Chapter 7
How Learning Process Data Can Inform Regulation in Collaborative Learning Practice

Sanna Järvelä, Eija Vuorenmaa, Ahsen Çini, Jonna Malmberg, and Hanna Järvenoja

7.1 Introduction

Computer supported collaborative learning (CSCL) has been implemented as part of various teaching and learning models, face-to-face, on-line and hybrid, at different educational levels and in work-life teams. Global changes in educational landscape are pushing a need for empowering learners as agentic participants in communities of learners (Rosé & Järvelä, 2020). Collaborative learning (CL) is a powerful way of enhancing individual learning and can also be effective in developing group working skills and practices. The social construction of knowledge is commonly made via collaborative efforts through dialogues and interactions and facilitated by differences in persons' perspectives (Roschelle & Teasley, 1995).

Transactive activities play a crucial role in CL (Kirschner et al., 2018). Learning is likely to occur in these synchronous and asynchronous activities when the collaborating students engage in transactive discourse, such as criticizing, challenging positions, and making mutual thoughts via discussion, because this form of discourse gives rise to cognitive activities that stimulate knowledge construction (Popov et al., 2017). Still, CL effort is influenced by how well students coordinate their activities across time and transact with each other's ideas (Schwartz, 1995). This is where regulation of CL plays a role.

Effective CL requires group members to ensure that they work toward the shared goals and reveal to each other when they become aware that their collaboration is not heading toward the shared goals. In successful cases, learners negotiate shared

S. Järvelä (✉) · E. Vuorenmaa · A. Çini · J. Malmberg · H. Järvenoja
University of Oulu, Oulu, Finland
e-mail: sanna.jarvela@oulu.fi; eija.vuorenmaa@oulu.fi; ahsen.cini@oulu.fi; jonna.malmberg@oulu.fi; hanna.jarvenoja@oulu.fi

O. Viberg, Å. Grönlund (eds.), *Practicable Learning Analytics*,
Advances in Analytics for Learning and Teaching,
https://doi.org/10.1007/978-3-031-27646-0_7

goals to ensure they all work toward the same outcome (Järvelä et al., 2018), maintain a positive socioemotional atmosphere to ensure fluent collaboration (Lajoie et al., 2015), and finally, coordinate and ensure that each member is responsible for the joint outcome of their collaborative task (Lin, 2018).

Socially shared regulation in learning (SSRL) (Hadwin et al., 2018) development has been guided by Winne and Hadwin's (1998) model, which describes self-regulated learning (SRL) as a cyclical feedback loop where metacognition is an "engine" that operates in the process of learning and activates regulation. SSRL empowers individuals and peers to have successful collective participation in groups and affords their collective agency and goal setting, proactive skill training for individual adaptation, and working in teams, as well guidelines for leveraging technologies for supporting human learning (Järvelä et al., 2021).

We have been studying when, how, and what makes regulation in CL functional, aiming to understand the process of collaboration so that we could better inform learners and teachers in practice. Understanding regulation in CL is still a challenge. Firstly, regulation in learning is a complex metacognitive level mental effort and, therefore, difficult to capture (Malmberg et al., 2019). Secondly, regulation in CL is a temporal and sequential process that needs to be characterized to guide participation timely and facilitate interactions (Vogel et al., 2022). Because there is more data available in today's digitalized tools and educational environments that could be leveraged to understand self-regulated learning process (Nguyen et al., 2021), computational methods and learning analytics (LA) allow us to study tendencies and patterns which help to characterize temporal processes of some core phenomena (Cukurova et al., 2018).

To understand the complex process of regulation in CL, we have been working by gathering and analysing multimodal data about self-regulated learning with intelligent learning technologies (Järvelä et al., 2021). Several data modalities from different channels have been collected to investigate the cognitive, metacognitive, emotional, and social processes related to learning regulation at both individual and group levels. These data include, e.g., tracking logs, video, audio, and physiological data such as electrodermal activity (EDA) and heart rate. With interdisciplinary efforts (Järvelä et al., 2020) we are progressing with the alignment between theoretical notions, data structures, and methodological assumptions underlying techniques used to analyse the data (Dindar et al., 2022).

Our research has shown that the role of metacognitive monitoring in CL is pivotal (Haataja et al., 2021). Metacognitive monitoring is always an internal mental process, but in collaborative situations, it can be externalized and possibly shared via interactions with other group members (Dindar et al., 2020b). The aim of this chapter is to discuss metacognitive awareness and participation in cognitive and socio-emotional interaction as essential aspects to support, while being the complex processes in CL. Collecting multimodal data about these processes and implementing LA can simplify the complex phenomena for researchers to understand and provide practical help to learning and teachers.

7.2 What Makes Regulation in Collaborative Learning Complex?

Collaborative groups can be considered systems where the cognitive, emotional, motivational, and behavioural states of the group and its' members are related to each other and in constant flux. In group interactions, the experiences of group members and the interpretations they give to the interactions frame the unique group dynamics (Järvenoja et al., 2013; Rogat & Adams-Wiggins, 2014). Understanding regulation in these collaboration settings requires comprehending their multifaceted relations not only between cognition, emotions, and motivation that take place while a group of people collaborate to learn, but also in relation to individual group members' personal history, experiences, and attitudes (Boekaerts & Pekrun, 2015; Järvenoja et al., 2018). For example, affective reactions in a learning situation build on and are built upon the cognitive appraisals and motivational beliefs individuals assign to situations (Frijda et al., 2000; Shuman & Scherer, 2014).

What makes CL particularly complex is the social context and interaction that constantly (re)shape the social plain for collaboration and individual appraisals. Previous research has addressed collaboration from different angles showing, for example, how affective states fluctuate throughout the learning situation in relation to social interactions (Bakhtiar et al., 2018; Pijeira-Díaz et al., 2019; Törmänen et al., 2021), and how group members construct knowledge together in constant exchange through negotiation and sharing of knowledge (Hmelo-Silver & Barrows, 2008; Kreijns et al., 2003; Mitchell et al., 2014; Scardamalia & Bereiter, 2014). All these different processes are essential for successful collaboration, and regulation of them is vital when these processes are jeopardized (Hadwin et al., 2018). Moreover, regulation in CL contexts is temporally alternating (Lee et al., 2014), calling evidently multimodal data to unpack the reasons, processes, and consequences of coordinated group regulation for overcoming challenges and adapting learning and interaction to progress with their goals (Azevedo et al., 2016; D'Mello et al., 2017; Sobocinski et al., 2017). Previous studies have provided preliminary evidence of how progress in CL requires conscious regulation of cognition, behaviour, and affect at both individual and group levels, targeting, for example, temporal fluctuation and sequential relationship of co- and socially shared regulation of cognition, emotions, and motivation (Fischer & Järvelä, 2014; Molenaar & Chiu, 2014). These results emphasize the focal role of metacognitive awareness between the group members.

