




Matching self-reports with electrodermal activity data: Investigating temporal changes in self-regulated learning

Muhterem Dindar¹  · Jonna Malmberg¹ · Sanna Järvelä¹ · Eetu Haataja¹ · Paul A. Kirschner²

Received: 18 September 2019 / Accepted: 7 November 2019 / Published online: 22 November 2019
© The Author(s) 2019

Abstract

This study investigated the interplay of temporal changes in self-regulated learning processes (i.e., behavioral, cognitive, motivational and emotional) and their relationship with academic achievement in computer-supported collaborative learning. The study employed electrodermal activity and self-report data to capture the dynamicity of self-regulated learning processes during 15 sessions of collaborative learning activities. Our findings revealed that the changes in motivational regulation was related to academic achievement. However, academic achievement was not related to behavioral regulation, cognitive regulation or emotional regulation. Physiological synchrony among the collaborating students was found to be related only to cognitive regulation. The results also showed that the concordance of self-report data among the collaborating students was related to higher physiological synchrony among them in the behavioral, cognitive, and motivational dimensions of self-regulated learning. The findings reflect the complexity of the relationships between self-regulated learning constructs and demonstrates the potential value of physiological measures in self-regulated learning research.

Keywords Computer-supported collaborative learning · Self-regulated learning · Physiological synchrony · Multimodal data

✉ Muhterem Dindar
muhterem.dindar@oulu.fi

¹ Learning and Educational Technology Research Unit, Faculty of Education, University of Oulu, FI-90014 Oulu, Finland

² Open University of the Netherlands, Heerlen, Netherlands

1 Introduction

Collaborative learning is “a shared social system” in which multiple agents have to agree on common learning goals and actively regulate their cognition, motivation and emotions both at the individual and group levels, until the goals are attained (Volet et al. 2009). The regulatory processes in collaborative learning can occur simultaneously at the individual and social levels and continuously affect each other (Järvenoja et al. 2017). Thus, to understand the cyclical progress of regulated learning (Zimmerman 2008), the situational interplay of psychological and interpersonal processes need to be captured as they unfold over time (Järvelä et al. 2016a, b, c).

Though much is known about the socio-emotional aspects of collaboration and their role in knowledge creation and co-construction (e.g. Zhao and Chan 2014), there is limited knowledge about how and at what level self-regulatory processes change within and across collaborative learning sessions and how they are related to learning outcomes. Given this, research on regulated learning is moving forward by adopting methods that track the emergence of behavioral, cognitive, motivational, and emotional processes in relation to time and context (Panadero et al. 2016). Utilization of measures that reflect the actual behaviors of students during learning (Perry and Winne 2006) and combination of multiple data sources to capture self-regulated learning (SRL) changes within and across episodes of learning without interfering in the learning process have become new topics of discussion in the field of collaborative learning in the recent years (Davidsen and Vanderlinde 2014). Drawing on this, the current study sought to examine the affordances of self-reported and physiological measures in revealing temporal changes in the dimensions of SRL. More specifically, it combined self-report data with physiological data, such as electrodermal activity data (EDA) to examine the temporal changes in the dimensions of behavioral, cognitive, motivational, and emotional processes and their relationship to academic achievement in the context of collaborative learning.

2 Theoretical framework

2.1 SRL framework and its critical dimensions

SRL emphasizes the pro-active role of individuals in completing academic tasks and focuses on the complex relationship between the cognitive, motivational, emotional, and behavioral regulatory components in the course of learning (Schunk and Zimmerman 2008). Decades of studies have reported that self-regulated learners apply effective strategies when setting learning goals, monitoring learning progress and adapting cognition, motivation, and behavior toward goal attainment, individually and with others (Schunk and Greene 2017). In collaborative learning contexts, research on SRL has been receiving more attention, such as research into the motivational and emotional aspects of collaboration (Isohäätä et al. 2017), but still mostly focused on the relationship between social interactions, cognitive processes, and their effects on knowledge construction and academic success (Hmelo-Silver and Barrows 2008). There is limited knowledge about the connections between the cognitive, behavioral, motivational, and emotional regulatory components of SRL and how they relate to learning outcomes in general (Efklides 2011), and collaborative learning in particular (Panadero and Järvelä 2015).

2.2 SRL dimensions and academic achievement

In educational contexts, *behavioral regulation* refers to sustaining attention, following instructions, and controlling actions to complete academic tasks (McClelland et al. 2007). Research has underlined the importance of behavioral regulation in adaptation to learning contexts and academic achievement (e.g. McClelland et al. 2006). On the other hand, lack of behavioral regulation as reflected in either activating or inhibiting a behavioral response was found to be detrimental to academic self-efficacy (Barkley 2004). Behavioral regulation also requires applying various cognitive skills (e.g., attention and working memory) to behavior (Sektan et al. 2010). In this regard, a close relationship exists between behavioral and cognitive regulation.

Cognitive regulation involves processes such as activating prior knowledge, applying effective strategies to integrate new and existing knowledge, and evaluating understanding (Molenaar et al. 2011). Individuals obtain more domain knowledge if they regulate their cognition and engage in a greater number of cognitive activities during the learning activity (Pardo et al. 2017). In addition, social interaction is necessary for the activation of cognitive processes (Kreijns et al. 2003). Thus, collaborative learning environments have been regarded as appropriate grounds for developing cognitive structures and applying cognitive regulatory strategies through social interactions (e.g., asking questions, giving explanations, giving feedback, and argumentation) (Chi 2009).

It is well documented that focusing solely on cognitive processes is not sufficient for understanding individuals' success or failure in naturalistic learning situations and that *motivational regulation* can substantially affect academic achievement (Schunk and Zimmerman 2008). Motivation refers to one's willingness to engage with a task and persistence on activities towards task completion (Wolters 2003). Several studies have reported that motivational regulatory activities are related to enhanced cognitive and metacognitive strategy use and improved learning outcomes (e.g. Schwinger et al. 2009). Studies have further found that shared regulation of motivation among individuals in collaborative learning groups facilitated cognitive regulation processes in completing academic tasks (Järvelä et al. 2016a, b, c).

Even though the amount of research into various aspects of SRL has increased substantially in recent years, the role of *emotional regulation* in SRL and collaborative learning has remained an underexplored area of study (Järvenoja et al. 2013; Webster and Hadwin 2015). Emotions in the academic context can be called as intense reactions directed towards learning situation (Goetz et al. 2006). The limited research that exists has revealed that emotional regulation plays a critical role in coping with social challenges that arise during collaborative learning (Efklides 2011). It was assumed that emotional regulation during collaborative learning enhances interaction, trust, and engagement among learners and facilitates adaptive cognitive and behavioral strategies that might prompt SRL and enhance learning performance (Efklides and Volet 2005).

