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Exploring the connection between task difficulty, task perceptions, physiological arousal and learning outcomes in collaborative learning situations

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When students approach a learning task, they generate metacognitive perceptions of the current learning situation. Their perceptions draw on their previous knowledge of similar types of tasks, such as procedures that were used in the past and how successful or unsuccessful they have been in the past in the same types of tasks (Efklides, 2008). These previous experiences affect the ways in which they approach new learning tasks (Molenaar & Chiu, 2014). When entering the new learning situations, the students can, for example, think "I have done these types of tasks earlier, so I know what I am supposed to do" or, they can think "I am not sure what I should do". Depending on the students' perceptions of their task understanding, they can further think "This task seems relatively easy for me" or "This task seems really difficult". Winne & Hadwin (1998) define these as students' perceptions of task understanding and perceptions of task difficulty, which are a part of internal metacognitive conditions that determine how students approach tasks. This is to say, depending on the student's internal metacognitive conditions, the learning situation can be perceived as a challenge to be mastered or a threat to be avoided (Zimmermann & Schunk, 2011).

In the context of collaborative learning, self-regulation (SRL), co-regulation (CoRl) and socially shared regulation of learning (SSRL) have been the main theoretical models for understanding how students can overcome challenges in their learning (Hadwin et al., 2018). When students collaborate, it involves multiple individuals with varying metacognitive conditions, and there are consequences for initiated regulation (Ucan & Webb, 2015). While collaborating, students are not often aware of their peers' level of task understanding or perceptions of task difficulty. While students' progress with the task, they can become more aware of their own and also their collaborating peers' strengths and weaknesses (Bakhtiar et al., 2018). Concerning collaborative learning, it is not known how students with varying metacognitive conditions can influence and be influenced by others' regulation and how regulation in collaboration changes situational metacognitive conditions. Earlier studies have shown that what students believe prior to the learning task also influences their learning outcomes and actualizes SRL (Azevedo & Cromley, 2004; Winne & Nesbit, 2009),

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meaning that the ways learners perceive a task is shaped by internal and external conditions for learning, including the social context (Bakhtiar et al., 2018). Understanding metacognitive conditions in the context of collaborative learning can increase knowledge of why some groups succeed and others fail, and of how we can influence productive regulation.

Students' situational metacognitive conditions are internal mental processes and, therefore, challenging to capture continuously and unobtrusively with traditional research methods (Järvelä et al., 2019). Contemporary research suggests that triangulating data from multiple sources can add to understanding individual metacognitive conditions and how they are shaped by the regulation of learning. The development of technological solutions that are viable for capturing multimodal data about human learning is contributing to and transforming the fields of learning and research on self-regulated learning (SRL; Azevedo & Gašević 2019). For example, there is a growing interest in capturing individual student learning traces and their temporal progress (Kovanović et al., 2016), which can be translated into adaptive learning environments for supporting self-regulated learning (Siemens, 2013; Wiedbusch et al., 2021). In addition, there has been progress in developing learning environments that can capture some characteristics of SRL "on the fly". For example, learners' metacognitive conditions can be captured, and based on those conditions, one can predict the learning outcomes of the individual students (Wiedbusch et al., 2020). Fortunately, there has been progress in technological devices that are able to capture (at least to some extent) the processes of SRL as they emerge (Sawyer et al., 2018). Multimodal data (e.g. physiological measures, log-traces, videos and situated self-reports) can provide an unobtrusive way to capture markers of metacognition when they emerge without interrupting the learning process (Järvelä et al., 2019). Recent studies have shown that a higher level of students' physiological arousal is related to learners' metacognition in individual and collaborative learning (Hajcak et al., 2003; Malmberg et al., 2017; Malmberg et al., 2019), and it relates positively to learning achievement (Pijeira-Díaz et al., 2018). The current study extends these findings by examining individuals' internal conditions in terms of how learners' perceptions of task understanding and task difficulty change through collaborative learning. The study also investigates how and whether perceptions of task understanding and perceptions of task difficulty are reflected in learners' physiological arousal and learning outcomes.

COPES framework in self-regulated learning

The Winne & Hadwin (1998) SRL model proposes that regulation occurs in four loosely sequenced, recursive phases: task perceptions, goal setting, strategic enactment and adaptation. Their COPES framework (conditions, operations, products, evaluations and standards) models the conditions and identifies the facets where learners exercise SRL. The conditions are task and context specific and frame the way learners perceive the task and themselves in the current learning situation (Butler & Cartier, 2004). External conditions (e.g. social and contextual features, task complexity, resources, time constraints and environment), along with internal cognitive conditions (e.g. metacognitive knowledge of the task characteristics, judgments of task difficulty, knowledge of strategies to carry out, prior domain knowledge and efficacy judgments of one's capability to perform the task), are influential throughout the learning process. These conditions therefore inform how and with which standards learners accomplish the task (Pintrich, 2000; Winne & Hadwin 1998, 2008). These internal conditions are metacognitive in nature, and they provide a foundation for the regulation of learning to occur in each phase of the SRL cycle (Veenman et al., 2006).

