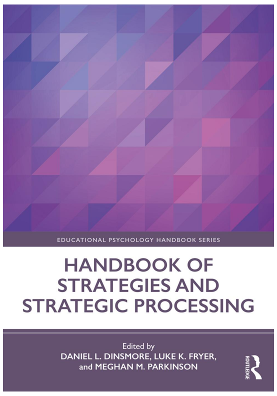

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SHARING THE LOAD

A Strategy to Improve Self-regulated Learning

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THE NEED FOR STRATEGIES TO IMPROVE SELF-REGULATED LEARNING

Self-regulated learning (SRL) entails the self-directive and proactive processes that learners can use to achieve academic success (Winne & Hadwin, 1998; Zimmerman, 2008). Examples of those processes are goal-setting, selecting and using learning strategies, and monitoring one's own effectiveness. These and other SRL processes are important for students to be able to regulate their own learning and development, not only during their school and college years but throughout their lives (e.g., Bjork, Dunlosky, & Kornell, 2013). In most models of SRL (for a review, see Panadero, 2017) both monitoring and control processes play an important role. That is, for SRL to succeed, students need to accurately monitor their learning processes and use that information to regulate further learning activities (e.g., Nelson & Narens, 1990).

Yet, research has shown that both children and adults tend to overestimate their own learning processes (e.g., Dunlosky & Lipko, 2007), which is problematic for decisions on their future learning processes and their future learning outcomes (e.g., Dunlosky

& Rawson, 2012). With complex tasks, SRL strategies such as self-monitoring of learning can be too demanding for an individual student. Using collaborative learning as a strategy to divide the demands of the learning task, learners can create a collective cognitive capacity which could potentially lead to a more efficient way of learning with more room for monitoring and regulating the learning process. In this chapter, a cognitive load perspective will be used to discuss how collaborative learning could be a strategy to improve SRL.

SELF-REGULATED LEARNING SKILLS

In order to self-regulate one's own learning processes, an interaction between cognition and metacognition needs to take place (Flavell, 1979). In the model by Nelson and Narens (1990) there are two levels that interact with each other through monitoring and control processes. The first level, the object-level, is the level at which cognitive processes like learning, language processing, or problem solving are going on. The meta-level contains a model of the learner's understanding of the task they are performing. This meta-level is partly informed via monitoring processes but also includes metacognitive knowledge about the task and the learner (i.e., strategies for specific tasks in relation to the experience of the learner; Flavell, 1979). Information gained when monitoring task performance at the object-level is used to update the model of the task at the meta-level. In turn, information from the meta-level is used to influence the activities at the object-level (i.e., control processes). These two levels, and the information flow between them, enable the learner to regulate ongoing learning processes (Dunlosky & Metcalfe, 2009).

Hence, an important strategy for effective SRL is self-monitoring in which learners evaluate their own performance against some standard or goal. Self-monitoring can be measured by asking learners to make monitoring judgments about their own learning process. Monitoring judgments can be made retrospectively (e.g., self-assessment), concurrently (e.g., confidence judgments), or prospectively (e.g., predicting future performance; Baars, Vink, Van Gog, De Bruin, & Paas, 2014; Schraw, 2009b). For example, a judgment of learning (JOL) could be used to have learners judge whether they have understood a text or are able to answers questions about the text on a future test. The accuracy of monitoring judgments is usually operationalized as the correspondence between the judgments and test performance. The correspondence can be expressed as relative accuracy, absolute accuracy, or bias (Schraw, 2009a). Relative monitoring accuracy shows the correspondence between monitoring judgments and performance, and is measured with intra-individual correlations (often the Goodman-Kruskal Gamma correlation, e.g., Maki, 1998; Thiede, Anderson, & Therriault, 2003). Relative accuracy expressed as the gamma correlation shows to what extent participants are able to discriminate between problems on which they perform poorly and problems on which they perform well (Maki, Shields, Wheeler, & Zacchilli, 2005). Absolute accuracy shows how precise the monitoring judgment is and it is measured by the actual deviation between monitoring judgments and performance (e.g., Baars et al., 2014; Baars, Visser, Van Gog, De Bruin, & Paas, 2013). For example, if a student made a monitoring judgment in which (s)he estimates to have five out of ten questions correct but only gets four questions correct on a performance test, the absolute accuracy is one. Bias would measure whether there is an over- or underestimation. In the previous example bias would be one, a positive outcome, indicating overestimation (for a review of accuracy measures, see Schraw, 2009a, 2009b).