While the association between cognitive, motivational, and emotional regulatory processes in SRL is based on dynamic, complex, and reciprocal interactions (Pintrich 2004), current literature says little about how SRL processes develop together in collaborative learning and how the co-occurrence of such processes relates to learning outcomes. This is mostly due to methodological challenges in capturing SRL processes.

2.3 Measuring SRL

In recent decades, there has been a rapid evolution of measurement in the field of SRL (Panadero et al. 2016). This is mostly because conventional measurement tools, such as questionnaires, treated SRL constructs as relatively stable aptitudes (Winne and Perry 2000). However, the current conceptual and operational definitions of SRL characterizes it as an unfolding series of events that are affected by both individual and the contextual factors, such as nature of the task and the social environment (McCardle and Hadwin 2015). Therefore, self-reported questionnaires might not be able to capture the dynamicity of SRL components (Pintrich 2004).

Nonetheless, self-report data has a solid place in SRL research and offers several advantages (Perry and Winne 2006). It does not interfere with the learning process, is practical for large-scale data gathering, and the scoring of self-report data is straightforward and takes little time (Schellings and van Hout-Wolters 2011). In addition, understanding learners' self-perceptions, self-evaluations, and reflections is critical for disclosing regulatory activities in SRL (Hadwin et al. 2011). Considering this, some scholars have asserted that the repeated utilization of single-item questionnaires can be useful in capturing on-task states and transitory learning processes (Ainley and Patrick 2006). Further, combining self-reports with process-oriented measures (e.g. physiological signals) might be a promising approach to match learners' perceptions of SRL processes with their actual behaviors during learning (Azevedo et al. 2016).

2.4 Physiological data collection and synchrony during collaboration

Physiological data derived from the autonomic nervous system can provide objective information about real-time alterations in cognitive and affective states allowing research to go beyond what can be observed to reveal often-invisible cognitive and emotional reactions of the body and brain (Reimann et al. 2014). Heart rate variability (HRV) and electrodermal activity (EDA) are, for example, common measures of the autonomic nervous system that have been used to try to understand the cognitive and affective processes of individuals, such as cognitive load (Fairclough et al. 2005), emotional state (Calvo and D'Mello 2010), motivation and effort (Gendolla and Richter 2005), and attention (Ravaja 2004). In addition, there has been an interest in observing interpersonal autonomic physiology (i.e., physiological synchrony) between multiple individuals in active, social, and natural interaction situations in recent years (Palumbo et al. 2016).

Physiological synchrony (PS) is defined as “*any interdependent or associated activity identified in the physiological processes of two or more individuals*” (Palumbo et al. 2016, p. 2). Several indices have been developed to measure and describe PS. For example, Marci and Orr (2006) introduced a physiological concordance index derived from measures of EDA and found that PS was significantly higher in real therapy interactions than in hypothetical pairs and significantly correlated with self-reported empathy.

Only few studies have utilized PS measures in educational contexts. For example, Gillies et al. (2016) used wireless wristbands to measure EDA and analyzed the data in terms of PS between students during a science class. They concluded that the high-level common engagement during whole-class activities and student-centered learning

during the collaborative group activities were reflected in the PS between the students. Ahonen et al. (2016) studied students executing a collaborative pair-programming task and found shared patterns in the students' heart rate variability to be significantly associated with their self-reported workloads. Despite the significant amount of research on PS and physiological data, the research focusing on utilizing physiological data in educational contexts is still scarce. Still, studies have overall revealed that physiological data can be an indicative of behavioral, cognitive or affective processes during collaboration (Palumbo et al. 2016). The extensive literature on regulated learning also states that SRL is comprised of cognitive and affective processes. Considering this, it is worth investigating whether physiological data can inform about the dimensions of SRL as well. Nonetheless, physiological has been utilized to a very limited extent to investigate SRL (Azevedo et al. 2018).

2.5 Purpose of the study

A plethora of studies in the literature have investigated the interactions between behavioral, cognitive, motivational, and emotional processes of SRL and academic achievement separately (Mega et al. 2014). Until now, however, few empirical studies have tried to incorporate multiple processes into a single study and examine how those processes are interconnected with each other and with learning outcomes (e.g., Ben-Eliyahu and Linnenbrink-Garcia 2015; Mega et al. 2014). This may be due to possible challenges in applying conventional self-report measures over multiple episodes of learning. In the traditional sense, measuring different learning processes requires asking multiple questions for each process. Consequently, the length of any questionnaire increases as more processes are included in the study. Unfortunately, long questionnaires come with significant limitations in terms of measuring learning progress at multiple time points and at short intervals (Pintrich 2004). Considering such limitations, the current study employed single-item questionnaires to measure behavioral, cognitive, motivational, and emotional changes in collaborative learning repeatedly and unobtrusively.

The aim of this study is to examine the temporal changes of behavioral, cognitive, motivational, and emotional processes during collaborative learning and their relationship to PS and academic achievement. The research questions are as follows: 1) Are there any relationships between behavioral, cognitive, motivational, and emotional regulatory processes and academic achievement?; 2) Are there any relationships between the PS of students and their self-reports about behavioral, cognitive, motivational, and emotional change during learning sessions?; 3) Is there any relationship between the PS of students and their academic success?

3 Methodology

3.1 Participants and context

Participants in the study were 31 (23 males, 8 females) Finnish high school students, whose ages ranged between 15 and 16 years. The students enrolled in an Advanced Physics course consisting of 15 lessons. The students were divided into 10

heterogeneous groups based on their previous grades in order to avoid clustering of high and low achieving students in the same groups. The groups comprised three (9 groups) to four members (1 group), and the students collaborated in the same groups in each lesson. Due to limitations in resources, only the 12 students in randomly chosen four groups given Empatica 4.0 (Empatica Inc., Boston, MA) wristbands for EDA measurement. To make the situation as similar as possible for all of the students, other six groups in the classroom (19 students) were asked to wear standard Polar Active activity monitors during the lessons. The data in the current study was collected with the authorization of the ethics committee at the university of the first author. Participation to the study was voluntary and no incentive was offered for participation.

3.2 EdX learning environment

Each of the physics lessons involved collaborative learning guided by an EdX online learning environment (<https://www.edx.org/>). The online environment further served as a data collection tool and asked students to evaluate their behavior, cognition, motivation, and emotion individually at the beginning and the end of the learning sessions.