The operations involved in memory storage and retrieval include searching the memory, monitoring the new information's fit with previously learned information, assembling new links to knowledge, and rehearsing and translating the knowledge. Operations create both internal and external products. An internal product might be a plan of how to solve a learning task or updated information about the task understanding. External products—or 'traces of cognition'—are concrete, observable events or strategies that are applied to reach the learning goal (Winne et al., 2011; Winne, 2001).

According to the COPES model, in each learning phase, these operations create products. These products include re-defined task perceptions, goals and plans, and strategy use. The products are then compared to self-set standards through the metacognitive monitoring process, and the alignment between the products and standards is determined so that the next phase of SRL can begin. Through evaluation, these products can also change the internal conditions for the following and current tasks.

Lastly, evaluations might occur during a learning cycle or after the learning task. For example, when the evaluation indicates a mismatch between a phase product and a standard, students can enact control functions that can alter the current and previous phase's products. Based on the evaluation, learners can make adaptations concerning task understanding, goals and plans, or the tactics and strategies used. The Winne & Hadwin (1998) COPES model aims to describe the ways in which students adapt SRL to the current learning task. Furthermore, it provides a means to understand how students' internal conditions change and affect the realized regulation in individual and collaborative learning (Bakhtiar et al., 2018).

Task understandings as conditions for self-regulated learning

Internal conditions, such as learners' metacognitive knowledge of the task's characteristics, shape the ways learners engage in the learning task (Greene & Azevedo, 2012). However, task understandings are constantly evolving and changing the internal conditions that evolve when students' progress at the task. These task perceptions also affect future SRL in similar types of tasks (Winne, 2017). Learners build metacognitive knowledge of different types of tasks, which is shaped by their previous learning experiences (Efklides, 2011a) in terms of metacognitive knowledge (Flavell, 1979). Metacognitive knowledge involves learners' perceptions of a task. It draws on prior knowledge in terms of similar types of tasks and procedures needed to perform those (Winne & Hadwin, 1998). When learners draw on their previous knowledge about the task, it is a thoughtful, analytical and cognitive process (Efklides, 2011b), and it constitutes both explicit and implicit task components. Explicit components of tasks include information that is overtly presented in problem descriptions, such as the task goal or requirements. Implicit features instead include any information beyond the problem description, such as relevant concepts or procedures (Hadwin et al., 2009).

Task understanding is the first phase in the cyclical model of SRL, and it can be considered as a first product according to the COPES framework (Winne & Hadwin, 1998). Task understanding draws on learners' task perceptions, including subjective factors of the individual student (e.g. prior knowledge) as well as external factors of the assigned task, such as task complexity. Being an initial phase of SRL, the interpretation of the task affects the types of goals the learners set, the strategies they select to accomplish the goals and the criteria they use to evaluate the outcomes for academic success (Butler & Cartier, 2004). However, empirical research has shown that learners do not always completely understand what the teacher or instructor expects for task accomplishment. The accuracy of students' task understanding depends on their ability to recognize and interpret the task cues and to recall metacognitive knowledge (Pieschl, 2009). For example, when the instructional guidance is minimal, learners are required to draw connections to prior knowledge of similar types of tasks and activities related to those tasks (Kirschner et al., 2006). Thus, if learners are provided with little explicit or implicit task information, it can hinder their task understanding and negatively affect the entire learning process (Miller & Hadwin, 2013; Sweller et al., 2013). For example, Lawanto et al., (2018) explored engineering students' task understanding as part of their self-regulated learning in a problem-solving task. The results of the study showed that the students' perceptions of the task varied with the teachers' expectations. However, the students' task understanding improved after accomplishing the problem-solving tasks. In a later study, it was found that when the same types of problem-solving tasks are given over longer periods of time, the students' perceptions of the task become more accurate (Lawanto et al., 2019). Fortunately, students' task understanding has been shown to evolve as they work in similar types of tasks over longer periods of time and collaborate with their peers (Hommes et al., 2014).

