Introduction paper Special Issue Computers in Human Behavior

Multidisciplinary Innovations and Technologies for Facilitation of Self-Regulated Learning

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Abstract

Technology-enhanced learning environments provide ample opportunities for learners to self-regulate their learning processes and activities for achieving the intended learning outcomes in various disciplines from soft to hard sciences and from humanities to the natural and social sciences. This special issue discusses the emerging technological advancements and cutting-edge research on self-regulated learning dealing with different cognitive, motivational, emotional, and social processes of learning both at the individual and group levels. Specifically, it discusses how to optimally use advanced technologies to facilitate learners' self-regulated learning for achieving their own individual learning needs and goals. In this special issue, seven researchers/research teams from the fields of collaborative learning, computational thinking, educational psychology, and learning analytics presented contributions to self-regulated learning with the goal of stimulating cross-border discussion in the field.

1. Introduction

The process of systematically organizing one's thoughts, feelings, and actions to attain specific learning goals is referred to as Self -Regulated Learning (SRL) (Zimmerman & Schunk, 2011). SRL can be seen as an active process where learners set specific goals on how to plan, monitor, regulate, and control their cognition, motivation, emotion, and social process to ensure appropriate actions during learning. Today, learning is no longer seen as only cognitive, but more as a process involving the interaction of different cognitive, motivational, emotional, and social processes (Järvelä, Järvenoja, Malmberg, Isohätälä, & Sobocinski et al., 2016; Malmberg, Järvelä, & Järvenoja., 2017; Zimmerman & Schunk, 2011). Learners are considered active agents in social and technology-mediated settings, interacting with tutors, teachers and peers, technologies, and numerous artefacts in their learning environments (Azevedo, Millar, Taub, Mudrick, Bradbury, & Price., 2017). This implies that learners are not only responsible for their own cognition and behavior but are also – at least partially - for their learning partners' thoughts, feelings, and actions (Hadwin, Järvelä, & Miller, 2017). Thus, learning and the learning process become more complex when multiple social factors contribute to learners' engagement during the learning process. This complexity brings with it a crucial challenge for the learning sciences community in their quest to understand these processes and to make use of innovative technologies to facilitate successful learning and the regulation thereof.

Despite progress in the theory and concept of SRL, the field lacks a unified perspective on recent advancements of innovative technologies. Rapid advancement of technology-enhanced learning environments and the swift growth of information, communication, and educational technologies such as Computer-Based Learning Environments (CBLEs), Computer-Supported Collaborative Learning (CSCL), Learning Analytics (LAs) tools, Open Educational Resources (OERs), and Personal Learning Environments (PLEs) offer ample opportunities to enhance students' SRL through awareness, control, and reflection on metacognitive abilities of their individual learning needs and goals.

It's time to advance our thinking about SRL by providing an overview of the use of cutting-edge multidisciplinary innovations and technologies to facilitate and accelerate successful self-regulated learning both from theoretical and practical point of view. The aim of this special issue is to report on leading-edge multidisciplinary work on pedagogical, methodological, and technological developments in the field of SRL. In this special issue, we have welcomed both conceptual, theoretical, methodological, and empirical articles that make multidisciplinary links between educational technologies, the learning sciences, learning psychology, motivational, emotional, cognitive aspects of learning, computer science, learning analytics, machine learning, and computing with SRL.

1.1. Contributors to this special issue

This special issue begins with a paper by Noroozi, Alikhani, Järvelä, Kirschner, and Juuso (this issue) who argue for the need of data modalities for reflecting on regulation mechanisms during collaborative learning. The challenge they aim to tackle is to make the large amount of complex and often invisible data during collaborative learning accessible for learning scientists to understand in a unified and visual manner. They claim that traditional subjective measures such as self-reported data of learners 'own intentions, beliefs, and perceptions of their learning experiences are inadequate for coherently and reliably capturing the complexity of different types of regulated learning activities in collaborative learning contexts since such data often do not match with what actually happens during learning process. Thus, they introduce a graphical user interface known as SLAM-KIT, designed in multidisciplinary collaboration, which can provide the learning sciences community a unified tool to study synchronized physiological signals of the participants in a learning session aligned with the recorded video and preprocessed annotations. The tool merges diverse physiological data sources (e.g., stress, excitement, enthusiasm) using a wealth of biometric information captured using unobtrusive sensors and cameras and provides a unified navigable view of the entire interaction situation.