When studying word pairs (i.e., paired-associates) both children and adults were found to be able to judge their memory accurately when there was a delay between studying the word pair and the monitoring judgment (for a review of the delayed-JOL effect, see Rhodes & Tauber, 2011). That is, a simple strategy to improve monitoring accuracy when studying word pairs would be to ask learners to make a monitoring judgment after a list of words instead of after each word directly. Yet, this delayed-JOL effect was not found for learning from texts (Maki, 1998) or problem-solving tasks (Baars, Van Gog, De Bruin, & Paas, 2018). Moreover, reviews of research on monitoring judgments when learning from texts (i.e., meta-comprehension) have shown that the accuracy of a single monitoring judgment after reading a text (200–1000 words) is generally very low (average gamma correlation of .27). This indicates that learners cannot accurately monitor their own learning processes when learning from text without any additional instructional support (e.g., Dunlosky & Lipko, 2007; Thiede, Griffin, Wiley, & Redford, 2009).

Similarly, studies on monitoring learning from problem-solving tasks (i.e., meta-reasoning) also found that learners experience difficulties in making accurate monitoring judgments (Ackerman & Thompson, 2017). In educational settings like schools and universities, usually well-structured problems are used in domains such as science, technology, engineering, and mathematics (STEM). In contrast to ill-structured problems that do not have a well-defined goal or solution procedure, well-structured problems are typically solved by applying a limited and known set of concepts and rules (Jonassen, 2011). Research has shown that without additional instructional support, students were found to overestimate themselves when making monitoring judgments about solving well-structured biology problems (Baars, Leopold, & Paas, 2018; Baars, Van Gog, De Bruin, & Paas, 2017; Baars et al., 2014; Baars et al., 2013).

Interestingly, generative strategies were found to improve self-monitoring accuracy when learning from expository text and problem-solving tasks. Generative strategies are learning activities that learners can use to generate (new) information about the learning materials by elaborating on those materials (Fiorella & Mayer, 2016; Wittrock, 1992). Examples of generative strategies that were found to improve monitoring accuracy are generating keywords (e.g., Thiede et al., 2003), making summaries (Thiede & Anderson, 2003), making concept maps (e.g., Redford, Thiede, Wiley, & Griffin, 2012), giving self-explanations (e.g., Griffin, Wiley, & Thiede, 2008), making diagrams (e.g., Van Loon, De Bruin, Van Gog, Van Merriënboer, & Dunlosky, 2014), practicing problems (e.g., Baars, Van Gog, De Bruin, & Paas, 2014), or completing partially worked-out examples (Baars et al., 2013). These generative strategies can provide students with predictive cues on their comprehension of learning materials (i.e., their mental representation), which can help to make more accurate self-monitoring judgments (e.g., Baars et al., 2014; Thiede et al., 2009).

However, in a study by Baars et al. (2018) it was shown that self-explaining during the learning phase or at the posttest did not improve monitoring accuracy or performance when learning to solve problems in secondary education. Furthermore, monitoring accuracy was lower for more complex problem-solving tasks than for less complex problem-solving tasks. These results seem to imply that the complexity of the learning materials plays an important role in monitoring and influences the effectiveness of strategies to improve monitoring.

Looking at SRL models (e.g., Winne & Hadwin, 1998; Zimmerman, 2008), inaccurate monitoring is problematic for the learning process. When monitoring is inaccurate, regulation choices on how to proceed with the learning process will most likely be useless or even harmful for learning. In line with these predictions, Dunlosky and Rawson (2012) found that without additional support, students tend to overestimate their learning, which led to premature termination of study efforts and lower retention. As the consequences of inaccurate monitoring are quite severe and generative strategies do not always suffice in supporting students to make more accurate monitoring judgments, it is important to know why making accurate monitoring judgments is so difficult.

THE COMPLEXITY OF MONITORING LEARNING PROCESSES

One possible explanation of why monitoring one's own learning seems to be difficult and prone to overestimation, is that it takes place at the same time as learning, or directly after learning. Moreover, learning tasks are often complex for students who are novices in a domain, leaving little room for monitoring and regulation processes. According to cognitive load theory (CLT; Sweller, Van Merriënboer, & Paas, 1998, 2019) it can be assumed that the competition for working memory (WM) resources between learning processes and self-regulation processes can have negative effects on either or both of these processes. Understanding the interplay between learning, monitoring, and the role of cognitive load is needed to provide insight into possible strategies to improve SRL processes when learning complex tasks.