Each learning session in the current study was organized as follows: 1) Students entered the classroom and sat at the same table as their group members. All students were given tablet computers and were asked to access the EdX learning environment with their tablet. 2) Teacher explained the theoretical background of the topic. 3) Students were presented with a collaborative learning task. Collaborative learning tasks consisted of conducting hands-on experiments (e.g. Finding out the circumstances convex mirror makes a virtual picture by using a specific simulation in the EdX environment), or paper-and-pencil problems (e.g. Designing an experimental setting on which one could possibly measure the speed of light. Drawing a picture about the setting with argumentation). 4) Following the task presentation, all students were asked to answer a pre-test questionnaire individually. 5) Students worked as groups to complete the collaborative learning task. 6) After completing the task, all students were asked to answer a post-test questionnaire individually. 7) Students left the classroom.

3.3 Data collection

3.3.1 Pre- and post-test questionnaire for behavior, cognition, motivation, and emotions

A 4 item 10-point Likert-type questionnaire was utilized to unfold the self-regulatory changes within the participants in each collaborative session. The questionnaire items were borrowed from the S-REG tool has been developed to measure situation-specific regulatory processes during collaboration (Järvenoja et al. 2017; Laru et al. 2015). Answers varied to the items between 1 (lowest) and 10 (highest). Each item in the questionnaire was designed to tap four different self-regulatory processes during learning. The questionnaire was applied as a pre- and post-test before and after each learning session. Pre-test items were “I know what to do” (cognition), “I am motivated to work” (motivation), “My feelings right now” (emotion), and “How will your group work during collaboration?” (behavior). Post-test items were presented in the past

tense, such as “I knew what to do,” “I was motivated to work,” “My feelings right now,” and “How did your group work during collaboration?”

3.3.2 Academic achievement

At the end of the course, students’ academic achievements were measured through an exam with an individual and a group part. The exam was based on the Finnish high-school curriculum with intend to also measure the competence demanded in the matriculation examination. The individual part included tasks of varying difficulty related to the main contents of the course, and each student completed the exam alone using a pen and paper. The group part included one problem-solving task with hands-on equipment, and the answer was given using pen and paper. The group task was completed in the same groups as the course. The end-of-term scores were calculated by the subject teachers through the application of a weighted formula, summing up the individual part scores (maximum 36 points, $M = 24.29$, $SD = 7.24$) and the group part scores (maximum 6 points, $M = 5.18$, $SD = 0.57$).

3.3.3 Electrodermal activity

Empatica E4 (Empatica Inc., Boston, MA) wearable wristbands were used to collect EDA data. To ensure good quality data, the placement of the wristband sensors was verified by a research assistant at the beginning of each session. Measures of EDA were used to determine PS through calculation of a physiological concordance (Marci et al. 2007).

3.4 Data analysis

In the data analysis, first, self-reported data and temporal changes in behavior, cognition, motivation, and emotion were investigated and then examined to compare if and how the changes correlated with learning outcomes. The correlational analysis about the relationship between SRL changes and group exam scores was left out due to low amount of variation in group exam scores. Second, the PS of the dyads in the collaborating groups was determined by calculating a single session index (SSI) of physiological concordance for each session. Third, the correlation between PS, learning outcomes, and the temporal dimension changes in behavior, cognition, motivation, and emotion were investigated. Finally, the connection was investigated between PS and self-reported changes in behavior, cognition, motivation, and emotion.

3.4.1 Temporal changes in behavior, cognition, motivation, and emotion

The temporal changes in SRL processes were calculated by subtracting students’ pre-test scores from their post-test scores for each session. Then, a single change score was calculated by taking the average of the differences for all sessions for each SRL construct. Descriptive statistics about temporal changes in the SRL dimensions are presented in Table 1.

As seen in Table 1, skewness and kurtosis values for the changes were all within the limit of -2 and $+2$ except for the motivational change. Screening of the dataset revealed that the non-normal distribution in motivational change was due to a single outlier case. The

exclusion of the single outlier case in motivational change resulted in normal distribution (skewness = -1.70 ; kurtosis = $.709$). In consideration of the outlier case, two separate analyses (with and without the outlier case) were conducted for motivational change.

3.4.2 PS of the dyads in collaborating groups

SSI of PS (Marci et al. 2007) between the dyads of collaborative groups was calculated for each session. First, the EDA signal was downsampled to 1hz frequency and transformed into Z-scores to neutralize the individual differences between the students. Second, the average slope of 5 s was calculated for each moment with the moving window. Third, the concordance for each pair in the group was calculated from the slope values with Pearson correlation by using a 15-s moving window with lag-zero. Fourth, a single SSI was calculated from the ratio of the sum of the positive correlations across each 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, the higher positive values of the SSI can be considered to reflect higher PS through the session. SSI scores for the sessions are presented in Table 2.

Monte Carlo shuffling was used to determine the significance of synchrony (see e.g. Karvonen et al. 2016). Only actual SSI values higher than the highest shuffled concordance of $p < .05$ were considered as significant and included for further analysis (see Table 2). For conceptual clarity, SSI scores will be mentioned as PS in the following parts of the manuscript.

Based on repeated measurements and the nested structure of the dataset, a multilevel model was then proposed to analyze the relationship between PS and changes in SRL dimensions. However, testing of unconditional multilevel models (i.e., random intercept only, random intercept and random slope), with PS being the dependent variable, revealed that the measurements between and within individual levels in the current study were independent and thus that multilevel modeling was not necessary. On the basis of these findings, the relationships between PS, change in the SRL processes, and academic success were investigated with correlational analyses conducted using SPSS21 software.