In the context of collaborative learning, learners can also share their perceptions of a task in a social plane (Hadwin et al., 2018). Besides explicit and implicit components, task understanding involves cognitive components such as prior knowledge of similar tasks and content knowledge, including perception of task outcome. These cognitive components of the task can be discussed and negotiated. Hence, the level or accuracy of task understanding is not required to be the same for all group members. Therefore, constructing a shared task understanding can create new perspectives for the problems and new ways of executing a task (Jones & Roelofsma, 2000). However, research has shown that without guidance, the students might not share their perceptions of the task with their collaborating peers, which can hinder their shared regulation process (Hadwin et al., 2018). Differences between individuals' task understanding potentially affect the collaborative learning outcomes and knowledge construction, either positively or negatively (Engelmann et al., 2009). For example, Bakhtiar et al., (2018) examined how internal conditions affect the regulation and socio-emotional interactions of group members in the context of collaborative learning. Their study revealed that collaborating groups with a positive socioemotional climate had established a high task understanding and prior knowledge of the task at hand prior to their collaboration. That is to say, the students were prepared to learn collaboratively, and high task understanding may have contributed to better preparation for collaborative learning; therefore, it affected the positive socioemotional climate and group members' ability to perform the task. However, when contrasted with negative socioemotional climate groups, the group members were seen to be less prepared for the collaborative task, indicating that they had low prior knowledge and less understanding of the task. Koivuniemi et al., (2017) investigated higher education students' learning challenges in the context of collaborative learning. Their study showed that major cognitive challenges were related to prior knowledge of the task at both the individual and collaborative levels. What they also found out was that the students with higher SRL skills reported more cognitive challenges when contrasted with students with low SRL skills. The conclusion was that strong SRL students are also able to recognize a larger variety of cognitive challenges while pursuing the task. That is to say, students' prior knowledge and understanding of the task affects how they regulate their learning at an individual and a group level.

Perceptions of task difficulty as conditions for self-regulated learning

Unlike task understanding, which is thoughtful, analytical and cognitive, perception of task difficulty is reactive and metacognitive and affective in nature. However, perception of task difficulty can also be informative for self-regulation of learning (Efklides et al., 1996). Efklides et al. (1996) define perception of task difficulty as a feeling that draws on metacognition. It consists of perception or reflection of the task and is based on the feelings (or difficulties) experienced during the learning task. Learners' perceptions of task difficulty have an influence on SRL. For example, learners can either choose to withdraw from a task or to engage in self-regulated learning by activating their prior knowledge, setting goals for learning, enacting strategically during the task to reach their goals, and reflecting on the learning experience (Winne, 2017). However, depending on the task difficulty, learners can also choose to use maladaptive learning strategies in an attempt to avoid possible failure (Sobocinski et al., 2020; Boekaerts & Niemivirta, 2000).

Metacognitive feelings, such as perceptions of task difficulty, are essential not only for self-regulation, but also for shared regulation of learning in the context of collaborative learning (Efklides, 2008). This is because despite perceptions of task difficulty being subjective, they can be externalized in the context of collaborative learning. In addition, when these perceptions are externalized, collaborating group members gain information not only about their own conditions for learning, but also those of other group members Therefore, externalizing perceptions of task difficulty can be informative when guiding regulation of learning and also serve as a trigger for socially shared regulation of learning (Iiskala et al., 2011).

Even though there has been plenty of research into perceptions of task difficulty at an individual student level, there is a lack of studies that explore the ways in which these perceptions are actualized in the context of collaborative learning. For example, Acuna et al., (2018) explored the ways in which learners interact with computer-based familiar and unfamiliar tasks. They found that when the task was perceived to be more difficult, it impeded the learners' activities (i.e. mouse clicks, selections of content). Cleary et al., (2015) examined how individual students' perceptions of task difficulty changed when they received negative feedback during a challenging medical problem-solving task at the end of the course. The results showed a systematic increase in learners' perceptions of task difficulty, which ultimately led to learners' withdrawal from SRL, indicating that learners' perceptions of task difficulty can be detrimental for SRL. Iiskala et al., (2011) examined how students engage in socially shared regulation of learning when the task characteristics are manipulated. In the study, they provided easy, moderate and difficult collaborative learning tasks (Iiskala et al., 2011). Their study revealed that socially shared regulation of learning emerged the most in difficult tasks. Moreover, externalized perceptions of task difficulty played a major role in terms of initiating socially shared regulation of learning.

Physiological arousal in SRL investigations

Despite measures of physiological arousal having been used for decades in psychological research, few studies have used them in self-regulated learning research (Järvelä et al., 2020). However, in recent years, SRL researchers have become increasingly interested in accessible wearable sensors for measuring arousal continuously, objectively, unobtrusively and in real time. Such features are in high demand as a complement to traditional subjective self-reports that dominate SRL measurements (Noroozi et al., 2020; Panadero, 2017).

Electrodermal activity (EDA) is a measurement of physiological arousal. It refers to changes in the electrical characteristics of the skin, which result from the activity of sweat glands (Dawson et al., 2017). Since the sweat glands are under sympathetic nervous system control, EDA is considered a proxy for sympathetic arousal, which can result from cognitive and/or affective processes (Critchley et al., 2013). In general, physiological arousal seen in the EDA signal has been connected to energy mobilization for preparing the individual for action (i.e. the so-called fight-or-flight response; Dawson et al., 2017). Therefore, it is used to index anticipated and appraised environmental demands (e.g. cognitive, social, or physical; Sterling 2012; Dawson et al., 2017), which also have a role in self-regulated learning.