According to CLT (Sweller, 2010; Sweller et al., 1998, 2019), complexity of learning tasks can be partially explained by the number of interacting information elements in a task. The higher the number of interacting information elements, the more complex a learning task is. Especially learning more complex materials can place a high demand on limited cognitive resources (Baddeley, 1986; Cowan, 2001). In addition, the expertise of the learner also plays a role in how complex a task is perceived by a learner. That is, with more expertise, information elements can be combined into schemata in long-term memory, and processed as one element in WM, lowering the number of interacting information elements. Therefore, the cognitive load a task imposes will be lower for learners with more expertise than for learners with less expertise (Kalyuga, 2007; Kalyuga & Sweller, 2004). Generally, it can be argued that monitoring one's own learning in education, where typically new, complex tasks have to be learned, is difficult for learners. Moreover, as SRL involves monitoring the object-level and thereby informing the meta-level to control the learning process at the object-level (Nelson & Narens, 1990), SRL presumably causes high element interactivity in and of itself.

Monitoring one's own learning can be seen as a secondary task next to the learning task itself (Griffin et al., 2008; Van Gog, Kester, & Paas, 2011). When tasks are complex and cognitive load is high, it can be hard to perform well on both the learning task and the monitoring task at the same time, because a learner will have to divide cognitive resources between the two tasks (Brünken, Plass, & Leutner, 2003). Due to

WM limitations, performance on one or both of the tasks may suffer when complexity is high and exceeds the learner's processing capacity. Furthermore, the ability to cope with this dual task is dependent on the cognitive resources of the learner. A study by Griffin et al. (2008) showed that reading abilities and working memory capacity (WMC) affected monitoring accuracy. In two experiments, college students read explanatory texts, made monitoring judgments about their comprehension, and took a comprehension test about the texts they read. In the first experiment it was found that re-reading the text improved monitoring accuracy for low-ability readers, but not for high-ability readers. In the second experiment this was confirmed and results further showed that lower-WMC readers benefitted from re-reading in terms of monitoring accuracy whereas high-WMC readers did not. Griffin et al. (2008) concluded that contextual factors such as re-reading and individual differences such as reading abilities are possibly related to the ability of monitoring meta-level cues while reading. They pointed out that monitoring is a secondary process next to the primary task of understanding the text itself. Moreover, monitoring accuracy was assumed to be dependent on the cognitive resources of the reader.

A study by Van Gog et al. (2011) also confirmed the idea that concurrent monitoring can be seen as an additional task demanding resources. In their study, secondary school students had to solve Sudoku problems and rate their mental effort as a measure of cognitive load (see Paas, 1992). There were two conditions: a condition in which students had to keep track of what they were doing (i.e., monitoring) and a condition in which they did not monitor their performance (Van Gog et al., 2011). Using a within-subjects design, the effect of the complexity of the Sudoku problems was investigated. Results showed that the instruction to monitor led to higher cognitive load for the complex problems but not for the simple problems. Also, performance and efficiency of performance (see Paas & Van Merriënboer, 1993) on the complex problems were lower for students in the monitoring condition. Hence, the instruction to monitor performance when solving complex problems increased cognitive load and decreased performance and efficiency (Van Gog et al., 2011).

In sum, SRL, being the combination of monitoring *and* performing a learning task (e.g., Winne & Hadwin, 1998; Zimmerman, 2008), presumably imposes high cognitive load. Monitoring can take place at the same time as learning or directly after a learning task. In both scenarios, the additional task of monitoring demands cognitive resources. Hence, in the case of complex learning tasks, there might be too few resources to accurately monitor and regulate the learning process (Griffin et al., 2008; Van Gog et al., 2011). This could explain why monitoring judgments have been found to be accurate for relatively simple learning materials (e.g., Rhodes & Tauber, 2011) and inaccurate for relatively complex learning materials like expository texts (e.g., Thiede et al., 2009) and problem-solving tasks (e.g., Baars et al., 2018). Yet students are expected to monitor and regulate their own learning to a gradually increasing extent while tasks are getting more complex in (higher) education, especially when learning takes place in digital learning environments in which students operate independently (e.g., Wong et al., 2019). Therefore, it is important to consider strategies to decrease the load of monitoring during learning. One possibility is the use of collaborative learning, which is becoming increasingly popular in many educational settings (Johnson & Johnson, 2009). Collaborative learning could potentially be used as a strategy to reduce the demands on individual cognitive resources when monitoring learning because collaboration creates the opportunity to divide the load between the learners in the group.