3.4.3 Concordance between collaborating students in terms of self-reported changes in behavior, cognition, motivation, and emotion

The dyads' self-reported changes for SRL processes were coded under two categories in each session. If the direction of self-reported change in a session was the same,

Table 1 Descriptive statistics for changes in SRL dimensions

Dimension	M	SD	Min	Max	Skewness	Kurtosis
Behavioral	0.053	0.049	−.50	0.67	0.198	−0.154
Cognitive	0.304	0.086	−.70	1.75	0.598	1.687
Motivational	0.245	0.088	−.75	1.17	−1.188	3.323
Emotional	0.236	0.081	−.00	1.00	−0.429	0.792

Table 2 SSI scores and their significance according to Monte Carlo Shuffling

Group	Pair 1	Pair 2	Session 1	Session 2	Session 3	Session 4	Session 5	Session 6	Session 7	Session 8	Session 9	Session 10	Session 11	Session 12	Session 13	Session 14	Session 15
1	StudentA	StudentB	.042	.335*		.092*	.271*	.038	.040	.520*	.070	-.049	.108*	.089*	.119*	-.299	
	StudentC	StudentA	-.030	.200*		-.172	.173*	-.097	-.082	.111*	-.144	-.050	.104*	.124*	-.363	.040	
	StudentC	StudentB	.264*	.282*	.005	-.298	-.030	.037	-.054	.023	.121*	.296*	-.115	.006	-.061	.002	-.117
2	StudentD	StudentE	.321*			-.036	.093*						.268*	.074*	.223*	.360*	
	StudentD	StudentF	-.218	.113*		.039	.162*			.038		-.053	-.197	-.082	-.332		
	StudentE	StudentF	-.143		.048	.089*	-.198	-.239	-.054	.031	.085*	.109*	.106*	-.054	.126	.111	-.311
3	StudentG	StudentH	.090*				.228*	-.078			-.042	.154*	-.090	-.090	.178*	.075*	
	StudentH	StudentI	-.012	.108*	-.202		.314*				-.166	.076*	-.197	-.048	.016	-.078	
	StudentG	StudentI	.009			-.028	.267*			.159	-.030	2.07*	-.036		.153*	-.128	
4	StudentJ	StudentK	-.046	-.129	.031	.000	.034	.214*	.274*	-.044	.014	.083*	.199	-.036	.108*	.058*	
	StudentK	StudentM	.061*	-.389	-.004	.088*	-.632	-.329	-.393	-.044	.014	-.070	-.176	-.077	-.022		
	StudentJ	StudentM	-.012	.052*	-.028	-.179	.011	.013	.127*	-.393	.016	.289*	.016		.002		

**p* < .05

meaning either an increase or decrease in self-reported interpretation of behavior, cognition, motivation, or emotion for both participants in a dyad, their self-reported change at that dimension was considered concordant. Otherwise the change in self-report was coded non-concordant. Table 3 presents the frequency of self-reported concordance and non-concordance at each dimension for all the sessions. Following the coding, independent sample t-tests were conducted to investigate whether dyads' PS scores differed in terms of their self-reported concordance in SRL processes.

4 Results

4.1 Temporal changes in SRL processes and academic achievement (RQ1)

A Pearson's correlation was calculated to examine how overall behavioral, cognitive, motivational, and emotional changes were related to each other and the learning outcomes. The results are displayed in Table 4.

The results show that there was a small-to-moderate correlation between overall motivational change and end-of-term scores. By contrast, behavioral, cognitive and emotional regulation were not related with any of the learning outcomes. The results in Table 4 also revealed that cognitive change was correlated only with behavioral change and that emotional change was only correlated with motivational change. Motivational change was, however, correlated with behavioral change. The magnitude of the significant correlations can be considered as small to medium. The inclusion or exclusion of the outlier case in motivational change did not affect the significance of the findings.

4.2 The relationship between PS, change in SRL processes (RQ2), and academic achievement (RQ3)

To investigate the relationship between PS and changes in SRL processes, first, the average of each dyad's self-reported change for every SRL dimension across the sessions was calculated. Second, academic achievement scores of the dyads were defined by calculating the average of the scores for the individual exam and end-of-term scores. Third, Spearman's rho correlation formula with SPSS21 software was applied to answer our second research question. The results showed that the only significant relationship was between PS and cognitive change ($r = .642$) in terms of SRL dimensions. No significant relationship was observed between PS and any of the academic achievement scores.

Table 3 Frequency of sessions in which collaborating students showed concordance or non-concordance according to their self-reported SRL processes

	Behavioral change	Cognitive change	Motivational change	Emotional change
Concordance (f)	19	13	11	14
Non-concordance (f)	15	21	23	20

Table 4 Correlations between the SRL dimensions and academic achievement scores

<i>N</i> = 31	Cognitive change	Motivational change (incl. outlier)	Motivational change (excl. outlier)	Emotional change	Written exam	Final end-of-term score
Behavioral change	.469**	.500**	.371*	.287	.167	.179
Cognitive change		.305	.090	.303	.036	.062
Motivational change (incl. outlier)				.624**	.351	.391*
Motivational change (excl. outlier)				.559*	.348	.366*
Emotional change					.152	.178
Written exam						.995**

* $p < .05$; ** $p < .01$

To investigate the interplay of PS and self-reported data further, for each SRL process, independent samples t-tests were conducted to see whether there was a difference between the PS scores of dyads who had concordance in their self-reported SRL processes and those who did not have concordance. A significant difference was observed at behavioral ($t_{(1,32)} = 2.044$; $p = .049$; $\eta_p^2 = .115$), cognitive ($t_{(1,32)} = 2.137$; $p = .040$; $\eta_p^2 = .125$), and motivational dimensions ($t_{(1,32)} = 3.866$; $p = .001$; $\eta_p^2 = .318$). No difference was observed for the emotional dimension ($t_{(1,32)} = -.174$; $p > .05$; $\eta_p^2 = .001$). Findings indicated that PS was significantly higher when there was concordance between the changes in dyads' self-reported behavioral, cognitive, and motivational processes (see Fig. 1).

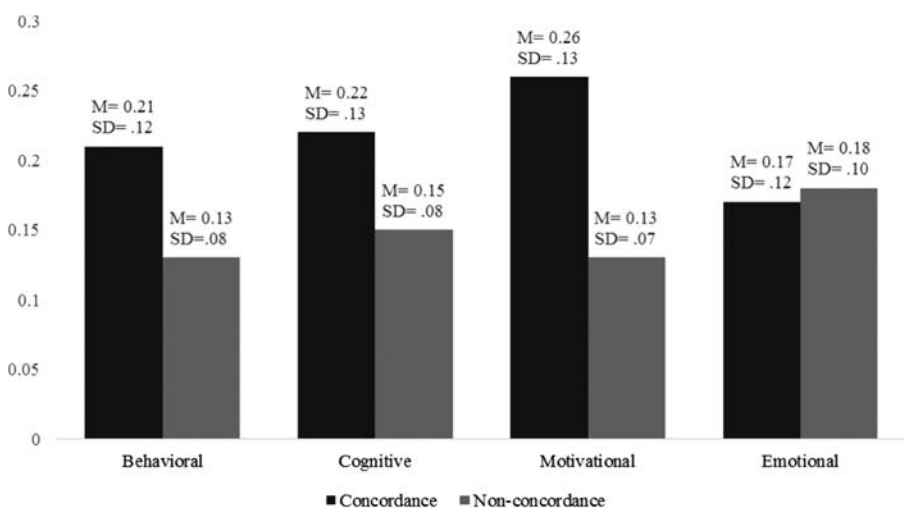


Fig. 1 Comparison of SSI means for the self-reported concordance and non-concordance situations across the SRL dimensions