EDA can be divided into two main components: tonic skin conductance level (SCL) and phasic skin conductance responses (SCR). SCLs change slowly and are often used to study the long-term unfolding of events. SCRs are rapid changes of skin conductance that appear as peaks in the EDA signal and are therefore more often used to study quickly unfolding contextual events such as collaborative learning (Pijeira-Díaz et al., 2019). From SCRs, it is possible to differentiate features such as amplitude and rise time of the peak, but it can also be used to study temporally unfolding events by counting the number of peaks occurring per minute (Dawson et al., 2017). What makes these features interesting for SRL research is that their intensity reflects the psychological significance of the events that trigger them (Boucsein, 2012).

In relation to learning, metacognition and SRL, physiological arousal has been connected to the monitoring of feelings of familiarity (Morris et al., 2008), the monitoring of errors (Hajcak et al., 2003), and the appraisal of potential for coping with tasks (Pecchinenda & Smith, 1996). This research has attracted interest in utilizing EDA to study self-regulated learning processes as they unfold. Studies utilizing EDA in the context of collaborative learning research have shown, for example, that when learners confront difficulties during task execution (i.e. they are confused and do not know what to do), their EDA increases (Malmberg et al., 2019a). In addition, the study by Malmberg et al. (2019b) showed that when learners engage in metacognitive monitoring in collaborative learning, the EDA of each collaborating student increases. There is also increasing research evidence suggesting that students' EDA becomes synchronized with each other, especially when they monitor challenges or face a high cognitive load in their collaboration (Dindar et al., 2020; Malmberg et al., 2020). In addition, Pijeira-Díaz et al.'s (2018) study revealed that the higher amplitude in EDA signals correlated positively with course grades. Therefore, it makes sense to expect that EDA signals are reflected in perceptions of task understanding and task difficulty. Changes in these processes before and after the learning task in relation to physiological arousal can be used as an indicator of the effort that has been invested to accomplish the learning task (ref). This study examines how individuals' perceptions of the task and its difficulty are connected with physiological arousal and whether they affect learning outcomes in the context of collaborative learning.

The research questions are as follows:

1) How do the students' perceptions of their task understanding and task difficulty change during collaborative learning?
2) How is the change in students' perceptions of the task and its difficulty reflected in physiological arousal?
3) How do the students' perceptions of task understanding and task difficulty predict physiological arousal during collaborative learning?
4) How do the students' perceptions of task understanding, task difficulty and physiological arousal predict students' learning outcomes during collaborative learning?

Methods

Participants and context

Participants in the study were upper elementary school students (n = 64) aged 13–14 (41 females, 23 males) enrolled in their compulsory five-week physics course. In each lesson, the students collaborated in the same groups of three to four students. The students were grouped by the teacher based on the prior achievement of the student's previous grades in physics. The groups were made as homogenous as possible to ensure that each group had low- and high-achieving students. The collaborative tasks were designed together between the science teachers and researchers. The science teachers ensured that the topics covered the required subjects and contents, and the researchers ensured that tasks promoted regulation of learning and required genuine collaboration. The topics of the lessons and collaborative tasks focused on sound and light, light and vision, lenses, and reflection. For example, when studying reflection, the students were asked to use different types of lenses and hypothesize how the beam of light would pass through different types of lenses and examine that by doing real experiments with the lenses. Altogether, the students had five 90-minute physics lessons.

Procedure

Each lesson followed the flipped classroom principles due to its potential to facilitate the regulation of learning (Jovanovic et al., 2019). According to the flipped classroom principles, the students were asked to familiarize themselves with the topic of the day as homework prior to the lesson.

Prior to the physics lesson, the students were instructed on how to use Shimmer3 GSR (Burns et al., 2010) sensors independently to measure their physiological arousal. Students were instructed to fit the Shimmer3 sensors at the beginning of each physics lesson, and they were informed that they could be taken off if they were uncomfortable. After that, the lesson started with a short moment of teacher-led teaching and instruction to ensure that students had familiarized themselves with the topic. This was followed by the collaborative learning tasks with the aim of co-constructing a more profound and shared understanding of the topic.

Before starting the collaborative task, the students were asked to rate their situation-specific perceptions related to task difficulty and task understanding. The same questions were asked after the collaborative task. In addition, after the collaborative task, the students were asked to individually fill in a quiz included in Qridi® to measure their learning about the contents of the task.

The Qridi® platform (https://kokoa.io/products/qridi) was used and tailored to coordinate the students' collaborative learning. Qridi® included a 6Q tool (authors et al., 2020), which was tailored to increase the students' awareness of collaborative learning and to support their awareness of the regulation of learning. Particularly, the 6Q tool provided the means to explore situational variations in individuals' task perceptions and task difficulty. In this study, two metacognitive dimensions of the 6Q tool were investigated. Namely, the students' evaluation of the task difficulty and task understandings were investigated before and after each collaborative task.