COLLABORATIVE LEARNING AS A STRATEGY FOR SRL: SHARING THE LOAD

Students can learn collaboratively by actively working together and putting effort into the attainment of a shared learning goal (e.g., Janssen, Kirschner, Erkens, Kirschner, & Paas, 2010; Johnson & Johnson, 2009; Kirschner, Sweller, Kirschner, & Zambrano, 2018; Slavin, 2014). Several meta-analyses have shown that collaborative learning is related to academic (individual and group) achievement (e.g., Lou, Abrami, & d'Apollonia, 2001; Roseth, Johnson, & Johnson, 2008; Springer, Stanne, & Donovan, 1999). There are several explanations from different disciplines as to why students learn from each other in collaborative settings. For example, social cohesion as a result of working interdependently in collaborative learning can aid learning (O'Donnell & O'Kelly, 1994). Also, collaborative learning can create cognitive conflict and students can question each other's understanding, which can enhance learning (Slavin, 1996). Social interaction and social support are elements in collaborative learning that can create the opportunity for students to develop higher order skills such as reasoning and critical thinking skills (Johnson & Johnson, 2009). Moreover, another explanation for why students can learn from each other in collaborative learning settings is that collaborative learning can facilitate information processing and memory (Topping, 1996).

Strategies to make collaborative learning effective are combining group goals with individual accountability (e.g., grades based on average performance on individual assignments), appealing to student's motivation (e.g., rewards, task attractiveness), and creating interdependence in goals, roles, and tasks (e.g., Slavin, 1996). For collaborative learning to be successful, students need to be able to operate as a team. A meta-analysis by DeChurch and Mesmer-Magnus (2010) showed that team cognition is essential for team effectiveness. Team cognition concerns the manner in which important knowledge for team functioning is organized and distributed within the team. There are two strategies to operationalize team cognition, that is shared mental models and transactive memory. Shared mental models are cognitive understandings of important aspects in the performance context that are shared (i.e., compatible) among the members of a team. Teams with shared mental models can operate efficiently without the need for overt communication, which is important for expert teams. Transactive memory can be seen as a cognitive architecture in which the knowledge of individual group members is included but also knowledge about who possesses what knowledge. Transactive memory is important if there is a degree of specialization or differentiation of knowledge within a team. DeChurch and Mesmer-Magnus (2010) showed that shared mental models and transactive memory were significantly related to team behavioral processes (e.g., planning, goal-setting, coordinating, and team-back-up behavior), motivational state, and team performance.

Similar to the concept of team cognition, it has been proposed that learners in a collaborative learning setting can be seen as an information processing system (Kirschner, Paas, & Kirschner, 2009a, 2009b). In this system the information in the learning task and the cognitive load associated with the task can be divided among the learners in the group. This way the load can be divided among multiple collaborating working memories. According to the mutual cognitive interdependence principle, this collective WM can be introduced by effective collaborative learning in which students communicate and coordinate the relevant knowledge they have with each other (Kirschner, Paas, & Kirschner, 2011). From a CLT-perspective, dividing the demands of learning a complex task among different learners who are collaborating, can lead to a more effective and efficient way of learning (Paas & Sweller, 2012). That is, the collection of individual WM capacities of the group members can create an expanded processing capacity, which makes it advantageous to work together on more complex tasks (Kirschner et al., 2009a). Especially for complex tasks, sharing the load of high element interactivity across multiple WMs, instead of one, could be effective. Collaboration would serve as a scaffold for the learning process (Kirschner et al., 2018). This will only be effective if WM costs of communication and coordination are decreased by training or by learning in structured or scripted learning environments (Kirschner et al., 2018; Paas & Sweller, 2012). This means that collaboration would be a beneficial approach to learning in which communication and coordination are important strategies to make the collaboration successful.