5 Discussion

5.1 The relationships between self-reported behavioral, cognitive, motivational and emotional changes and academic achievement

Based on the self-report data here, students' behavioral change was positively correlated with their cognitive and motivational changes. In the context of SRL, the term *behavioral processes* refers to executive control in maintaining attention to a task and inhibiting unnecessary actions that might interfere with the completion of the task (McClelland et al. 2007) requiring conscious control of thoughts and actions (Happaney et al. 2004). Cognitive processes can be considered an important companion of behavioral processes. The moderate correlation between behavioral and cognitive changes in the current study supports this assumption. Behavioral processes further incorporate time and effort management and the seeking of help in collaborative learning environments (Pintrich 2004). In this regard, behavioral processes involve elements of persistence and determination. Supporting such claims, the correlation between behavioral and motivational changes in the current study indicated that behavioral management of collaborative learning processes are related to motivational change. By contrast, no significant correlation was observed between behavioral change and emotional change in the current study, nor was any found in previous studies. Although there was no direct relationship found between behavioral and emotional change, it is possible that their relationship may be mediated by motivational or cognitive processes. Therefore, rejection of any relationship between behavioral and emotional change seems to be premature. Unfortunately, the association between behavioral and emotional regulation has been so far neglected in SRL research. Further studies are necessary to develop a better understanding of the relationship between behavioral and emotional processes.

Previous studies have shown that emotions are associated with cognitive and motivational processes in SRL (e.g. Efklides 2011; Mega et al. 2014). Some scholars have asserted that positive emotions lead to effective use of cognitive and motivational strategies when completing academic tasks (Efklides and Volet 2005; Järvenoja et al. 2013). The findings here partially support this claims. In the sample, motivational change was significantly correlated with emotional change, whereas cognitive change was not. It should be also noted that there was no significant correlation between cognitive and motivational change. These findings do not support the general understanding in the SRL field that emotional and motivational regulatory processes enhance cognitive regulatory activities (Järvelä et al. 2016a, b, c; Malmberg et al. 2015; Schunk and Zimmerman 2008).

Behavioral, cognitive and emotional change did not correlate with any of the academic achievement scores. By contrast, motivational change correlated with end-of-term scores. With regard to behavioral change, some scholars have reported a significant relationship between behavioral regulation and academic success (McClelland et al. 2007) whereas others could not find any direct relationship between behavioral regulation and academic success (Ben-Eliyahu and Linnenbrink-Garcia 2015). Our findings here are in line with those of the latter group of scholars. However, the attributes of the research design here had specific differences from those of other studies. Ben-Eliyahu and Linnenbrink-Garcia (2015) measured behavioral regulation as a trait without focusing on SRL in collaborative learning contexts, and Janssen et al. (2012) coded student activities during collaborative work. Considering that all the

learning activities took part in a collaborative format, in the current study we asked students to report their expectations and evaluations about how the group would and did perform during each collaborative learning session. The findings here showed that students' evaluations of group-level behavioral changes did not affect their individual academic achievement.

With regard to cognitive change, several studies have reported a positive relationship between cognitive regulation and academic success (Chi 2009). However, other studies found no direct relationship between cognitive regulation and achievement (Ben-Eliyahu and Linnenbrink-Garcia 2015; Janssen et al. 2012) which was also the case here. Ben-Eliyahu and Linnenbrink-Garcia (2015) also found that cognitive regulation may predict academic achievement through mediation of learning strategies and engagement. As in Ben-Eliyahu and Linnenbrink-Garcia (2015), it is possible that cognitive processes interacted with academic achievement scores through other variables, such as learning strategies and engagement, in the current study.

Past studies have found that positive emotions enhanced cognitive and motivational regulatory processes and eventually led to academic success (Ahmed et al. 2013; Goetz et al. 2006). Similarly, motivational regulation was found to be influential on activation of cognitive and metacognitive strategies and successful task completion (Malmberg et al. 2015; Schwinger et al. 2009). Partly supporting the previous studies, the findings of the current study showed motivational changes to be significantly related to learning outcomes. However no direct relationship was found between emotional regulation and academic success.

5.2 The relationships between PS and self-reported behavioral, cognitive, motivational, and emotional changes

There was a significantly positive relationship between cognitive change and PS. However, the correlations between PS and other changes (i.e., behavior, motivation, and emotion) were not significant. According to the literature, EDA can be an indicator of motivational, emotional, or cognitive arousal (Palumbo et al. 2016). Moreover, some scholars have reported that PS was not dependent on behavioral regulation (Henning et al. 2001). In terms of behavioral and cognitive change, our findings support previous studies. The lack of connection between PS and emotional change might be explained by the fact that self-report of emotional processes in this study focused more on valence dimension of emotion instead of arousal.

The findings further revealed that PS values were higher in collaborating pairs for the learning sessions in which the self-reported data showed concordance among the pairs in terms of behavioral, cognitive, and motivational changes. Specifically, if the perceived behavioral, cognitive, or motivational changes of the pairs were in the same direction (either increased or decreased together), the PS between the students was higher. These findings indicate that physiological signals can serve as a possible triangulation tool for SRL and collaborative learning research.

5.3 The relationship between PS and academic success

Finally, no relationship was observed between PS and academic achievement. The findings do not corroborate several previous studies that found a relationship between

PS and performance (Elkins et al. 2009; Walker et al. 2012). On the other hand, in some studies, the relationship between performance and PS was not significant when task conditions were controlled (Montague et al. 2014). Therefore, one can assume that the relationship between PS and academic achievement may be context or task dependent.