The study by Cui, Wise, and Allen (this issue) explore the overall potential of utilizing computational analytic methods to gain useful insights for understanding and supporting SRL by processing large quantities of student reflections. They argue that reflection is a critical part of the health professions education as it supports the development of effective lifelong-learning health professionals. As a result, they develop a multi-dimensional reflection framework for conceptualizing reflection analytics in health professions education. This framework consists of six elements, namely description, analysis, feelings, perspective, evaluation, and outcome. These elements are used as a conceptual grounding for a computational analysis in which dental students' reflections are investigated using linguistic inquiry and word-count indices as data features for computationally extracting meaning from the reflections. The findings indicate a large variation in the type and quality of students' reflections, strongly supporting the use of a multi-dimensional analysis framework to increase precision of research claims and diagnose aspects of reflection. Such reflection analytics can provide students with feedback on missing elements of reflection and recommendations for what they can do to improve self-regulation.

Verstege, Pijeirra-Diaz, Noroozi, Biemans, and Diederen (this issue) explore the relation between students' perceived (i.e., self-reported) SRL level and their behavior (e.g., number of attempts and hints, number of answers requested) and learning outcomes in a virtual experiment environment in the field of enzymology. They argue that to successfully complete learning tasks in a virtual experiment environment, students need to adopt active learning behaviors based on their SRL skills. The findings confirm their hypothesis indicating that students with a high level of self-regulation obtain better learning outcomes, even though such learning behavior could not be achieved by middle-level self-regulated learners. They speculate that middle-level self-regulated learners are characterized by an increase in perceived agency, ownership over the learning process, and use of strategies and resources, but still lack goal-directed activity and appropriate planning and execution to meet the goals. Thus, special attention should be paid in SRL interventions to this group, and to support students to move to a higher level of self-regulation, where they could benefit from their increase in agency for accomplishment of their goals and improving their learning outcomes. They also show that highly self-regulated students rely less on their prior knowledge to accomplish learning tasks.

Dindar, Alikhani, Malmberg, Järvelä, and Seppänen (this issue) investigate the relationship between shared monitoring of collaborative learning processes and physiological synchrony between collaborating group members. They argue that monitoring learning progress is an essential dimension of socially-shared regulation of learning in collaborative contexts involving the temporal dynamics of coordination among the group members (e.g., joint attention and mutual efforts to keep track of the collective work and update regulatory strategies) during joint work on a shared task. A promising approach for investigating temporal sequences in collaborative learning is to measure physiological synchrony in terms of measuring physiological responses of interacting individuals (e.g., electrodermal activity, heart rate) as learners in teams collaboratively carry out a task. They find that the relationship between physiological synchrony and group monitoring of socially-shared regulation of learning might be dependent on the task type and group characteristics, and that not all monitoring events in a collaborative task lead to a physiological synchrony. In addition, their findings reveal that interactions at the content space of collaboration could produce physiological synchrony, even in the absence of the emotional or motivational regulation that takes place at the relational space. At the end, they claim that capturing invisible physiological signals and matching them with visible instances of monitoring processes might facilitate identification of critical moments in collaboration that lead to success or failure in performance.