A study by Kirschner et al. (2009b) investigated groups as information processing systems. Secondary school students learned how to solve biology problem-solving tasks either individually or in small groups. Students indicated their experienced mental effort (i.e., measure of cognitive load; Paas, 1992), and took a test consisting of retention and transfer tasks. The results showed that students who learned in small groups invested less mental effort during the learning phase. Most importantly, an interaction between the type of test (retention or transfer) and condition was found, which indicated that students who learned individually showed more efficient retention performance, and learners who learned collaboratively showed more efficient transfer performance. Presumably, because learners in the small groups could use each other's processing capacity (i.e., information processing system), they were able to process the learning content more deeply and construct higher quality schemata in long-term memory.

To sum up, collaborative learning was found to be successful (e.g., Roseth et al., 2008) and, more importantly, has the potential of ameliorating the limitations of individual WM (e.g., Kirschner et al., 2011). Looking back at the problem of inaccurate monitoring and its effect on the SRL process, possibly collaborative learning could be a way to free up cognitive resources that could then be used to monitor and regulate learning processes more successfully at both the individual and the group level. In order to make collaborative learning effective, several strategies such as training communication and coordination between team members are important. Both from a CLT perspective and the concept of team cognition, one could argue that there is potentially more WMC (Kirschner et al., 2011) in effective collaborative learning, which in turn could affect behavioral processes such as planning and goal-setting if team cognition is achieved (DeChurch & Mesmer-Magnus, 2010). Hence, effective collaborative learning could also be a scaffold for other SRL processes like monitoring and control at the individual level and at the group level.

CO-REGULATION AND SOCIALLY SHARED METACOGNITIVE REGULATION OF LEARNING

Research on co-regulation, socially shared metacognitive regulation (SSMR), and socially shared regulation of learning (SSRL), has looked at SRL processes such as monitoring and regulation during collaborative learning. The terms metacognition, self-regulation, and SRL are often used in parallel to each other (Dinsmore, Alexander, & Loughlin, 2008). This is also the case for studies on shared regulation of learning (Panadero & Järvelä, 2015). The study by Dinsmore et al. (2008) has shown important commonalities in the definitions of metacognition, self-regulation, and SRL. That is, the idea that learners monitor their thoughts and actions during learning, and use that information to regulate or control their learning process, was found to be at the core of each of the three concepts. Similarly, co-regulation, SSMR, and SSRL also seem to have an important commonality, that is, all three fields look at the regulation of learning at the group level (Panadero & Järvelä, 2015). Therefore, all three will be described in this section in order to explore collaborative learning as a strategy to improve SRL processes.

Co-regulation refers to the process of acquiring SRL skills (e.g., monitoring, goal-setting, evaluation) through interactions with others when working on a learning task (Hadwin, Järvelä, & Miller, 2011; Hadwin & Oshige, 2011). Co-regulation is based on emergent temporary interactions with peers or teachers who bring different self-regulatory challenges and expertise into the learning process. In these interactions peers and teachers can prompt each other's regulation processes. The process of co-regulation should lead to the internalization of self-regulation processes. For example, a teacher can co-regulate a learning task together with a student to help improve the student's SRL skills. Research on co-regulation has focused on how learners regulate their learning in interaction with others, how peers can mediate each other's regulation of learning, and how social context or culture constrains co-regulation processes. Hence, co-regulation can be seen as a strategy to learn how to self-regulate one's learning.

SSRL is the collective regulation of learning processes that lead to a shared outcome (Hadwin et al., 2011; Panadero & Järvelä, 2015). It is based on the idea of shared regulation during learning, which provides learners with the opportunity to learn from each other's regulation through modeling (Järvelä et al., 2015). In SSRL the ultimate goal is for individually regulated learners to reach co-constructed planning, monitoring, strategies, evaluation, goal-setting, and beliefs in relation to the learning process with a shared outcome. The process of SSRL could be seen as a strategy to have learners model cognitive and metacognitive strategies during learning in an iterative fashion. This could improve the SRL skills of the other collaborators who in turn can model this behavior to the other learners again. That way, the shared metacognitive regulation of learning is built upon individual's metacognitive regulation (Winne, Hadwin, & Perry, 2013). Research into SSRL has focused on co-constructed SRL knowledge, beliefs, and procedures, and on shared SRL skills such as planning, monitoring, and evaluation (Hadwin et al., 2011). Thus, SSRL describes how groups can use collaborative learning as a strategy to regulate shared learning processes by co-creating and learning from each other.