Data collection and data preparation

This study collected (1) students' situation-specific perceptions related to task understanding and task difficulty before and after each collaborative task, (2) quiz scores to measure students' learning about the contents after each collaborative task and (3) continuous physiological data from each student measuring their physiological arousal in five collaborative learning tasks.

Specifically, the 6Q tool implemented in the Qridi® environment measured the students' task understanding (Schraw & Dennison, 1994) with the single question "How well do you understand the task?" The students used a slider scale from 0 to 100 (0 being not at all and 100 being very well). The tool also measured task difficulty (Efklides et al., 1998) with the single question "How difficult is the task?" (0 being very easy and 100 being very difficult). Single item questions that draw on existing literature were used in order to ensure minimal interference to group interaction (Dindar et al., 2020). The quiz was also implemented in Qridi® and involved five to six multiple choice questions. All the activities performed in the Qridi® environment were recorded with time-stamped information for the external server.

The students' situation-specific ratings related to task understanding consisted altogether of 283 responses before the collaborative task and 270 responses after the collaborative task.

The students' situation-specific ratings related to task difficulty consisted altogether of 281 responses before the collaborative task and 269 responses after the collaborative task.

Students' learning outcomes were measured for each task from students' answers in the quiz. This consisted altogether of 201 responses. The quiz involved five to six questions, in which each correct answer was scored as one point. The mean value of the quiz score was 4.23 (Std = 1.26).

Physiological arousal was measured via Shimmer 3 sensors, resulting altogether in 222 continuous recordings of physiological data. First, parts of the data before the attachment and after the de-attachment of the sensor were cut out from the dataset. Second, data was down-sampled from 128hz to 16hz to speed uphe further analysis. Physiological data recordings indicating a missing contact of the electrode were removed from the data set. The Butterworth low pass filter with frequency 1 and order 5 was used to remove the small movement artefacts from the signal. Non-specific skin conductance responses with a minimum amplitude of 0.05 µS were detected from the signal with the trough-to-peak method (Benedek & Kaernbach, 2010; Dawson et al., 2017). This resulted in a mean of 10.53 (Std = 2.18) peaks per minute.

Data analysis

For the first research question, a paired-sample t-test was used to evaluate changes in students' perceptions of the task and its difficulty.

For the second research question, the independent sample t-test was used to evaluate whether there was a relationship between learners' physiological arousal in terms of the change between situational task perceptions and task difficulty before and after each collaborative learning session. First, the learning sessions were divided into two categories based on the change in students' perceptions of the task and task difficulty. The categorization for task difficulty resulted in 86 learning sessions where learners perceived the collaborative task as more difficult after completing the task and 166 learning sessions where learners perceived the collaborative task as less difficult after completing the task. The categorization for task understanding resulted in 98 learning sessions where students' task understanding was lower after completing the task and 176 learning sessions where students' task understanding was higher after completing the learning task.

For the third and fourth research question, Generalized Estimating Equations (GEE) models were fitted to determine the students' perceptions as predictors for physiological arousal and learning outcomes. GEE can be used to estimate regression parameters for clustered data, such as repeated measures coming from the same students, as it statistically adjusts the standard error estimates based on the dependency in clusters (McNeish et al., 2017). It allows inferences on how the mean result obtained in the whole population changes according to the changes in the independent variable(s). To estimate which factors predict learning outcomes, the students' perceptions of the task understanding and task difficulty before and after the collaborative task and measures of physiological arousal were used as independent variables. Regarding perceptions of task understanding and task difficulty, pre- and post-measures were considered as separate variables as the pre-measure is more future oriented and post-measure is more of an evaluation considering the past. Collinearity diagnostics indicated that multicollinearity was not a concern in the predictors (Task perceptions before, Tolerance = 0.542, VIF = 1.84; Task perceptions after, Tolerance = 0.375, VIF = 2.66; Task difficulty before, Tolerance = 0.505, VIF = 1.97; Task difficulty after, Tolerance = 0.347, VIF = 1.84).

Results

How do the students' perceptions of a task and its difficulty change during collaborative learning?

In order to answer the first research question, a paired samples t-test was conducted to evaluate the ratings of students' perceptions of task difficulty before and after each collaborative task. A value of 0 indicated that the task was easy and a value of 100 indicated that the

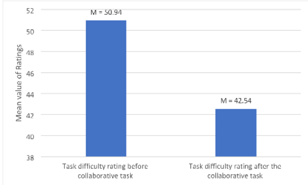

Fig. 1 Mean values of task difficulty ratings before and after the collaborative task

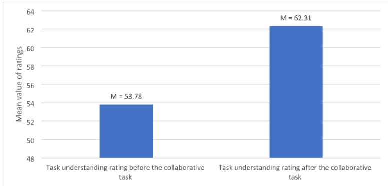

Fig. 2 Mean values of task perceptions before and after the collaborative task

task was difficult. There was a significant difference in the ratings for task difficulty before the collaborative task (M=50,94, SD=22,89) and after the collaborative task (M=42,54, SD=26,25, t(262)=6,047, p=.00), d=0.373. This means that the students perceived the task as less difficult after completing it (Fig.1).