7.2.1 The Role of Metacognition in Awareness of Regulation Needs

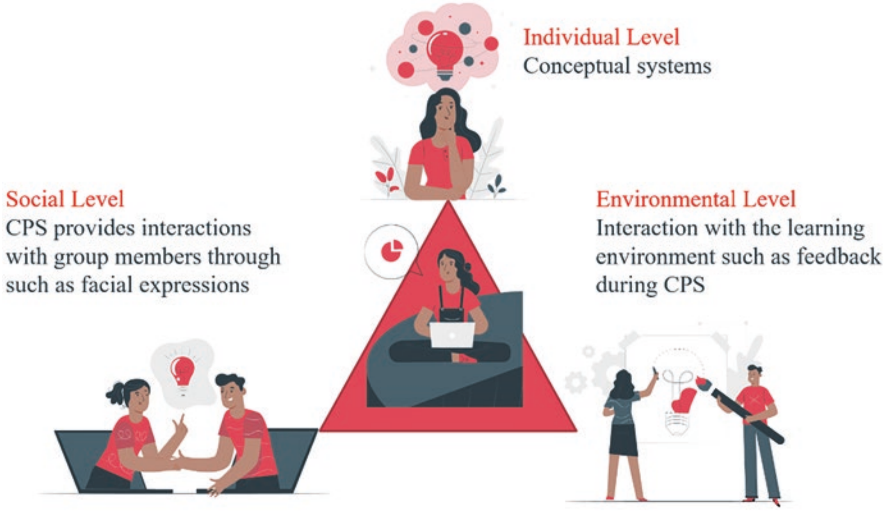
Metacognition enables students to determine weaknesses that can be addressed and regulated. Therefore, metacognition and especially building on metacognitive awareness enhance students' abilities for better regulation (Schraw, 1998). In the context of CL, learners can externalize their thinking processes and make their metacognition visible by sharing their thoughts on a social plane (Hadwin et al., 2017). Earlier research has shown that, for example, students' views of their task perceptions might vary which might lead to different views in terms of how the collaborative task should be done and how it should look like (Bakhtiar et al., 2018). In addition, when perceptions of task understanding are shared in the context of CL group members gain information not only about their own perceptions for learning, but also those of other group members. Therefore, externalizing perceptions of task understanding can be informative when guiding regulation of learning and inviting group members for socially shared regulation of learning (Iiskala et al., 2011). Students find the task easier and they understand it better once their CL has progressed and their content knowledge has increased (Çini et al., 2020). These findings align with SRL theory (Winne & Hadwin, 1998) which explain that regulation involves a cyclical loop, which allows learners to define and re-define their evolving understanding of the task as they co-construct interpretations of the collaborative task by externalizing their metacognition (Malmberg et al., 2017; Miller & Hadwin, 2015).

While students can be metacognitively aware of their cognition, motivation, emotions, or behaviour (Hadwin et al., 2017), it is possible that they do not even recognize the need for regulation (Malmberg et al., 2015). For this reason, there has been a body of empirical research that has developed ways and methods to increase metacognitive awareness. Despite the methodological progress in the field of education, the field still struggles to promote metacognitive awareness timely. Because of that, there has been a growing tendency toward using LA and Educational Data Mining (EDM), especially in the field of SRL (ElSayed et al., 2019). The premise of LA in the field of education is that, for example, the data resulting from on-line learning systems can be used to predict the learning outcomes (Di Mitri et al., 2017), recognize traces or processes of various learners (Jovanović et al., 2017), or enable learners to reflect about their actual learning activities (Poitras et al., 2017). Ultimately, the purpose of LA or EDM is to develop new ways to support learners to develop their SRL by in various contexts by providing scripts, prompts or guidance for learning processes. For example, Sonnenberg and Bannert (2015) investigated how applying metacognitive prompts affect learning performance and the appearance of phases of regulated learning. They found that metacognitive prompts assist not only with the learning performance but also that compared to low-performing students, high-performing students showed more frequent changes between phases of regulation, such as planning and task enactment. Similarly, a study by Malmberg et al. (2017) showed that metacognitive monitoring promoted task enactment, which eventually provided grounding for socially shared regulation to occur.

Earlier work promoting metacognitive awareness has focused on planning and reflection tools for prompting individual and group planning and reflection processes (Sonnenberg & Bannert, 2019; Hadwin et al., 2018), providing visualisations of individuals and group members emotional, cognitive, and motivational states (Järvelä et al., 2016b; Phielix et al., 2011) or prompting collaborating group members to collectively think how the group could enhance their cognition, motivation of emotions in their CL (Vogel et al., 2022; Järvenoja et al., 2020). These awareness tools have been designed to support regulation by prompting learners and groups to increase awareness of their own, others', and their group's metacognition and externalise their own, others', and their group's learning processes in a social plane, and activate key regulation processes, such as setting goals, making plans, adopting strategies, and monitoring and evaluating. Promoting metacognitive awareness begins with building awareness among learners that metacognition exists (Schraw, 1998). Learners are not often aware of challenges that occur during learning, and therefore learners' ability to engage in metacognitive monitoring is a key to successful regulation (Winne & Hadwin, 2008). However, metacognitive monitoring might be misleading if learners cannot connect what they think they are doing versus what they did (Winne & Jamieson-Noel, 2002). In such scenarios, for example, LA or traces collected from on-line learning system could help learners to accurately reflect their activities and how those activities relate to performance. Recently Vogel et al. (2022) examined the effects of adaptable scripts in the context of CL. What their study results showed, was that scripts were partly helpful for students with higher levels of self-regulation skills. This is to say, the ways how support is provided for the learners depends on their SRL and metacognitive awareness.