6 Limitations and future directions

The current study carries limitations that raise important concerns about the generalizability of its findings. First, it investigated the change in SRL processes and physiological signals of high school students for multiple sessions in a natural collaborative setting. Considering the complexity of SRL processes, the unique interactions, and the variety of activities during the course, generalization to other collaborative settings may be limited. Second, the limited sample size that is dominated by males, missing data, and non-significant PS values in multiple sessions brings caution in interpreting and generalizing the findings. Third, single-item self-report measures were used to capture the perceived transitory changes in the behavioral, cognitive, motivational, and emotional aspects of each learning session. Single-item scales have been found to be reliable and useful in several SRL studies (e.g., Ainley et al. 2002; Ainley and Patrick 2006). However, their psychometric attributes are questionable since common statistical analyses (e.g. cronbach alpha, exploratory and confirmatory factor analysis) to test the reliability and validity of single-items scales cannot be computed. Therefore, the questionnaires used in the current study might be subjected to modification and fine-tuning in future studies. Finally, learning outcomes in the current study were measured at the end of the course. Thus, it was not possible to investigate the relationship between SRL changes and learning outcomes in each session. Future studies can tackle this limitation by applying intermediate tests throughout the course.

Considering the limitations stated above, future studies can align self-reports and other data types with physiological data to explore the complex nature of regulatory processes in collaborative learning. For example, video coding of group interactions can help to identify the regulatory phases (i.e. planning, task enactment, monitoring and reflection) or specific regulation types (i.e. cognitive, motivational, emotional and behavioral) within a collaborative session. Calculating PS separately for such regulatory phases and regulation types might help to understand the association between PS and regulated learning events at a finer detail. Log-data traces of group learning activities gathered from a digital learning environment can also help to explore the relationship between PS and regulatory processes further. Log-data can provide time-stamped information about digital learning activities (Winne 2017), and makes it possible to investigate the alterations in PS during specific phases of group learning.

7 Conclusions

Measuring changes in the dimensions of SRL within or between the learning sessions has been a topic of debate in recent years (McCardle and Hadwin 2015). It has been well documented that objective and unobtrusive measures are necessary to capture the development of self-regulatory processes when learning. In this regard, this study

combined single-item self-report questionnaires with EDA data to unpack the interplay of perceptions and physiological changes during collaborative learning and their effect on academic performance. The current study is a nascent attempt to map self-regulatory processes with PS. This is important because providing adaptive and immediate feedback to the learners during learning is increasingly discussed topic in educational sciences (Azevedo et al. 2018). The current technological advancements allow to collect physiological data without interfering the learning activities. Thus, detecting the critical moments that trigger successful or unsuccessful regulation with physiological data might help to develop interventions that can provide momentarily support to the learners as they struggle with a challenge at a specific SRL dimension. In this regard, the existing study points out the possible affordances of physiological data in developing tools to provide immediate support to the learners as the learning occurs.

Acknowledgements Open access funding provided by University of Oulu including Oulu University Hospital. This work was supported by the Academy of Finland [SLAM project number: 275440].

Open Access This article is distributed under the terms of the Creative Commons Attribution 4.0 International License (<http://creativecommons.org/licenses/by/4.0/>), which permits unrestricted use, distribution, and reproduction in any medium, provided you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license, and indicate if changes were made.

References

- Ahmed, W., van der Werf, G., Kuyper, H., & Minnaert, A. (2013). Emotions, self-regulated learning, and achievement in mathematics: A growth curve analysis. *Journal of Educational Psychology, 105*(1), 150. <https://doi.org/10.1037/a0030160>.
- Ahonen, L., Cowley, B., Tornainen, J., Ukkonen, A., & Vihavainen, A. (2016). Cognitive collaboration found in cardiac physiology: Study in classroom environment. *Plos One, 11*(7). <https://doi.org/10.1371/journal.pone.0159178>.
- Ainley, M., & Patrick, L. (2006). Measuring self-regulated learning processes through tracking patterns of student interaction with achievement activities. *Educational Psychology Review, 18*(3), 267–286. <https://doi.org/10.1007/s10648-006-9018-z>.
- Ainley, M., Hidi, S., & Bemdorff, D. (2002). Interest, learning, and the psychological processes that mediate their relationship. *Journal of Educational Psychology, 94*(3), 545–561. <https://doi.org/10.1037/0022-0663.94.3.545>.
- Azevedo, R., Taub, M., Mudrick, N., Farnsworth, J., & Martin, S. A. (2016). Interdisciplinary research methods used to investigate emotions with advanced learning technologies. In M. Zembylas & P. A. Schutz (Eds.), *Methodological advances in research on emotion and education* (pp. 231–243). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-319-29049-2_18.
- Azevedo, R., Taub, M., & Mudrick, N. V. (2018). Understanding and reasoning about real-time cognitive, affective, and metacognitive processes to foster self-regulation with advanced learning technologies. In D. H. Schunk (Ed.), *Handbook of self-regulation of learning and performance*. Routledge: New York, NY.
- Barkley, R. A. (2004). Attention-deficit/hyperactivity disorder and self-regulation: Taking an evolutionary perspective on executive functioning. In R. F. Baumeister & K. D. Vohs (Eds.), *Handbook of self-regulation: Research, theory, and applications* (pp. 301–323). New York: Guilford.
- Ben-Eliyahu, A., & Linnenbrink-Garcia, L. (2015). Integrating the regulation of affect, behavior, and cognition into self-regulated learning paradigms among secondary and post-secondary students. *Metacognition and Learning, 10*(1), 15–42. <https://doi.org/10.1007/s11409-014-9129-8>.
- Calvo, R. A., & D’Mello, S. (2010). Affect detection: An interdisciplinary review of models, methods, and their applications. *IEEE Transactions on Affective Computing, 1*(1), 18–37. <https://doi.org/10.1109/TAFFC.2010.1>.
- Chi, M. T. (2009). Active-constructive-interactive: A conceptual framework for differentiating learning activities. *Topics in Cognitive Science, 1*(1), 73–105. <https://doi.org/10.1111/j.1756-8765.2008.01005.x>.