Rienties, Tempelaar, Nguyen, and Littlejohn (this issue) investigate the relations between students' timing decisions with respect to what, how, and when to study in a blended mathematics environment called Sowiso and their SRL. The notion of time is an essential but complex concept, whereby students make (un)conscious and self-regulated decisions when and how to study. As a result, they investigate whether behavioral temporal data (i.e. the timing decisions made in the learning process) can be associated to the types of activities students choose to engage with, and their SRL. They then distinguish four unique profiles, namely: Early Mastery, Strategic, Exam-driven, and Inactive blended-learners. Students in these different profiles not only differ in their engagement, but also in their respective timings of when they engage with the Sowiso exercises and how they make use of specific learning resources. In other words, beyond differences in overall engagement patterns in terms of number of attempts, mastery, and time spent in Sowiso, their temporal analyses show substantial differences in when students self-regulate themselves. These profiles differ substantially in how students make use of the learning resources, which is important for providing them with automated feedback. They also find out that these different temporal engagement patterns of students over the three phases of the course (i.e., before the tutorial, before the quiz, before the exam) are significantly associated with academic performance. Finally, the results show that the timing decisions that students take with regard to using Sowiso are anteceded by differences in their approaches to learning and differences in epistemic learning emotions. All of these findings show the importance of the notion of SRL for mathematics learning.

Spann, Shute, Rahimi, and D'Mello (this issue) investigate affective regulation strategies in a game-based learning environment; the set of processes individuals use to increase, decrease, or maintain particular affective states in order to achieve desired outcomes. Affect regulation is an important component of SRL. It refers to efforts (e.g., attempts to think about a situation differently, focusing on one's breathing, punching a wall, etc.) to influence one's affective states, when one has them, and how one experiences or expresses them. In the same vein, active cognitive and/or physical engagement of a game-based learning environment contribute to a rich affective experience during gameplay, which makes it important to know about how learners regulate those states and which regulation strategies are beneficial, harmful, or benign. In this regard, they find that learners primarily experience determination/curiosity or frustration/confusion in their game and that these affective states increase and decrease, respectively, in conjunction with game difficulty. They also find that cognitive reappraisal and acceptance were the strategies learners use for regulating their affectation, whereas the others (e.g., attentional redirection, suppression) are exceedingly rare. Additionally, the results of their study show that cognitive reappraisal can predict successful gameplay and posttest scores when learners are frustrated/confused, but not when they are determined/curious.

Lund (this issue) provides a multi-theoretical and interdisciplinary model called multi-grain collaborative knowledge construction to describe the logical space of individuals, dyads, and groups when they are busy with knowledge elaboration in relation to their regulation. The model allows for investigating the relationship between knowledge elaboration and regulation of such knowledge from diverse disciplines on varied types of knowledge (e.g., cognitive, interactional, linguistic, emotional, social, neurological, technological). Building on this model, she explores two case studies (physics learning and collaborative game learning) to describe what counts as knowledge in two different pedagogical situations and to distinguish between elaboration and regulation of knowledge both at the individual and collective levels. The results reveal that knowledge regulation occurs in action and not just verbalization, regulation interventions are multifunctional, meta knowledge about learning can help regulation, and knowledge acquisition during development is more difficult to regulate.

Concluding this special issue is a paper from van Merrienboer and de Bruin (this issue) which critically synthesizes the findings of all the articles in this special issue.

2. Conclusion

The seven articles in this special issue provide a comprehensive discussion of different views on SRL constructs and how to measure and facilitate them in diverse learning environments in different fields. In this regard, while some articles propose conceptual frameworks (e.g., multi-dimensional reflection framework and multi-grain collaborative knowledge construction) based on the theoretical backgrounds to promote SRL in professional and interdisciplinary settings, others explore the role of SRL in relation to various learning processes and outcomes in technology enhanced learning. Also, some articles advance the field of SRL from a methodological perspective by pointing to the weaknesses associated with traditional approaches for measuring SRL and monitoring students' learning progress in different contexts. Specifically, these methodological articles provide the learning sciences community an opportunity to coherently and reliably capture the complexity of SRL by considering different modalities and data types (i.e., cognitive, motivational and emotional) as a set of indicators for reflecting on regulation mechanisms during the learning processes. For example, they propose to monitor learners' physiological synchrony through measuring physiological responses of interacting individuals. They also argue for utilizing computational analytics using linguistic inquiry and word count indices as data features to computationally extract meaning from the reflections. Furthermore, they suggest using a wealth of biometric information captured through unobtrusive sensors to merge the diverse physiological data sources together during the learning processes.