7.2.2 How Multiple Levels of Metacognitive Awareness Operate in Collaborative Problem Solving

Since metacognitive awareness is "thinking about your thinking" and learning developing "introspection" that can be facilitated by external sources in addition to internal ones. When individuals work in collaborative groups, they evaluate their own and group members' ideas through task processing and activating their metacognitive awareness (Hurme et al., 2009). In other words, metacognition is an individual process, but it cannot be explained exclusively by individualistic conceptions, especially in a collaborative group context (See Picture 7.1). At the *individual level*, the sources of metacognitive awareness are the conceptual systems of individuals (Lesh & Doerr, 2003). For example, we can regulate and control our learning with planning, monitoring, information management skills, and evaluation. At the *social level,* the sources of metacognitive awareness are one's interaction with others (Taub et al., 2021). In practice, interactions with peers and teachers, students can be encouraged to retest their current thinking, monitor their current level of knowledge and understanding, and detect and correct their misconceptions. For example, consider a collaborative problem-solving task, which provides sharing knowledge construction through interactions in written and spoken language, body movements, facial expressions, and manipulation of the task conditions by the computer. At the *environmental level*, metacognitive awareness sources are the one's interaction with the learning environment, such as classroom activities, task complexity/difficulty, stages of problem-solving, and multiple cycles of feedback, where students criticize and revise each other's thinking (Kim et al., 2013).



Picture 7.1 Multiple levels of metacognitive awareness

While metacognition has been traditionally studied with rather a static approach, e.g., self-reports, different kind of data and analytics could be used to understand multiple levels of metacognitive awareness, and more ways to facilitate, support and train metacognitive awareness in practice could be developed. Çini et al. (2022) studied how metacognitive awareness at individual, social and environmental levels is associated with collaborative problem solving (CPS) task performance and related to facial expressions. Seventy-seven higher education students collaborated in triads on a computer-based simulation about running a fictional company for 12 simulated months. Both static and dynamic measures were used in this study, such as traditional questionnaire, situated self-reports, and facial recognition implemented from video data to reveal multiple levels of metacognitive awareness in a collaborative context. The individual level of metacognitive awareness was measured with Metacognitive Awareness Inventory (MAI) (Schraw & Dennison, 1994). The sources of metacognitive awareness at the social level, i.e., metacognitive judgements and the perception of task difficulty, were measured through situated self-reports applied during collaboration multiple times. Finally, a complex CPS process with multiple feedback provided during the simulation-based CPS task ensuring the learners a place to implement, develop and provoke various metacognitive processes was used to measure the environmental level of metacognitive awareness. Group members' interactions for 96 min (SD 28.08) collaboration was further video recorded. Perceived individual and group performance were measured with self-reports at the end of the CPS task. A structural equation modelling (SEM) was conducted to observe the relationships between the multiple levels of metacognitive awareness and CPS performance. In addition to that, three-level multilevel modelling was used to understand the effect of environmental source of metacognitive awareness in the CPS environment.

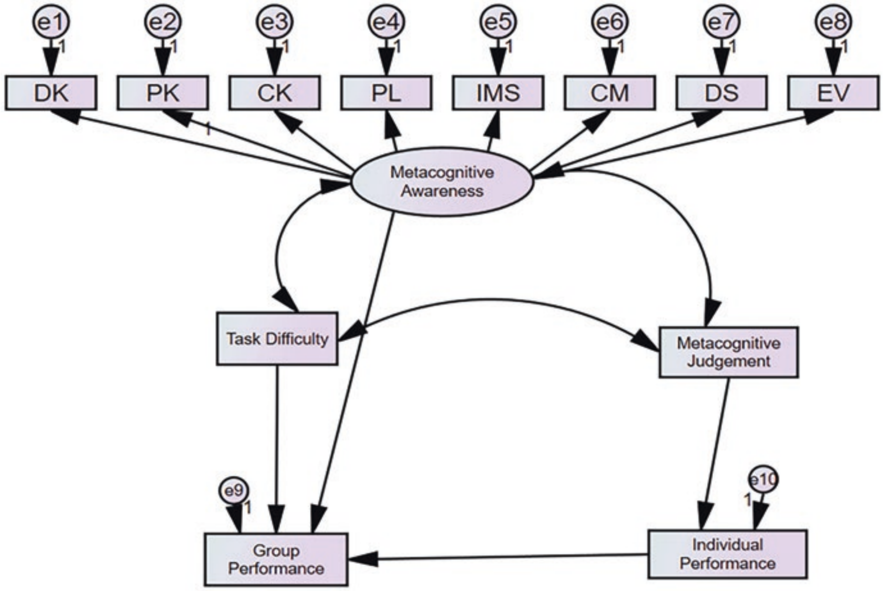


Fig. 7.1 Structural Equation Model (SEM) of relationships between multiple levels of metacognitive awareness and performance. (From: Çini, A, Järvelä, S, Dindar, M & Malmberg, J 2022, 'How multiple levels of metacognitive awareness operate in collaborative problem solving [Manuscript under preparation]', Learning & Educational Technology Research Unit (LET), University of Oulu. Note. *DK* declarative knowledge, *PK* procedural knowledge, *CK* conditional knowledge, *PL* planning, *IMS* information management strategies, *CM* comprehension monitoring, *DS* debugging strategies, *EV* evaluation)

The structural equation analysis was conducted to test the effect of individual and social levels of metacognitive awareness on perceived individual and group collaborative performance at an individual level (See Fig. 7.1). In addition to that, three-level multilevel modelling was used, which provides a useful framework for thinking about problems with this type of hierarchical structure: Level 1 (time: participants' responses to the metacognitive judgement and task difficulty questions and their facial expressions at the feedback times); Level 2 (individuals) and Level 3 (groups in collaborative learning). In all sub-questions, the dependent variable is feedback.

Çini et al. (2022) study indicates that the sources of metacognitive awareness at individual and social level predict collaboratively perceived group performance. Earlier research shows that learners' individual metacognitive awareness does not predict learning outcomes at an individual level (Çini et al., 2020). However, this study extended earlier research and examined the effects of different aspects of metacognitive awareness to collaborative performance and found a direct effect from individual metacognitive awareness to perceived group performance at an individual level. Similarly, Dindar et al. (2020a, b) highlighted the importance of metacognitive experiences in successful CPS. Also, this study contributes it via focusing on feedback as an environmental source of metacognitive awareness to understand more about metacognitive awareness in CL specifically in CPS. According to three-level multilevel modelling, feedback predicts metacognitive judgements and facial expressions in the CPS environment but does not predict the perception of task difficulty. A closer look at the results of the relationship between feedback and facial expression and metacognitive judgement indicates that facial expressions are indicators of judgement of confidence. In other words, facial expression recognition makes visible these and, thus, can add a new data channel and methodological means to understand metacognitive awareness.