- Davidson, J., & Vanderlinde, R. (2014). Researchers and teachers learning together and from each other using video-based multimodal analysis. *British Journal of Educational Technology*, *45*(3), 451–460. <https://doi.org/10.1111/bjet.12141>.
- Efklides, A. (2011). Interactions of metacognition with motivation and affect in self-regulated learning: The MASRL model. *Educational Psychologist*, *46*(1), 6–25.
- Efklides, A., & Volet, S. (2005). Emotional experiences during learning: Multiple, situated and dynamic. *Learning and Instruction*, *15*(5), 377–380. <https://doi.org/10.1080/00461520.2011.538645>.
- Elkins, A. N., Muth, E. R., Hoover, A. W., Walker, A. D., Carpenter, T. L., & Switzer, F. S. (2009). Physiological compliance and team performance. *Applied Ergonomics*, *40*(6), 997–1003. <https://doi.org/10.1016/j.apergo.2009.02.002>.
- Fairclough, S. H., Venables, L., & Tattersall, A. (2005). The influence of task demand and learning on the psychophysiological response. *International Journal of Psychophysiology*, *56*(2), 171–184. <https://doi.org/10.1016/j.ijpsycho.2004.11.003>.
- Gendolla, G. H., & Richter, M. (2005). Ego involvement and effort: Cardiovascular, electrodermal, and performance effects. *Psychophysiology*, *42*(5), 595–603. <https://doi.org/10.1111/j.1469-8986.2005.00314.x>.
- Gillies, R. M., Carroll, A., Cunnington, R., Rafter, M., Palghat, K., Bednark, J., & Bourgeois, A. (2016). Multimodal representations during an inquiry problem-solving activity in a year 6 science class: A case study investigating cooperation, physiological arousal and belief states. *Australian Journal of Education*, *60*(2), 111–127. <https://doi.org/10.1177/0004944116650701>.
- Goetz, T., Pekrun, R., Hall, N., & Haag, L. (2006). Academic emotions from a social-cognitive perspective: Antecedents and domain specificity of students' affect in the context of Latin instruction. *British Journal of Educational Psychology*, *76*(2), 289–308. <https://doi.org/10.1348/000709905X42860>.
- Hadwin, A. F., Järvelä, S., & Miller, M. (2011). Self-regulated, co-regulated, and socially shared regulation of learning. *Handbook of Self-Regulation of Learning and Performance*, *30*, 65–84.
- Happaney, K., Zelazo, P. D., & Stuss, D. T. (2004). Development of orbitofrontal function: Current themes and future directions. *Brain and Cognition*, *55*(1), 1–10. <https://doi.org/10.1016/j.bandc.2004.01.001>.
- Henning, R. A., Boucsein, W., & Claudia Gil, M. (2001). Social-physiological compliance as a determinant of team performance. *International Journal of Psychophysiology*, *40*(3), 221–232. [https://doi.org/10.1016/S0167-8760\(00\)00190-2](https://doi.org/10.1016/S0167-8760(00)00190-2).
- Hmelo-Silver, C. E., & Barrows, H. S. (2008). Facilitating collaborative knowledge building. *Cognition and Instruction*, *26*(1), 48–94. <https://doi.org/10.1080/07370000701798495>.
- Isöhätäälä, J., Näykki, P., Järvelä, S., & Baker, M. J. (2017). Striking a balance: Socio-emotional processes during argumentation in collaborative learning interaction. *Learning, Culture and Social Interaction*. <https://doi.org/10.1016/j.lcsi.2017.09.003>.
- Janssen, J., Erkens, G., Kirschner, P. A., & Kanselaar, G. (2012). Task-related and social regulation during online collaborative learning. *Metacognition and Learning*, *7*(1), 25–43. <https://doi.org/10.1007/s11409-010-9061-5>.
- Järvelä, S., Järvenoja, H., Malmberg, J., Isöhätäälä, J., & Sobocinski, M. (2016a). How do types of interaction and phases of self-regulated learning set a stage for collaborative engagement? *Learning and Instruction*, *43*, 39–51. <https://doi.org/10.1016/j.learninstruc.2016.01.005>.
- Järvelä, S., Kirschner, P. A., Hadwin, A., Järvenoja, H., Malmberg, J., Miller, M., & Laru, J. (2016b). Socially shared regulation of learning in CSCL: Understanding and prompting individual- and group-level shared regulatory activities. *International Journal of Computer-Supported Collaborative Learning*, *11*(3), 263–280. <https://doi.org/10.1007/s11412-016-9238-2>.
- Järvelä, S., Malmberg, J., & Koivuniemi, M. (2016c). Recognizing socially shared regulation by using the temporal sequences of online chat and logs in CSCL. *Learning and Instruction*, *42*, 1–11. <https://doi.org/10.1016/j.learninstruc.2015.10.006>.
- Järvenoja, H., Volet, S., & Järvelä, S. (2013). Regulation of emotions in socially challenging learning situations: An instrument to measure the adaptive and social nature of the regulation process. *Educational Psychology*, *33*(1), 31–58. <https://doi.org/10.1080/01443410.2012.742334>.
- Järvenoja, H., Järvelä, S., & Malmberg, J. (2017). Supporting groups' emotion and motivation regulation during collaborative learning. *Learning and Instruction*. <https://doi.org/10.1016/j.learninstruc.2017.11.004>.
- Karvonen, A., Kykyri, V. L., Kaartinen, J., Penttonen, M., & Seikkula, J. (2016). Sympathetic nervous system synchrony in couple therapy. *Journal of Marital and Family Therapy*, 1–13. <https://doi.org/10.1111/jmft.12152>.