Similarly, the paired sample t-test was conducted to evaluate the ratings of the students' perceptions of task understanding before and after each collaborative task. A value of 0 indicated that the students did not understand the task, whereas a value of 100 indicated that the students were confident in their task understanding. There was a significant difference in the ratings for task understanding before the collaborative task (M=53.78, SD=20.79) and after the collaborative task (M=62.31, SD=25.17, t(266) = -6.06, p=.00), d=0.37. This means that the students were more confident about what the task was about after completing it (Fig.2).

How is the change in students' perceptions of task and its difficulty reflected in physiological arousal?

The second research question focused on investigating whether there was a relationship between the level of physiological arousal and students' perception of task understanding and task difficulty. Independent t-tests showed a significant difference in students' physiological arousal in learning situations where the students perceived the task as less difficult at the end of the learning session than before the learning session. However, the results were not significant for changes in students' task understanding. Students demonstrated significantly fewer EDA peaks, t(196) = -2.15, p=.032 in the 68 learning sessions where the task was perceived as less difficult at the end of the learning session (M=10.06, SD=2.41), when compared to the 130 learning sessions where the task was perceived as more difficult at the end of the learning session (M=10.7, SD=1.88) d=0.32. This means that the level of physiological arousal was higher when the student's perceived the task as being easier at the end of the collaborative learning session.

Table 1 GEE model output for predicting students´ physiological arousal

Dependent variable	EDA peaks in one minute			
Distribution	Gamma with Log link			
Covariate	β (SE)	Wald χ2	95% CI	*p* value
Intercept	2.30 (0.07)	1012.23	[2.162–2.446]	0.000**
Pre-task understanding	0.00 (0.0007)	0.452	[-0.001–002]	0.501
Post-task understanding	0.001 (0.0005).	0.178	[-001,001]	0.673
Pre-task difficulty	0.002 (0.0006)	9.421	[0.001-0.003]	0.002**
Post-task difficulty	0.000 (0.0005)	6.865	[.-002-0.00]	0.009*
Model criteria				
QIC	18.45			
QICC	21.04			

Note. QIC = Quasi-likelihood under independence criterion (a lower likelihood means a better fit), QICC = Corrected quasi-likelihood *p < .01 **p < .005

How do the students' perceptions of their task understanding and task difficulty predict physiological arousal during collaborative learning?

Since the dependent variable was continuous, gamma with logarithmic (log) and identity link functions to select the best fitting models (Garson, 2012) were tested. Those two specifications were selected because they yielded the lowest quasi-likelihood under the independence criterion (QIC) values, meaning they were the best fitting models. The results indicate that higher values in students' perceptions of task difficulty at the beginning and at the end of the collaborative learning task predicted higher physiological arousal (EDA peaks in one minute) ($p < .05$). That is to say, higher ratings of task difficulty predict physiological arousal. The more difficult the students perceived the task as being both before and after the collaborative task, the higher the level of arousal. Table1 summarizes these findings and the results of the GEE analysis.

How do the students' perceptions of their task understanding, task difficulty and physiological arousal predict students' learning outcomes during collaborative learning?

With regard to the fourth research question, GEE was used to examine the effects on learning outcomes of task difficulty and task perceptions before and after the collaborative task. In addition, the effect of physiological arousal (number of EDA peaks in one minute) was also used. Since the dependent variable was continuous, gamma with logarithmic (log) and identity link functions to select the best fitting models (Garson, 2012) were tested. Those two specifications were selected because they yielded the lowest quasi-likelihood under the independence criterion (QIC) values, meaning they were the best fitting. Table2 summarizes the results of the GEE analysis. The results of the GEE indicate that the student's improved perceptions of task understanding after the collaborative task positively predicted the learning outcomes ($p < .005$). In addition, the level of physiological arousal predicts the students' learning outcomes ($p = < 0.000$). The results also indicate that higher values in students' perceptions of task difficulty at the beginning ($p < .05$ and at the end of collaborative learning task predict higher learning outcomes ($p < .005$).