This study shows the importance of metacognitive awareness for CPS since the results indicate that interaction with the learning environment is a potential source encouraging students to develop metacognitive ability. These interactions help students unpack misconceptions and repair them through metacognitive processes operating at both the individual and social levels. In collaborative contexts such as CPS, students often have difficulties evaluating their own solutions, but peers can help with this evaluation. They evaluate each other's ideas, serving a metacognitive role for one another (Goos et al., 2002; Hurme et al., 2009) via facial expressions, as was seen in this study. Some other studies show the importance of facial expression for intelligent tutoring systems for practical help in student metacognitive awareness. For example, estimating student's perception of lesson difficulty and student's preference about lesson's speed while watching it (Whitehill et al., 2008). Çini et al. (2022) study add that if multiple level of data and advanced analytics are implemented novel awareness tools/tutors that support effective collaboration during complex problem solving can be developed by studying different aspects of metacognitive awareness.

7.2.3 Implementing Process Mining to Characterize the Role of Participation in Cognitive and Socio-emotional Interactions for Regulation

As noted, regulation plays a role in adaptive process of CL (e.g. Sobocinski et al., 2017). Previous research also reports about the sequential patterns of regulatory processes, such as patterns and strategies in students' self-regulation (Bannert et al., 2014) or sequential interconnection between regulation and cognition in collaborative learning (Molenaar & Chiu, 2014). As CL evolves over time in social interactions among learners (Kirschner et al., 2018), investigating patterns in regulatory processes as such may not be enough to understand the role of regulation in CL, but more is needed to know about what kinds of interaction patterns may precede or follow regulation in context. Characterizing the role of learners' participation in these processes will add, since it acts as a key mechanism in collaboration. For example, favourable participation is known to enhance group productivity and learner achievement during collaboration (Cohen, 1994), whereas problems in participation (e.g., some group members invest little to no effort in group work) can hinder collaboration (Karau & Wilhau, 2020). Participation refers to learner's contribution to verbal communications and interactive exchanges in the group (Clark & Brennan, 1991) and it plays a role in cognitive interaction, enabling learners to discuss and analyse their domain-focused content knowledge (Baker, 1999), as well as in socio-emotional interaction, through which learners can share their emotions and build group's socio-emotional climate (Sinha et al., 2015).

Previous research has suggested that regulation of learning may relate to how individual learners or group participates in collaborative interactions, and highlighted, for example, equal participation (Grau & Whitebread, 2012), all group members' contribution (Iiskala et al., 2015), and active and cohesive interactions (Sinha et al., 2015). However, these studies still have not been able to explain the temporal processes or relations of regulation, interactions, and participation. If we understood more about the time-related patterns of these processes, more could be learned about how and when to support collaborative groups in their interactions so that they facilitate regulation of learning when needed. We have implemented process mining to reveal how regulation emerges in time-related cognitive and socio-emotional interaction processes during collaborative learning. Process mining aims is to discover, monitor, and advance real-life processes by using information from event logs. It utilizes sequentially recorded events where each event represents an activity that is related to a certain case (van der Aalst, 2011), and generalized visualization of the sequences, their interconnections, and patterns are represented in a process model (Reimann et al., 2009). While process mining techniques are traditionally used in computer science, they can also be utilized in educational context to explore learning processes, such as regulation of learning (Bannert et al., 2014). The value of utilizing process mining in educational context is that it can discover the most dominant real-life processes that the learner(s) or small group(s) engage in during a certain learning process, which can help in recognizing, for example, what kind of group interactions may enable or hinder regulation of learning. Next, we introduce in more detail how process mining was used in our research to reveal favourable participation and interaction patterns for regulation in CL context.

Vuorenmaa et al. (2022) investigated the sequential patterns in groups' social interactions for group-level regulation during CL tasks. The participants were secondary school students (N = 92, 29 groups of three to four students) performing various collaborative light and sound related tasks during a physics course. The data collection was implemented in the students' own classroom, where the student groups were videotaped for five 90-min sessions over 8 weeks. In all, 175 h and 30 min of video recorded data were analysed with Observer XT12 data analysis software regarding participation, cognitive and socio-emotional interactions, and co- and socially shared regulation (i.e., group-level regulation) (Bakhtiar et al., 2018; Hadwin et al., 2018; Järvelä et al., 2016a, c; Rogat & Linnenbrink-Garcia, 2011). For the participation, interaction, and regulation coding, the video data were divided into 30-s sequences since it was long enough to include relevant interactions, enable detailed observations, and make valid judgments of behaviour. The coding categories were not mutually exclusive and could occur parallel to each other in different combinations. Based on the interactivity coding, three social interaction states were defined in the sequences: simultaneous cognitive and socio-emotional interaction (COG & SOC-EM), cognitive interaction (COG), and socio-emotional interaction (SOC-EM). Two participation levels, whole group (WHOLE), and partial group (PART), were identified in the sequences, characterizing the intensity of groups' participation in the interactions. After this, the concurrence between group-level regulation types and social interaction states (including participation level) was investigated. The analysis was continued by utilizing process mining with the help of Fluxicon's Disco analysis software (https://fluxicon.com/disco/) to investigate the sequential interaction and participation patterns for group-level regulation in CL. This was done by using the 30-s sequences before, during, and after each observed group-level regulation sequence. Since process models can illustrate each possible interconnection and path of extremely complex real-life processes, the models require simplification (Dolak, 2019; Malmberg et al., 2015). Thus, it was decided to focus on the most frequent emergence of group-level regulation in social interaction states and participation levels. The level of activities and paths was restricted to show only the strongest, most frequent paths of interconnectivity. However, the sequences before and after regulation were not restricted in terms of regulation, interaction, or participation, allowing all possible combinations of these facets to emerge in the preceding and following sequences of regulation. These procedures enabled us to find the strongest patterns for regulation in a relevant interaction state. Figure 7.2 presents an example of a process model dealing with collaborative interactions and regulation by characterizing the strongest patterns between social interaction states and SSRL. It demonstrates that the SSRL episode most frequently started with a state of simultaneous cognitive and socio-emotional interaction with whole group participation (COG & SOC-EM & WHOLE, f = 48), and was followed by SSRL in the same interaction state (f = 68 for occurrence and f = 24 for path), again continuing with simultaneous interaction and whole group participation (f = 26 for path).