- Kreijns, K., Kirschner, P. A., & Jochems, W. (2003). Identifying the pitfalls for social interaction in computer-supported collaborative learning environments: A review of the research. *Computers in Human Behavior, 19*, 335–353. [https://doi.org/10.1016/S0747-5632\(02\)00057-2](https://doi.org/10.1016/S0747-5632(02)00057-2).
- Laru, J., Malmberg, J., Järvenoja, H., Sarenius, V.-M., & Järvelä, S. (2015). Designing simple tools for socially shared regulation: Experiences of using Google Docs and mobile SRL tools in math education. In *Proceedings of the 12th International Conference on Computer Supported Collaborative Learning*, (pp. 403–410). Gothenburg, Sweden.
- Malmberg, J., Järvelä, S., Järvenoja, H., & Panadero, E. (2015). Promoting socially shared regulation of learning in CSCL: Progress of socially shared regulation among high- and low-performing groups. *Computers in Human Behavior, 52*, 562–572. <https://doi.org/10.1016/j.chb.2015.03.082>.
- Marci, C. D., & Orr, S. P. (2006). The effect of emotional distance on psychophysiological concordance and perceived empathy between patient and interviewer. *Applied Psychophysiology and Biofeedback, 31*(2), 115–128. <https://doi.org/10.1007/s10484-006-9008-4>.
- Marci, C. D., Ham, J., Moran, E., & Orr, S. P. (2007). Physiologic correlates of perceived therapist empathy and social-emotional process during psychotherapy. *The Journal of nervous and mental disease, 195*(2), 103–111.
- McCardle, L., & Hadwin, A. F. (2015). Using multiple, contextualized data sources to measure learners' perceptions of their self-regulated learning. *Metacognition and Learning, 10*(1), 43–75. <https://doi.org/10.1007/s11409-014-9132-0>.
- McClelland, M. M., Acock, A. C., & Morrison, F. J. (2006). The impact of kindergarten learning-related skills on academic trajectories at the end of elementary school. *Early Childhood Research Quarterly, 21*, 471–490. <https://doi.org/10.1016/j.ecresq.2006.09.003>.
- McClelland, M. M., Cameron, C. E., Connor, C. M., Farris, C. L., Jewkes, A. M., & Morrison, F. J. (2007). Links between behavioral regulation and preschoolers' literacy, vocabulary, and math skills. *Developmental Psychology, 43*(4), 947–959. <https://doi.org/10.1037/0012-1649.43.4.947>.
- Mega, C., Ronconi, L., & De Beni, R. (2014). What makes a good student? How emotions, self-regulated learning, and motivation contribute to academic achievement. *Journal of Educational Psychology, 106*(1), 121. <https://doi.org/10.1037/a0033546>.
- Molenaar, I., Chiu, M. M., Slegers, P., & van Boxtel, C. (2011). Scaffolding of small groups' metacognitive activities with an avatar. *International Journal of Computer-Supported Collaborative Learning, 6*(4), 601–624. <https://doi.org/10.1007/s11412-011-9130-z>.
- Montague, E., Xu, J., & Chiou, E. (2014). Shared experiences of technology and trust: An experimental study of physiological compliance between active and passive users in technology-mediated collaborative encounters. *IEEE Transactions on Human-Machine Systems, 44*(5), 614–624. <https://doi.org/10.1109/THMS.2014.2325859>.
- Palumbo, R. V., Marraccini, M. E., Weyandt, L. L., Wilder-Smith, O., McGee, H. A., Liu, S., & Goodwin, M. S. (2016). Interpersonal autonomic physiology: A systematic review of the literature. *Personality and Social Psychology Review, 1*–43. <https://doi.org/10.1177/1088868316628405>.
- Panadero, E., & Järvelä, S. (2015). Socially shared regulation of learning: A review. *European Psychologist, 20*(3), 190–203. <https://doi.org/10.1027/1016-9040/a000226>.
- Panadero, E., Klug, J., & Järvelä, S. (2016). Third wave of measurement in the self-regulated learning field: When measurement and intervention come hand in hand. *Scandinavian Journal of Educational Research, 60*(6), 723–735. <https://doi.org/10.1080/00313831.2015.1066436>.
- Pardo, A., Han, F., & Ellis, R. A. (2017). Combining University student self-regulated learning indicators and engagement with online learning events to predict academic performance. *IEEE Transactions on Learning Technologies, 10*(1), 82–92. <https://doi.org/10.1109/TLT.2016.2639508>.
- Perry, N. E., & Winne, P. H. (2006). Learning from learning kits: gStudy traces of students' self-regulated engagements with computerized content. *Educational Psychology Review, 18*(3), 211–228.
- Pintrich, P. R. (2004). A conceptual framework for assessing motivation and self-regulated learning in college students. *Educational Psychology Review, 16*(4), 385–407. <https://doi.org/10.1007/s10648-004-0006-x>.
- Ravaja, N. (2004). Contributions of psychophysiology to media research: Review and recall paradigm. *International Journal of Human-Computer Studies, 67*(8), 607–627.
- Reimann, P., Markauskaite, L., & Bannert, M. (2014). E-research and learning theory: What do sequence and process mining methods contribute? *British Journal of Educational Technology, 45*(3), 528–540. <https://doi.org/10.1111/bjet.12146>.
- Schellings, G., & Van Hout-Wolters, B. (2011). Measuring strategy use with self-report instruments: Theoretical and empirical considerations. *Metacognition and Learning, 6*(2), 83–90. <https://doi.org/10.1007/s11409-011-9081-9>.

- Schunk, D., & Greene, J. A. (2017). *Handbook of self-regulation of learning and performance*. New York: Routledge.
- Schunk, D. H., & Zimmerman, B. J. (2008). Motivation: An essential dimension of self-regulated learning. In D. H. Schunk & B. J. Zimmerman (Eds.), *Motivation and self-regulated learning: Theory, research, and applications* (pp. 245–266). New York: Erlbaum.
- Schwinger, M., Steinmayr, R., & Spinath, B. (2009). How do motivational regulation strategies affect achievement: Mediated by effort management and moderated by intelligence. *Learning and Individual Differences, 19*(4), 621–627. <https://doi.org/10.1016/j.lindif.2009.08.006>.
- Sektman, M., McClelland, M. M., Acock, A., & Morrison, F. J. (2010). Relations between early family risk, children's behavioral regulation, and academic achievement. *Early Childhood Research Quarterly, 25*(4), 464–479. <https://doi.org/10.1016/j.ecresq.2010.02.005>.
- Volet, S., Vauras, M., & Salonen, P. (2009). Self- and social regulation in learning contexts: An integrative perspective. *Educational Psychologist, 44*(4), 215–226. <https://doi.org/10.1080/00461520903213584>.
- Walker, A. D., Muth, E. R., Switzer, F. S., & Rosopa, P. J. (2012). Predicting team performance in a dynamic environment: A team psychophysiological approach to measuring cognitive readiness. *Journal of Cognitive Engineering and Decision Making, 7*(1), 69–82. <https://doi.org/10.1177/1555343412444733>.
- Webster, E. A., & Hadwin, A. F. (2015). Emotions and emotion regulation in undergraduate studying: Examining students' reports from a self-regulated learning perspective. *Educational Psychology, 35*(7), 794–818. <https://doi.org/10.1080/01443410.2014.895292>.
- Winne, P. H. (2017). Leveraging big data to help each learner and accelerate learning science. *Teachers College Record, 119*(3), 1–24.
- Winne, P., & Perry, N. (2000). Measuring self-regulated learning. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 531–566). San Diego: Academic.
- Wolters, C. A. (2003). Regulation of motivation: Evaluating an underemphasized aspect of self-regulated learning. *Educational Psychologist, 38*(4), 189–205. https://doi.org/10.1207/S15326985EP3804_1.
- Zhao, K., & Chan, C. K. (2014). Fostering collective and individual learning through knowledge building. *International Journal of Computer-Supported Collaborative Learning, 9*(1), 63–95. <https://doi.org/10.1007/s11412-013-9188-x>.
- Zimmerman, B. J. (2008). Investigating self-regulation and motivation: Historical background, methodological developments, and future prospects. *American Educational Research Journal, 45*(1), 166–183. <https://doi.org/10.3102/0002831207312909>.

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.