Table 2 GEE model output for predicting students′ learning outcomes

Dependent variable	Learning outcome			
Distribution	Gamma with Log link			
Covariate	β (SE)	Wald χ2	95% CI	*p* value
EDA peaks in one minute	0.053 (0.0148)	12.775	[0.0.24-0.082]	0.000**
Pre-task understanding	0.003 (0.0016)	3.673	[0.000-0.006]	0.055
Post-task understanding	0.006 (0.0019)	9.710	[0.002-0.009]	0.002*
Pre-task difficulty	0.003(0.0015)	5.049	[0.000-0.006]	0.025*
Post-task difficulty	0.004 (0.0014)	9.322	[0.002-0.007]	0.002*
Model criteria				
QIC	27.35			
QICC	24.61			

Note. QIC = Quasi-likelihood under independence criterion (lower is better fit), QICC = Corrected quasi-likelihood $^{*}p<.05$ $^{**}p=.000$**

Discussion

The current study explored the ways in which learners' internal conditions, such as their perceptions of task understanding, task difficulty and physiological arousal, are connected, as well as whether these constructs can predict learning outcomes in the context of collaborative learning. To answer these research questions, the study utilized situated self-reports (Järvenoja et al., 2020) and physiological sensors to capture markers of students' metacognition. The results indicate that physiological arousal is related to higher perceptions of task difficulty and positively predicts learning outcomes along with improved perceptions of task understanding. According to Critchley (2002) and Dawson et al., (2017), physiological arousal is expected to increase, especially when confronting difficulties, which was also shown in the current study.

The first research question investigated whether the students' perceptions of task understanding and difficulty changed during collaborative learning. The results showed that the students perceived the task to be less difficult after completion of the collaborative task, and they were also more confident in their understanding of what the task was about. While the student's perceptions of the task difficulty are based on metacognitive feelings (Efklides et al., 1998), perceptions of the task difficulty prior to task execution refer to students' past experiences. In this study, each of the collaborative tasks was complex in nature and there was no immediate solution for them; therefore, the students might have estimated the task complexity from only their own perspective, without considering other group members' contributions. Nevertheless, after completing the collaborative task, the students perceived the task as less difficult. Efklides et al., (1998) explain that perceptions of task difficulty asked after the learning task are based on the experiences during the collaborative task. Therefore, students' perceptions of task difficulty during collaborative learning may have implications, since collaborative learning consists of group members' reciprocal interaction to construct a shared understanding of the task (Rochelle & Teasley, 1995). This involves learners asking their peers to clarify and justify any ideas they do not understand (Kruger, 1993). Learners' perceptions of task difficulty may change due to the result of collaborative learning while solving complex tasks (Goos et al., 2002). This, however, implies that perception of task difficulty after the task is a reflection of the group collaborative learning process. In can be concluded that in this study, collaborative learning in general had a positive influence on students' perceptions of task difficulty after the collaborative task.

Students seemed to become more confident in terms of their task understanding through collaboration. This is understandable, as before the task, students mostly rely on the given instructions and may be uncertain about some aspects of the task. However, the meaning of the instruction may become clearer when the task is being executed in practice. Therefore, executing the task can confirm for the students whether or not they understood the task. Earlier studies have shown that when students work on similar types of tasks over longer periods of time, the way they understand the task becomes more accurate (Lawanto et al., 2019). In addition, through collaborating with peers, learners can improve their metacognitive knowledge of the collaborative task at hand (Hadwin et al., 2018).

The second research question addressed if and how physiological arousal is connected to the students' perceptions of task understanding and task difficulty. The results showed that the level of physiological arousal was higher when the student's perceived the task as being easier at the end of the collaborative learning session. This result might indicate that learners invested more "mental effort" during the collaborative learning task, which was shown as physiological arousal. Earlier research has shown that lower arousal might be more detrimental for learning, whereas high arousal can be a marker of optimal effort and attention during learning (Pijeira-Díaz et al., 2018). In earlier research, the student's perceptions of task difficulty have also been linked to increased effort (Efklides et al., 2006) and increased physiological arousal (Mehler et al., 2009; Smith, 1996). This result is in line with earlier evidence that perception of task difficulty relates to physiological arousal (Darzi & Novak, 2021; Pecchinenda & Smith 1996).

The third research question explored how learners' internal conditions, such as perceptions of task understanding and task difficulty, can predict physiological arousal. The results showed that the more difficult the students perceived the task both before and after the collaborative task, the higher the level of arousal. This result is complementary to previous results, indicating that physiological arousal associated with task difficulty is a potential indicator of effort, since students who perceived the task as being easier at the end of the collaborative learning session also showed higher levels of physiological arousal when contrasted to the students who perceived the task as being more difficult after the collaborative learning session. In general, previous research suggests that in order to be able to optimally invest effort in the task, tasks should be located just beyond the point where a person is capable of learning proficiently, that is, in the zone of proximal development (ZPD) (Vygotsky, 1978).

Finally, the fourth research question examined the effects of physiological arousal, perceptions of task understanding, and task difficulty before and after the collaborative task on learning outcomes. The results showed that improved task understanding after the collaborative learning task, higher levels of physiological arousal and higher perceptions of task difficulty at the beginning and at the end of the collaborative learning task predicted higher learning outcomes. Earlier studies have also evidenced that the ways students understand the task are related to learning outcomes (Greene et al., 2012). In addition, the study by Pijeira-Díaz et al., (2018) demonstrated that physiological arousal was highly positively correlated with learning outcomes.