The example in Fig. 7.2 shows how SSRL emerged the most frequently, when the groups' collaboration included both cognitive and socio-emotional interaction on a whole group participation level. Overall, Vuorenmaa et al. (2022) results highlight how regulation of learning, which is fuelled by metacognition, is related to cognitive processes that can be captured through cognitive interactions in group settings. However, in collaborative settings regulating merely cognitive processes is not sufficient, since learners in groups can experience a range of emotions regarding for example the task, other group members or the group's joint strategies (Lobczowski, 2020), thus, the interplay of both cognitive and socio-emotional interactions during SSRL process can be seen in the example. Implementing learning process analytics, as the process model in this example, can elaborate the earlier findings, which have highlighted that SSRL is a jointly constructed group-level process which requires reciprocal exchanges between learners (Iiskala et al., 2015; Järvenoja & Järvelä, 2013). It can be seen from the example, that SSRL not only emerges the most frequently, when the whole group is actively engaging in cognitive and socio-emotional interactions, but similar participation and interaction processes also precede and follow SSRL. These kinds of results that reveal time-related

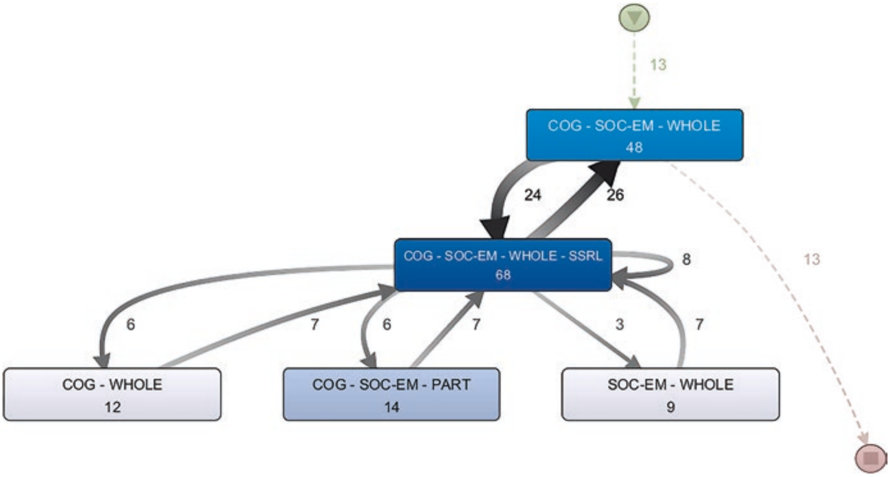


Fig. 7.2 A process model illustration of SSRL episodes. (From: Vuorenmaa, E, Järvelä, S, Dindar, M & Järvenoja, H (2022), 'Sequential patterns in social interaction states for regulation in collaborative learning', Small Group Research)

interaction processes in CL can help in defining characteristics of participation in social processes that can facilitate SSRL during collaborative process. With this understanding for example teachers can plan their CL designs to give more adequate and timely support to learners in small groups so that they can engage in cognitive and socio-emotional interactions, proceed with the task collectively, and maintain a positive socio-emotional group climate. Receiving timely support for cognitive and socio-emotional processes can eventually help learners to learn how to adapt in continuously changing learning situations.

7.3 Conclusions

Decade of research on regulation in CL has shown that regulation is a crucial process for making the maladaptive process of CL more adaptive (Järvelä & Hadwin, 2013; Volet et al., 2009). MMLA are showing promise to reveal new understanding of the temporal and sequential aspects of regulation in CL (Saint et al., 2022) in designing and utilizing various learning technologies and tools to support regulation in learning and tailoring just-in-time support for teachers and learners (Martinez-Maldonado, 2019).

When considering CL as a temporal, social interaction process, understanding the patterns of the type of social interaction (e.g., Vuorenmaa et al., 2022) can explain what are the targets that need regulation, whether it is cognitive processes, socioemotional conflicts, or motivational problems. For this MMLA can provide many new means, for example, measuring the intensity of students' CL from their observable interactions as Cukurova et al. (2020). They used video data and bodily gestures to measure students' CL showing that the nature of the bodily gestures, such as hands distance and distance between collaborating group members' faces predicted collaborating groups learning outcomes. Similarly, Tang et al. (2022) used video data to investigate quality of CL and electroencephalogram (EEG) to measure students' attention. Their study revealed that intensity of attention was related to learning outcomes and especially in CL situations where students' collective efforts we aligned between the group members. In addition, Malmberg et al. (2019) measured occasions of physiological synchrony from collaborating groups EDA and verified from the video data what actually happens in those situations. This study revealed that in those occasions the students struggled with the learning task.

Empirical research and conceptualisation of regulation in CL calls a need for teachers or other intelligent systems to monitor student collaborative interactions and intervene so that support for metacognitive awareness, active and reciprocal interactions can be provided when needed (Strauß & Rummel, 2021). Interactions with and about "metacognitive awareness" can help practitioners in recognizing problems during the learning process that may hinder regulation and help in reacting to them appropriately at an early stage. Çini et al. (2022) study suggest that with the help of multiple level of metacognitive awareness data, systems could be created when students are having trouble understanding the tasks. Further studies can help identify the optimal design of awareness tools to prompt both metacognitive awareness and SRL skills. It is also important to keep in mind that the field of MMLA is still in its early stages and requires in details operationalisation and empirical research to utilize its potential in education (Alwahaby et al., 2022).

Collecting multimodal data and implementing learning process analytics has helped us to proceed in our SSRL research so that both inductive and deductive analyses have complemented our understanding about metacognitive level components in regulation and social interaction processes in collaborative learning. While detailed qualitative analyses have uncovered contextual interactions, process models have revealed patterns, sequences, and regularities. For example, capturing participation and social dimensions in collaboration through social network analysis could add to understanding student participation (Saqr et al., 2020). Currently, we aim to investigate how machine learning techniques could be implemented to examine the multiple facets and processes of regulation in learning. For example, Nguyen et al. (2022) used the artificial intelligence (AI) deep learning approach on multimodal data to detect regulatory interactions for successful and less successful groups in CL, hence predicting and supporting CL success.

In today's education, digital tools will have much data available and with the help of LA and AI-based methods we can create a deeper understanding of the learning process. More these sources of data can provide means for researchers to examine the frequency, timing and sequence of regulatory traces situated in authentic learning activities to identify learners or teams that might be struggling and provide timely intervention or prompts to deploy regulatory strategies as needed.

References

Alwahaby, H., Cukurova, M., Papamitsiou, Z., & Giannakos, M. (2022). The evidence of impact and ethical considerations of Multimodal Learning Analytics: A Systematic Literature Review. *The Multimodal Learning Analytics Handbook,* 289–325.

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). Springer.

Baker, M. J. (1999). Argumentation and constructive interaction. In P. Coirier & J. Andriessen (Eds.), *Studies in writing: Foundations of argumentative text processing* (pp. 179–202). University of Amsterdam Press.

Bakhtiar, A., Webster, E. A., & Hadwin, A. F. (2018). Regulation and socio-emotional interactions in positive and a negative group climate. *Metacognition and Learning, 13*, 57–90.

