups mean SSI
Group 1	All	0.253 *
	Cognition	0.175
	Behavior	0.176
Group 2	All	0.223 *
	Cognition	0.191 *
	Behavior	0.152 *
Group 3	All	0.099
	Cognition	0.088
	Behavior	0.057

* $p > .05$ (One-tailed)

6. Discussion and conclusions

This study explored how students monitor cognition, affect and behavior during collaborative learning and the co-occurrence of monitoring with physiological synchrony. Three case groups were chosen for detailed analysis, and the selection was prioritized by the quality of the data. A number of novel features were applied in this study, including: a) investigation of monitoring of affect and behavior in addition to cognition; b) use of multimodal data for studying monitoring in a collaborative learning setting; and c) using physiological synchrony as a variable in learning research.

Few prior studies have investigated how groups monitor their affect and behavior during collaborative learning, and such studies found that in successful groups, students monitor their own and other students' task progress and interests (Näykki et al., 2017). The results of this study, however, indicate that the main targets of the monitoring for these case groups were cognition and behavior, while monitoring of affect occurred the least. The reason for this difference might be that the students considered cognitive and behavioral aspects to more task-related, which led those to be elaborated upon in the discussion and therefore more easily recognized as behavior from the video. This is because shared regulation and monitoring of emotion is embedded in collaboration, and therefore it is challenging to connect them with any individual utterance in behavior (Järvenoja & Järvelä, 2013). This, however, does not mean that monitoring of affect would not be important for group success (Näykki, Järvelä, Kirschner, & Järvenoja, 2014).

Analysis of the physiological signals showed that physiological synchrony does occur during collaborative learning at a statistically significant level. This means that for eight pairs out of nine, the concordance in the direction of the EDA signal cannot be explained by coincidence

or the general flow of the lesson. This result could be partly explained by the nature of the context. When individuals are staying in the same space so that they can see each other, their physiological signals tend to synchronize (Liu, Zhou, Palumbo, & Wang, 2016; Palumbo et al., 2017). Few studies, however, have shown this phenomenon to occur in an educational setting before (Ahonen et al., 2016; Gillies et al., 2016; Authors, 2017d).

The combination of the physiological data with video observations revealed that the amount of monitoring and physiological synchrony varied distinctively throughout the lesson. Many of the moments during which the synchrony between individual students was high co-occurred with intensive periods of monitoring. However, the time series analysis revealed only weak connections between these variables, and only for two of the groups. The strongest connection between synchrony and monitoring seemed to exist when all forms of monitoring were considered together. It's likely that there are some key, stand-out variables that do affect how monitoring and synchrony co-occur (e.g., quality of monitoring, empathy, shared understanding). It's also important to acknowledge that these connections among others in learning processes are likely to be dynamic in nature, meaning the strength of the connection is likely to vary temporally. Therefore, future studies on the learning process should be ready to adopt analysis techniques that are able to further examine these relations.

Although the results of this study cannot verify a generalizable connection between monitoring instances and high-synchrony moments, the results support the view that physiological synchrony might be a relevant condition when joint understanding is being built in learning groups through monitoring and regulation. Earlier studies have revealed a link between the level of physiological synchrony with joint understanding (Järvelä et al., 2014) and empathy (Marci et al., 2007), which are both important aspects in collaborative learning. It must be noted

that as such, this variable alone cannot tell much about monitoring and regulation; it requires other forms of data as a base. Still, the implication is that research on learning processes might greatly benefit from triangulation of this variable with the traditional data streams (i.e., self-reports or observations) when studying critical trigger moments and the regulation process. Further studies investigating complex interactions between students' monitoring, regulation and physiological synchrony are needed before this method can be applied to support learning.

It must be noted that this study holds both strengths and weaknesses. First, the case study approach makes it possible to take a detailed view on the monitoring process with several variables. This can serve as a stepping stone for future hypotheses and research. However, it is clear that with any case study, it is impossible to make general interpretations from the results that could be applied to student populations. Therefore, more research in different contexts is needed to better understand the monitoring of cognitive, affective and behavioral aspects in collaborative learning. Second, the type of intensive longitudinal data used in this study reveals more about the temporal unfolding process of regulation and gives depth for the study when compared to traditional methods like self-reports and video observations. At the same time, it sets challenges for statistical analysis in terms of serial dependency and autocorrelation. Therefore, it is important to be careful when using such techniques to interpret results in this exploratory phase. It has to also be acknowledged that several variables most likely have an impact on the temporal process of monitoring and regulation. Third, we claim that when studying SRL, the importance of ecological validity shouldn't be ignored. Since goals have an important role in the SRL process (Zusho, Karabenick, Bonney, & Sims, 2007), they should be as authentic as possible when conducting optimal research. On one hand in this study, the learning task was authentic in the sense that it was designed in collaboration with the teacher and applied during a

course that students attended. On the other hand, the task and its content weren't part of the students' curriculum or course exam, which may have affected the goals that students set for their task. Ecologically, a valid research setting also sets its own challenges for the measurement of psychophysiological signals (i.e., movement artifacts), which have traditionally been captured in a controlled setting. With groups, this is especially challenging because losing data of one participant excludes the whole group from the analysis. This study took a careful approach and considered the quality of the data when the case groups were chosen.

Next, more advanced analysis methods should be applied to investigate this type of data. While big multimodal sets of data provide possibilities (Authors, 2017a), they also set up challenges in terms of the combination of expertise needed for research (Azevedo, 2014). For example, this type of fine-grained intensive longitudinal data needs special expertise for correct interpretation in terms of statistics. There are already signs that advancing machine-learning technologies give possibilities for analysis and application for realtime support for learners (e.g. D'Mello et al., 2017). Developing methods and new physiological indices of social signal processing (Knight, Kennedy, & McComb, 2016; Wallot, Roepstorff, & Mønster, 2016) offers novel ways to investigate the regulation process of the group on many levels.

Finally, in terms of future research and methods to investigate the temporal process of regulation, this study shows an example of how multimodal data can be utilized in a collaborative learning context to better understand the learning process, namely monitoring in it. It also points out the potential that physiological synchrony as a variable holds for explaining temporally unfolding regulation processes in groups. However, it has to be noted that as such, many of the novel data modalities do not provide direct information about regulation, and therefore, the use of many data channels is needed.

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Appendix

Reliability of Motivated Strategies for Learning Questionnaire (Sample N=48)

Variable	Cronbach's Alpha	N of items
Value Component: Intrinsic Goal Orientation	0.750	4
Value Component: Extrinsic Goal Orientation	0.730	4
Value Component: Task Value	0.855	6
Expectancy Component: Control of Learning Beliefs	0.774	4
Expectancy Component: Self-Efficacy for Learning and Performance	0.878	8
Affective Component: Test Anxiety	0.693	5
Cognitive and Metacognitive Strategies: Rehearsal	0.662	4
Cognitive and Metacognitive Strategies: Elaboration	0.759	6
Cognitive and Metacognitive Strategies: Organization	0.710	4
Cognitive and Metacognitive Strategies: Critical Thinking	0.721	5
Cognitive and Metacognitive Strategies: Metacognitive Self-Regulation	0.798	12
Resource Management Strategies: Time and Study Environment	0.689	8
Resource Management Strategies: Effort Regulation	0.677	4
Resource Management Strategies: Peer Learning	0.604	3
Resource Management Strategies: Help Seeking	0.441	4
	Average	0.716
	Range	0.441 - 0.878