Theoretically, the current study contributes to supporting the distinction between metacognitive experiences and metacognitive knowledge. In addition, the study results suggest that constructs such as task perceptions and perceptions of task difficulty represent different constructs of metacognition. First, task perceptions draw on metacognitive knowledge, which is knowledge stored in long-term memory. Second, perceptions of task difficulty can be considered metacognitive experiences, which are manifested in a learning situation but are also informative for cognition. The current study supports this finding, since the level of physiological arousal was related to students' perceptions of task difficulty, but not to the task perceptions. Efklides (2011) argues that metacognitive experiences, such as perceptions of task difficulty, are both affective and cognitive at the same time. Theoretically, this would imply that, especially in the context of collaborative learning, the ways in which students externalize their perceptions of task difficulties in collaborative interactions and how their peers react to it can either hinder or promote regulation of learning. Especially in the face of difficulties, both regulation of emotions and cognition are needed, and they cannot be separated. In addition, empirical research has continuously emphasized the role of emotions in the context of collaborative learning (Hadwin et al., 2018), showing that if the students fail to regulate their emotions, it can be detrimental for collaborative learning (Bakhtiar et al., 2018).

The current study did not explore the ways in which students engaged in CoRL or SSRL during the collaborative learning task. In the future, it would be interesting to explore whether there were some differences in the ways in which, for example, students who perceived the task as being more difficult engaged in the regulation of learning when compared to the students who perceived the task as being less difficult. This type of research could illuminate more precisely the influence of regulated learning on metacognitive conditions of the students and groups.

There is also research evidence suggesting that when learners externalize their difficulties that when learners externalize their difficulties during collaborative learning that such externalization serves as a trigger for regulation of learning during for their collaborating peers' difficulties during learning serves as a trigger for regulation of learning (Iiskala et al., 2011). In addition, there is increasing evidence that physiological arousal can serve as a marker of task difficulty. For example, Malmberg et al. (2019) found that especially when the students were confused and expressed difficulties in their collaborative learning, the level of their physiological arousal increased. Therefore, physiological arousal can be informative for task difficulties, but not for task perceptions.

From the learning process perspective, research has demonstrated for years that an optimal level of physiological arousal can be beneficial for learning, since it accounts for cognitive or affective activation of learners (Hebb, (Doherty et al. 1995)). Thus, physiological measures have advantages when compared to subjective measures, such as self-reports. Physiological measures are objective and sensitive to metacognitive processes, and they provide continuous data. However, physiological measures are difficult to interpret without subjective data (Järvelä et al., 2020). Yet, physiological data has the potential to reveal metacognition within complex processes of learning and interaction.

The advantage of the current study is that the data was collected in authentic classroom situations, where collaborative learning takes place, which means that the collaborative learning situations were genuine. At the same time, this causes limitations, as the generalizability of the current study findings is limited in various respects. First, the sample size is quite modest, making it difficult to draw strong conclusions; in addition, the effect sizes were relatively small. Second, the sample size varied throughout the study because of missing data. For example, sometimes the students did not complete the situated questionnaire, they did not fill in the quiz after the learning task, or their physiological data was corrupted. In addition, this study did not investigate the collaborative learning process and, for example, how students engage in metacognitive monitoring or regulate their learning during the learning task. Despite these limitations, the study confirmed earlier findings indicating that physiological arousal is connected to students' metacognition, and especially their perception of task difficulty.

The study results also have practical implications. First, in the current study, we used the Qridi® platform to provide the students with the opportunity to evaluate their level of task understanding and task difficulty. In this study, the information was offered only to the students, but this information could also be offered to the teacher. Perhaps the teacher could already, prior to the task or during the task, identify the students or collaborating groups who struggle with the task and then provide targeted support for the students. Today, there is a plethora of different types of technology-enhanced learning environments and mobile tools that can be tailored to measure the student's metacognitive experiences and metacognitive skills related to the learning task.

Second, as wearable sensor technologies continue to develop in the future and their applications in everyday life become more powerful and user-friendly, more opportunities for learning, and the subsequent implications for teaching, will become available. So far, wearable sensors have been used mostly to track processes that can provide information about health, such as sleep, activity, or heart rate. However, when we have progressed further in the research on the relationship between physiological arousal and metacognition, it will be possible to envision the use (to some extent at least) of physiological data in the context of education.

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Declarations

Disclosure of potential conflicts of interest The authors have no conflicts of interest with the research reported in this submission.

Informed consent All students and their parents completed informed consent before agreeing to participate. They also received a description about the aims of the study and data sources to be collected.

Research involving human participants and/or animals The research reported did involve human participants. The research was conducted by following ethical guidelines of the Finnish National Board of Research Integrity and the [blinded]. Since physiological measures intervene with the physical integrity of a person, permission to carry out the research was approved by The Ethics Committee of Human Sciences, [blinded]. Student participation in the study was voluntary and they could withdraw at any time. Students were informed that they can withdraw from the study at any point. No adverse effects on participants were observed during data collection.

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