SSMR refers to self-regulation skills such as planning, monitoring, and evaluation that students can use to control, coordinate, and regulate their learning (De Backer, Van Keer, & Valcke, 2012, 2015; Hadwin et al., 2011). Like in SSRL, students who are working together in a collaborative setting can collectively undertake regulation activities and transfer them to others. This process leads to metacognitive regulation at a social level which promotes successful collaborative learning (De Backer et al., 2012, 2015). According to De Backer et al. (2015), successful collaborative learning requires and, to some extent, also elicits, students to use metacognitive skills (i.e., SSMR). De Backer et al. (2012) found that students who were learning collaboratively in reciprocal peer tutoring groups, increased their use of metacognitive regulation skills such as monitoring and evaluation during the semester.

De Backer et al. (2015) make a distinction between two levels of metacognitive regulation: low-level and deep-level. Low-level metacognitive regulation concerns exploring the demands of the learning task. Deep-level metacognitive regulation refers to processing the task demand and activation of prior knowledge. Students checking the progress of their group can be considered an example of low-level monitoring whereas reflective comments on the quality of the group's progress would be deep-level monitoring. In their study the development and use of SSMR by students in reciprocal peer tutoring groups were investigated. Sessions of reciprocal peer tutoring groups were videotaped, coded, and analyzed. Results showed that from co-regulation by the tutor, students progressed into peer co-regulation and shifted to a socially shared regulation focus. Moreover, this socially shared regulation focus was found to be related to orientation, monitoring, and deep-level regulation. De Backer et al. (2015) suggested it would be interesting to develop and investigate interventions that can support SSMR in collaborative learning. Again, SSMR shows how learners can use collaborative learning as a strategy to regulate their learning by sharing it and transferring regulation from a tutor or more advanced learner to themselves.

In a review study by Panadero and Järvelä (2015), 17 articles addressing SSRL, or SSMR, were analyzed in order to characterize SSRL, levels of social regulation, and relations of SSRL with other learning variables such as performance. The results showed that the studies in the review mostly investigated SSRL using qualitative data (i.e., video-recorded observation data) to investigate the joint regulation of cognition, metacognition, behavior, emotion, and motivation. Furthermore, two types of shared regulation of learning were found: co-regulation in which one or more group members regulated other members' activity, and SSRL in which group members jointly regulated their learning. In addition, a small number of studies in which performance was investigated showed a positive relation between higher levels of SSRL and performance.

Possible interventions to support SSMR and SSRL can be found in work by Järvelä et al. (2015). They identified three strategies to support SSRL: (1) increase learners' awareness of their own and others' learning processes (i.e., Radar Tool), (2) support externalization of students' and others' learning processes and the interaction (i.e., Ourplanner), and (3) prompt acquisition and activation of regulatory processes (i.e., Ourevaluator).

Interestingly, these SSRL supports could theoretically also support team cognition or mutual cognitive interdependence. In addition, this relation between team cognition and SSRL could also be explained the other way around – without team cognition, SSRL would probably be ineffective. Support for awareness of each other's learning process could enhance shared mental models, and externalization of the learning process could enhance transactive memory about who knows what in a team. Using the

SSRL tools could improve communication and coordination of relevant knowledge between students in a collaboration group and thereby introduce a collective WM. Possibly this could free cognitive resources within the group to monitoring their learning process and use this for regulation in an effective way.

To conclude, research on SRL skills and metacognitive skills of learners in groups (e.g., co-regulation, SSMR, SSRL) has shown how learning processes can be regulated in interaction between peers or teachers and peers (De Backer et al., 2012, 2015; Hadwin et al., 2011; Panadero & Järvelä, 2015). Regulation of learning in interaction with others can also lead to acquiring SRL skills as an individual (Hadwin et al., 2011; Järvelä et al., 2015), as well as shifting toward socially shared forms of regulation within a group (De Backer et al., 2015). Collaborative learning settings seem to demand regulation of learning by the learners involved but also to elicit regulation of learning by learners. Hence, there seems to be a relation between team cognition and mutual cognitive interdependence on the one hand, and effective shared regulation of learning, on the other. That means collaborative learning could be an effective strategy to support SRL processes for groups and individuals. Furthermore, instructional supports for SRL or metacognitive processes during collaborative learning could theoretically also support team cognition (DeChurch & Mesmer-Magnus, 2010) and the use of collective WM (Kirschner et al., 2011). Therefore, it would be promising to investigate how the concepts of team cognition, collective WM, and socially shared regulation would overlap, strengthen, or constrain each other. Possibly, team cognition and mutual cognitive interdependence are important prerequisites of shared regulation of learning and could be used to develop interventions to improve shared regulation.