Bannert, M., Reimann, P., & Sonnenberg, C. (2014). Process mining techniques for analysing patterns and strategies in students' self-regulated learning. *Metacognition and Learning, 9*(2), 161–185.

Boekaerts, M., & Pekrun, R. (2015). Emotions and emotion regulation in academic settings. In L. Corno & E. M. Anderman (Eds.), *Handbook of educational psychology* (pp. 76–90). Routledge.

Clark, H. H., & Brennan, S. E. (1991). Grounding in communication. In L. B. Resnick, J. M. Levine, & S. D. Teasley (Eds.), *Perspectives on Socially Shared Cognition* (pp. 127–149). American Psychological Association.

Cohen, E. G. (1994). Restructuring the classroom: Conditions for productive small groups. *Review of Educational Research, 64*, 1–35.

Cukurova, M., Luckin, R., Millán, E., & Mavrikis, M. (2018). The NISPI framework: Analysing collaborative problem-solving from students' physical interactions. *Computers & Education, 116*, 93–109.

Cukurova, M., Zhou, Q., Spikol, D., & Landolfi, L. (2020, March). Modelling collaborative problem-solving competence with transparent learning analytics: Is video data enough?. In *Proceedings of the tenth international conference on learning analytics & knowledge* (pp. 270–275).

Çini, A., Malmberg, J., & Järvelä, S. (2020). How individual metacognitive awareness relates to situation-specific metacognitive interpretations of collaborative learning tasks. *Educational Studies*, 1–22.

Çini, A., Järvelä, S., Dindar, M., & Malmberg, J. (2022). *How multiple levels of metacognitive awareness operate in collaborative problem solving* [Manuscript under preparation]. Learning & Educational Technology Research Unit (LET), University of Oulu.

D'Mello, S., Dieterle, E., & Duckworth, A. (2017). Advanced, analytic, automated (AAA) measurement of engagement during learning. *Educational Psychologist, 52*(2), 104–123.

Di Mitri, D., Scheffel, M., Drachsler, H., Börner, D., Ternier, S., & Specht, M. (2017). Learning pulse: a machine learning approach for predicting performance in self-regulated learning using multimodal data. In *Proceedings of the seventh international learning analytics & knowledge conference* (pp. 188–197).

Dindar, M., Järvelä, S., & Haataja, E. (2020a). What does physiological synchrony reveal about metacognitive experiences and group performance? *British Journal of Educational Technology, 51*(5), 1577–1596.

Dindar, M., Järvelä, S., & Järvenoja, H. (2020b). Interplay of metacognitive experiences and performance in collaborative problem solving. *Computers & Education, 154*, 103922.

Dindar, M., Järvelä, S., Nguyen, A., Haataja, E., & İricioğlu, A. Ç. (2022). Detecting shared physiological arousal events in collaborative problem solving. *Contemporary Educational Psychology, 69*, 102050.

Dolak, R. (2019). Using process mining techniques to discover student's activities, navigation paths, and behavior in lms moodle. In *International Conference on Innovative Technologies and Learning* (pp. 129–138). Springer.

ElSayed, A. A., Caeiro-Rodríguez, M., MikicFonte, F. A., & Llamas-Nistal, M. (2019). Research in learning analytics and educational data mining to measure self-regulated learning: A systematic review. In *World conference on mobile and contextual learning* (pp. 46–53).

Ferguson, R., & Clow, D. (2015). Consistent commitment: Patterns of engagement across time in massive open online courses (MOOCs). *Journal of Learning Analytics, 2*(3), 55–80.

Fischer, F., & Järvelä, S. (2014). Methodological advances in research on learning and instruction and in the learning sciences. *Frontline Learning Research, 2*(4), 1–6.

Frijda, N. H., Manstead, A. S. R., & Bem, S. (2000). The influence of emotions on beliefs. In N. H. Frijda, A. S. R. Manstead, & S. Bem (Eds.), *Emotions and beliefs: How feelings influence thoughts* (pp. 1–9). Cambridge University Press.

Goos, M., Galbraith, P., & Renshaw, P. (2002). Socially mediated metacognition: Creating collaborative zones of proximal development in small group problem solving. *Educational Studies in Mathematics, 49*(2), 193–223.

Grau, V., & Whitebread, D. (2012). Self and social regulation of learning during collaborative activities in the classroom: The interplay of individual and group cognition. *Learning and Instruction, 22*, 401–412.

Haataja, E., Malmberg, J., Dindar, M., & Järvelä, S. (2021). The pivotal role of monitoring for collaborative problem solving seen in interaction, performance, and interpersonal physiology. *Metacognition and Learning, 17*(8), 1–28.

Hadwin, A. F., Järvelä, S., & Miller, M. (2017). Self-regulation, co-regulation and shared regulation in collaborative learning environments. In D. H. Schunk & J. A. Greene (Eds.), *Handbook of self-regulation of learning and performance* (pp. 83–106). Routledge.

Hadwin, A. F., Bakhtiar, A., & Miller, M. (2018). Challenges in online collaboration: Effects of scripting shared task perceptions. *International Journal of Computer-Supported Collaborative Learning, 13*, 301–329.

Hmelo-Silver, C. E., & Barrows, H. S. (2008). Facilitating collaborative knowledge building. *Cognition and Instruction, 26*(1), 48–94.

Hurme, T. R., Merenluoto, K., & Järvelä, S. (2009). Socially shared metacognition of pre-service primary teachers in a computer-supported mathematics course and their feelings of task difficulty: A case study. *Educational Research and Evaluation, 15*(5), 503–524.

Iiskala, T., Vauras, M., Lehtinen, E., & Salonen, P. (2011). Socially shared metacognition of dyads of pupils in collaborative mathematical problem-solving processes. *Learning and Instruction, 21*(3), 379–393.

Iiskala, T., Volet, S. E., Lehtinen, E., & Vauras, M. (2015). Socially shared metacognitive regulation in asynchronous CSCL in science: Functions, evolution and participation. *Frontline Learning Research, 3*, 78–111.

Järvelä, S., & Hadwin, A. F. (2013). New frontiers: Regulating learning in CSCL. *Educational Psychologist: Theoretical Underpinnings of Successful Computer-Supported Collaborative Learning, 48*(1), 25–39.

Järvelä, S., Järvenoja, H., Malmberg, J., Isohätälä, 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.

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.

Järvelä, S., Malmberg, J., Sobocinski, M., Haataja, E., & Kirschner, P. (2016c). What multimodal data tell about selfregulated learning process. *Learning and Instruction, 72*(7).