Despite the fact that this special issue touches various aspects of SRL as a theoretical, conceptual, and methodological phenomenon, there is still a need for further research on how to facilitate SRL for different learners in multidisciplinary settings using modern and innovative technologies. Actually, the papers invite future work in the field. Future research is necessary to triangulate various types of data, such as log-files, eye-movements, physiological measures, video data, and self-report measures to get a better understanding of the notion of SRL. Such triangulation could help verify the connections between reflection sequences and learning outcomes. This can be done, for example, by identifying different components exhibited within students' reflections and then modeling the common sequences in which they occur, using temporal methods such as lag-sequence analysis or statistical discourse analysis. In addition, with regard to students' SRL levels, further research is needed to shed light on ways to promote low- and medium-level self-regulated learners perform well in technology enhanced learning environments. In line with fine-grained methods using wearable, eye-tracking, and multi-modal sensors (Malmberg et al., 2017), it is important to understand how students' SRL behaviors and decisions are shaped in different face-to-face, offline and online learning settings. Finally, in the context of game-based environments and other future environment, such as augmented and virtual reality, future work should focus on manipulating key variables (e.g., inducing specific affective states) to encourage learners engage in regulatory strategies.

References

Azevedo, R., Millar, G. C., Taub, M., Mudrick, N. V., Bradbury, A. E., & Price, M. J. (2017). Using data visualizations to foster emotion regulation during self-regulated learning with advanced learning technologies. In J. Buder & F. W. Hesse (Eds.), *Informational environments: Effects of use, effective designs* (pp. 225–247). New York, NY: Springer.

Cui, Y., Wise A. F., & Allen K. L. (this issue). Developing reflection analytics for health professions education: A multi-dimensional framework to align critical concepts with data features. *Computers in Human Behavior*.

Dindar, M., Alikhani, I., Malmberg, J., Järvelä, S., & Seppänen, T. (this issue). Examining shared monitoring in collaborative learning: A case of a recurrence quantification analysis approach. *Computers in Human Behavior*.

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

Järvelä, S., Järvenoja, H., Malmberg, J., Isohätälä, J., & Sobocinski, M. (2016). How do types of interaction and phases of self-regulated learning set a stage for collaborative engagement? *Learning and Instruction, 43*(1), 39-51.

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.

Lund, K. (this issue). Building and regulating cognitive, linguistic, and interactional aspects of knowledge between the individual and the group. *Computers in Human Behavior*.

Noroozi, O., Alikhania, I., Järveläa, S., Kirschner, P. A., Juusoa, I., & Seppänena, T. (this issue). Multimodal data to design visual learning analytics for understanding regulation of learning. *Computers in Human Behavior*.

Rienties, B., Tempelaar, D., Nguyen, Q., & Littlejohn, A. (this issue). Unpacking the intertemporal impact of self-regulation in a blended mathematics environment. *Computers in Human Behavior*.

Spann, C. A., Shute, V. J., Rahimi, S., & D'Mello, S. K. (this issue). The productive role of cognitive reappraisal in regulating affect during game-based learning. *Computers in Human Behavior*.

Verstege, S., Pijeira-Díaz, H. J., Noroozi, O., Biemans, H., & Diederen, J. (this issue). Relations between students' perceived levels of self-regulation and their corresponding learning behavior and outcomes in a virtual experiment environment. *Computers in Human Behavior*.

Zimmerman, B.J., & Schunk, D.H. (2011). Self-regulated learning and performance: An Introduction and an overview. In B.J. Zimmerman & D.H. Schunk (Eds.), *Handbook of Self-Regulation of Learning and Performance* (pp. 1-12). New York, NY: Routledge.