CONCLUSION AND DISCUSSION

SRL concerns the self-directive and proactive processes, such as monitoring and regulation of learning, which learners can use to achieve academic success (Winne & Hadwin, 1998; Zimmerman, 2008). To be successful at self-regulating learning processes, monitoring and control processes need to be accurate. However, making monitoring judgments about complex learning materials such as texts or problem-solving tasks, has been found to be difficult for learners, that is, without additional strategies or instructions monitoring judgments are usually inaccurate (e.g., Baars et al., 2014, 2013; Dunlosky & Lipko, 2007; Thiede et al., 2009). Prior research indicated that task complexity and high demands on cognitive resources can explain why monitoring is difficult for learners (Griffin et al., 2008; Van Gog et al., 2011). A good strategy to improve SRL processes would be to have learners work together and learn collaboratively. That is, collaborative learning could be a scaffold for SRL processes like monitoring and control. In collaborative learning, there is potentially more (collective) WMC (Kirschner et al., 2011) which could affect behavioral processes such as planning and goal-setting (DeChurch & Mesmer-Magnus, 2010). Different strategies can be employed to facilitate effective collaborative learning. For example, combining group goals with individual accountability, appealing to student's motivation, and creating interdependence in goals and roles (e.g., Slavin, 1996). But also, team cognition which consists of shared mental models and transactive memory are necessary for effective collaboration (DeChurch & Mesmer-Magnus, 2010). Moreover, from a

CLT perspective, it is crucial that the communication and coordination demands on WM during collaboration be decreased by training learners in those skills or providing them with carefully structured learning environments to collaborate in (Kirschner et al., 2018; Paas & Sweller, 2012). Especially with instructional support (cf. Järvelä et al., 2015), collaborative learning could elicit regulation of learning potentially leading to socially shared regulation or (improved) individual SRL skills. Informed by research on team cognition, future research could investigate the effect of collaborative learning compared to individual learning on cognitive load, learning outcomes, and SRL skills such as monitoring and regulation.

Yet, to our knowledge, there are no studies on how the concepts of team cognition, collective WM, and socially shared regulation would interact and affect SRL in individuals and groups. This would be an interesting endeavor, especially because it has been suggested that SRL is difficult for an individual and therefore must be even more difficult for a group (Järvelä et al., 2015). Yet based on research about team cognition (DeChurch & Mesmer-Magnus, 2010) and collective WM (e.g., Kirschner et al., 2011), it seems that learning collaboratively in a group would offer better opportunities for learners to monitor and regulate their learning individually or as a group. Future studies could investigate the effect of supporting team cognition in collaborative learning on SRL skills and learning outcomes. Also, the role of (collective) WM could be taken into account. Both qualitative and quantitative approaches would be valuable, as both insights into SRL behaviors in relation to team cognition and collective WM, and empirical evidence about the possible effects of team cognition and collective WM on SRL skills and learning outcomes, are needed.

As previous research on monitoring accuracy (e.g., Baars et al., 2018; Thiede et al., 2009) and collaborative learning (e.g., Kirschner et al., 2009b) has already shown, the type of task and the complexity of the task are important factors to take into account when investigating monitoring accuracy, cognitive load, and collaborative learning. As most tasks in education are new to students, it seems logical to focus on the more complex tasks when investigating collaborative learning, cognitive load, and SRL skills. Also, the development of SRL skills during a course (e.g., De Backer et al., 2015) but also over the years (e.g., Schneider, 2008), in relation to growing expertise (Kalyuga, 2007; Kalyuga & Sweller, 2004) could have important implications for the relation between SRL skills, cognitive load, and collaborative learning. Perhaps studies in different educational settings and with longitudinal design could provide more clarity on this issue. In addition, it seems a fruitful avenue to combine insights from educational studies and organizational studies to investigate SRL in groups of students. Especially the work on the effectiveness of teams (e.g., DeChurch & Mesmer-Magnus, 2010) provides interesting leads to follow up in educational settings.

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