Järvelä, S., Hadwin, A., Malmberg, J., & Miller, M. (2018). Contemporary perspectives of regulated learning in collaboration. In *International handbook of the learning sciences* (pp.127–136). Routledge.

Järvelä, S., Malmberg, J., Haataja, E., Sobocinski, M., & Kirschner, P. A. (2019). What multimodal data can tell us about the students' regulation of their learning process. *Learning and Instruction, 4*.

Järvelä, S., Gašević, D., Seppänen, T., Pechenizkiy, M., & Kirschner, P. A. (2020). Bridging learning sciences, machine learning and affective computing for understanding cognition and affect in collaborative learning. *British Journal of Educational Technology, 51*(6), 2391–2406.

Järvelä, S., Malmberg, J., Sobocinski, M., & Kirschner, P. A. (2021). Metacognition in collaborative learning. In *International handbook of computer-supported collaborative learning* (pp. 281–294). Springer.

Järvenoja, H., & Järvelä, S. (2013). Regulating emotions together for motivated collaboration. In M. J. Baker, J. Andriessen, & S. Järvelä (Eds.), *Affective learning together: Social and emotional dimensions of collaborative learning* (pp. 162–181). Routledge.

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.

Järvenoja, H., Järvelä, S., Törmänen, T., Näykki, P., Malmberg, J., Kurki, K., Mykkänen, A., & Isohätälä, J. (2018). Capturing motivation and emotion regulation during a learning process. *Frontline Learning Research, 6*(3), 85–105.

Järvenoja, H., Järvelä, S., & Malmberg, J. (2020). Supporting groups' emotion and motivation regulation during collaborative learning. *Learning and Instruction, 70*, 101090.

Jovanović, J., Gašević, D., Dawson, S., Pardo, A., & Mirriahi, N. (2017). Learning analytics to unveil learning strategies in a flipped classroom. *The Internet and Higher Education, 33*(4), 74–85.

Karau, S. J., & Wilhau, A. J. (2020). Social loafing and motivation gains in groups: An integrative review. In S. J. Karau (Ed.), *Individual motivation within groups: Social loafing and motivation gains in work, academic, and sports teams* (pp. 3–51). Academic.

Kim, Y. R., Park, M. S., Moore, T. J., & Varma, S. (2013). Multiple levels of metacognition and their elicitation through complex problem-solving tasks. *The Journal of Mathematical Behavior, 32*(3), 377–396.

Kirschner, P. A., Sweller, J., Kirschner, F., & Zambrano, J. R. (2018). From cognitive load theory to collaborative cognitive load theory. *International Journal of Computer-Supported Collaborative Learning, 13*, 213–233.

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*(3), 335–353.

Lajoie, S. P., Lee, L., Poitras, E., Bassiri, M., Kazemitabar, M., Cruz-Panesso, I., Hmelo-Silver, C., Wiseman, J., Chan, L. K., & Lu, J. (2015). The role of regulation in medical student learning in small groups: Regulating oneself and others' learning and emotions. *Computers in Human Behavior, 52*, 601–616.

Lee, A., O'Donnell, A. M., & Rogat, T. K. (2014). Exploration of the cognitive regulatory subprocesses employed by groups characterized by socially shared and other-regulation in a CSCL context. *Computers in Human Behavior, 52*, 617–627.

Lesh, R. A., & Doerr, H. M. (2003). *Beyond constructivism: Models and modeling perspectives on mathematics problem solving, learning, and teaching*. Routledge.

Lin, J. W. (2018). Effects of an online team project-based learning environment with group awareness and peer evaluation on socially shared regulation of learning and self-regulated learning. *Behaviour & Information Technology, 37*(5), 445–461.

Lobczowski, N. G. (2020). Bridging gaps and moving forward: Building a new model for socioemotional formation and regulation. *Educational Psychologist, 55*(2), 53–68.

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.

Malmberg, J., Järvelä, S., & Järvenoja, H. (2017). Capturing temporal and sequential patterns of self-, co-, and socially shared regulation in the context of collaborative learning. *Contemporary Educational Psychology, 49*, 160–174.

Malmberg, J., Haataja, E., Seppänen, T., & Järvelä, S. (2019). Are we together or not? The temporal interplay of monitoring, physiological arousal and physiological synchrony during a collaborative exam. *International Journal of Computer-Supported Collaborative Learning, 14*(4), 467–490.

Martinez-Maldonado, R. (2019). A handheld classroom dashboard: Teachers' perspectives on the use of real-time collaborative learning analytics. *International Journal of Computer-Supported Collaborative Learning, 14*(3), 383–411.

Miller, M., & Hadwin, A. (2015). Scripting and awareness tools for regulating collaborative learning: Changing the landscape of support in CSCL. *Computers in Human Behavior, 52*, 573–588.

Mitchell, R., Boyle, B., Parker, V., Giles, M., Joyce, P., & Chiang, V. (2014). Transformation through tension: The moderating impact of negative affect on transformational leadership in teams. *Human Relations, 67*(9), 1095–1121.

Molenaar, I., & Chiu, M. M. (2014). Dissecting sequences of regulation and cognition: Statistical discourse analysis of primary school children's collaborative learning. *Metacognition and Learning, 9*, 137–160.

Nguyen, A., Järvelä, S., Wang, Y., Rosé, C., Malmberg, J., & Järvenoja, H. (2021). Multimodal deep learning model for detecting types of interactions for regulation in collaborative learning. In *Proceedings of the 15th international conference of the learning sciences – ICLS 2021*. International Society of the Learning Sciences.

Nguyen, A., Järvelä, S., Wang, Y., & Róse, C. (2022). Exploring socially shared regulation with an AI deep learning approach using multimodal data. In *Proceedings of International Conference of the Learning Sciences (ICLS).*

Phielix, C., Prins, F. J., Kirschner, P. A., Erkens, G., & Jaspers, J. (2011). Group awareness of social and cognitive performance in a CSCL environment: Effects of a peer feedback and reflection tool. *Computers in Human Behavior, 27*(3), 1087–1102.

Pijeira-Díaz, H. J., Drachsler, H., Järvelä, S., & Kirschner, P. A. (2019). Sympathetic arousal commonalities and arousal contagion during collaborative learning: How attuned are triad members? *Computers in Human Behavior, 92*, 188–197.

Poitras, E. G., Doleck, T., Huang, L., Li, S., & Lajoie, S. P. (2017). Advancing teacher technology education using open-ended learning environments as research and training platforms. *Australasian Journal of Educational Technology, 33*(3), 32–45.

Popov, V., van Leeuwen, A., & Buis, S. C. (2017). Are you with me or not? Temporal synchronicity and transactivity during CSCL. *Journal of Computer Assisted Learning, 33*(5), 424–442.

Reimann, P., Frerejean, J., & Thompson, K. (2009). Using process mining to identify models of group decision making in chat data. *Proceedings of the 9th International Conference on Computer Supported Collaborative Learning, 1*, 98–107.

Rogat, T. K., & Adams-Wiggins, K. (2014). Other-regulation in collaborative groups: Implications for regulation quality. *Instructional Science, 42*(6), 879–904.

Rogat, T. K., & Linnenbrink-Garcia, L. (2011). Socially shared regulation in collaborative groups: An analysis of the interplay between quality of social regulation and group processes. *Cognition and Instruction, 29*, 375–415.

Roll, I., & Winne, P. H. (2015). Understanding, evaluating, and supporting self-regulated learning using learning analytics. *Journal of Learning Analytics, 2*(1), 7–12.

Roschelle, J., & Teasley, S. D. (1995). The construction of shared knowledge in collaborative problem solving. In *Computer supported collaborative learning* (pp. 69–97). Springer.

Rosé, C. P., & Järvelä, S. (2020). Building community together: Towards equitable CSCL practices and processes. *International Journal of Computer-Supported Collaborative Learning, 15*(3), 249–255.

Saint, J., Fan, Y., Gašević, D., & Pardo, A. (2022). Temporally-focused analytics of self-regulated learning: A systematic review of literature. *Computers and Education: Artificial Intelligence, 3*, 100060.

Saqr, M., Viberg, O., & Vartiainen, H. (2020). Capturing the participation and social dimensions of computer-supported collaborative learning through social network analysis: Which method and measures matter? *International Journal of Computer-Supported Collaborative Learning, 15*, 227–248.

Scardamalia, M., & Bereiter, C. (2014). Knowledge building and knowledge creation: Theory, pedagogy, and technology. In R. K. Sawyer (Ed.), *Cambridge handbook of the learning sciences* (pp. 397–417). Cambridge University Press.

Schraw, G. (1998). Promoting general metacognitive awareness. *Instructional Science, 26*(1), 113–125.

Schraw, G., & Dennison, R. S. (1994). Assessing metacognitive awareness. *Contemporary Educational Psychology, 19*(4), 460–475.

Schwartz, D. L. (1995). The emergence of abstract representations in dyad problem solving. *The Journal of the Learning Sciences, 4*(3), 321–354.

Shuman, V., & Scherer, K. R. (2014). Concepts and structures of emotions. In R. Pekrun & L. Linnenbrink-Garcia (Eds.), *International handbook of emotions in education* (pp. 13–35). Routledge.

Sinha, S., Rogat, T. K., Adams-Wiggins, K. R., & Hmelo-Silver, C. E. (2015). Collaborative group engagement in a computer-supported inquiry learning environment. *International Journal of Computer-Supported Collaborative Learning, 10*(3), 273–307.

Sobocinski, M., Malmberg, J., & Järvelä, S. (2017). Exploring temporal sequences of regulatory phases and associated interactions in low- and high-challenge collaborative learning sessions. *Metacognition and Learning, 12*, 275–294.

Sonnenberg, C., & Bannert, M. (2015). Discovering the effects of metacognitive prompts on the sequential structure of SRL-processes using process mining techniques. *Journal of Learning Analytics, 2*(1), 72–100.

Sonnenberg, C., & Bannert, M. (2019). Using process mining to examine the sustainability of instructional support: How stable are the effects of metacognitive prompting on self-regulatory behavior? *Computers in Human Behavior, 96*, 259–272.

Strauß, S., & Rummel, N. (2021). Promoting regulation of equal participation in online collaboration by combining a group awareness tool and adaptive prompts. But does it even matter? *International Journal of Computer-Supported Collaborative Learning, 16*(1), 67–104.

Tang, H., Dai, M., Yang, S., Du, X., Hung, J. L., & Li, H. (2022). Using multimodal analytics to systemically investigate online collaborative problem-solving. *Distance Education, 43*(2), 290–317.

Taub, M., Azevedo, R., Rajendran, R., Cloude, E. B., Biswas, G., & Price, M. J. (2021). How are students' emotions related to the accuracy of cognitive and metacognitive processes during learning with an intelligent tutoring system? *Learning and Instruction, 72*, 101200.

Törmänen, T., Järvenoja, H., & Mänty, K. (2021). All for one and one for all – How are students' affective states and group-level emotion regulation interconnected in collaborative learning? *International Journal of Educational Research, 109*, 101861.

van der Aalst, W. M. P. (2011). *Process mining: Discovery, conformance and enhancement of business processes*. Springer.

Viberg, O., Khalil, M., & Baars, M. (2020). Self-regulated learning and learning analytics in online learning environments: A review of empirical research. In *Proceedings of the Tenth International Conference on Learning Analytics & Knowledge* (pp. 524–533).

Vogel, F., Kollar, I., Fischer, F., Reiss, K., & Ufer, S. (2022). Adaptable scaffolding of mathematical argumentation skills: The role of self-regulation when scaffolded with CSCL scripts and heuristic worked examples. *International Journal of Computer-Supported Collaborative Learning, 17*, 39–64.

Volet, S. E., Summers, M., & Thurman, J. (2009). High-level co-regulation in collaborative learning: How does it emerge and how is it sustained? *Learning and Instruction, 19*, 128–143.

Vuorenmaa, E., Järvelä, S., Dindar, M., & Järvenoja, H. (2022). Sequential patterns in social interaction states for regulation in collaborative learning. *Small Group Research*.

Whitehill, J., Bartlett, M., & Movellan, J. (2008). Automatic facial expression recognition for intelligent tutoring systems. In *2008 IEEE computer society conference on computer vision and pattern recognition workshops* (pp. 1–6). IEEE.

Winne, P. H., & Hadwin, A. F. (1998). Studying as self-regulated engagement in learning in metacognition in educational theory and practice. In *Metacognition in educational theory and practice* (pp. 277–304). Routledge.

Winne, P. H., & Hadwin, A. F. (2008). The weave of motivation and self-regulated learning. In D. H. Schunk & B. J. Zimmerman (Eds.), *Motivation and self-regulated learning: Theory, research, and application* (pp. 297–314). Erlbaum.

Winne, P. H., & Jamieson-Noel, D. (2002). Exploring students' calibration of self reports about study tactics and achievement. *Contemporary Educational Psychology, 27*(4), 551–572.