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Towards Visible Socially-Shared Regulation of Learning: Exploring the Role of Learning Design

Cristina Villa-Torrano, Universidad de Valladolid, cristina@gsic.uva.es

Rosanna Vitiello, Jiaxin Shi, Carolyn P. Rosé
rvitiell@andrew.cmu.edu, jiaxins1@andrew.cmu.edu, cp3a@andrew.cmu.edu
Carnegie Mellon University

Juan I. Asensio-Pérez, Yannis Dimitriadis, Eduardo Gómez-Sánchez, Miguel Bote-Lorenzo
juaase@tel.uva.es, yannis@tel.uva.es, edugom@tel.uva.es, migbot@tel.uva.es
Universidad de Valladolid

Abstract: Socially Shared-Regulation of Learning processes are critical for successful collaborative learning. Despite the work done to develop a theoretical understanding of it, much less work has focused on what SSRL processes look like. This study explores how the use of the learning design, tuned to foster the phases of SSRL, and the use of tools that collect trace data, can be useful to provide evidence of where and when SSRL processes occur. The goal is to shed light on how SSRL processes look like with the global aim of supporting collaborative learning in real time. The study involved two undergraduate courses with 33 students. We identified the SSRL processes from conversations during collaboration and checked their alignment with student actions in the available learning tools. Results suggest that, at least for high performing groups, trace data interpreted in the light of the Learning Design align well with SSRL phases.

Introduction

Socially-Shared Regulation of Learning (SSRL) is a field in the framework of self-regulated learning theories that integrates different types of collective regulatory processes that contribute to shared regulation. Specifically, it is theorized to consist of four phases: i) negotiation and construction of the perception of the task; ii) sharing of objectives and generating plans to achieve them; iii) coordination and monitoring of progress; and iv) reflection and adaptation of objectives, planning, or perception of the activity (Malmberg et. al, 2015). Many empirical studies suggest that regulatory processes are critical to the success of collaborative learning (Järvelä et. al, 2016), and much past work has focused on developing a theoretical understanding of it and proposing scaffolding for its support (Järvelä et. al, 2015). However, much less work has targeted what SSRL processes look like, in part because regulatory processes most often operate in the background, awaiting such a time as they are needed to become visible and active, in order to address a problem that is either anticipated or detected through those invisible processes (Nguyen et. al, 2022).

For a decade and a half, the field of Computer-Supported Collaborative Learning (CSCL) has observed many successes of dynamic support for collaborative learning, where interventions are triggered in real time based on real-time monitoring of collaborative processes. In order to eventually enable dynamic support for SSRL, real-time monitoring of collaborative processes relevant to SSRL is required. As a precursor, research is needed to extend our knowledge of what SSRL processes look like. In some past work aiming to observe SSRL, triggers have been used to prompt SSRL to provide signposts for finding where it is most likely to occur (Järvelä et. al, 2019). Our work takes a different approach. In particular, we design an activity and environment with tools designed to foster the phases of SSRL in ways that make the processes visible in a more naturalistic setting so that they can be recorded and analyzed. We then concretize annotation practices for enhancing the visibility and analyzability of the processes to advance knowledge about where and when those processes become visible and what they look like. We begin by describing the design and what it is intended to foster. We then code the process data connected to a number of tools. We finally provide evidence regarding where and when the processes occur in relation to elements of the design of the task and environment. These builds understanding about SSRL, not just in terms of impact on outcomes, but also on a moment-by-moment process level. What we learn this way will enable the development of principles that will become tools for more extensive design work to further bolster understanding of how to see and track SSRL processes, with an eye set on eventual development of analytics for SSRL that will enable the dynamic triggering of needed SSRL interventions.

The study

Context, participants, and activity design

The learning activity took place at 2 undergraduate courses on Computer Networks during 5 weeks in the spring semester of the academic year 2022 in a European University. There were 33 students that were grouped into 16 different groups of 2-3 people to carry out a lab assignment, identical in both courses, aimed at challenging their knowledge about certain computer network topics. The participation in the study was voluntary, and only one group of two students opted out. To complete the assignment, the students were provided with all the necessary resources in Moodle, a personalized Google Docs for each group to write the final report, and access to a web platform called DNSE3, used to set up and run network simulations (Serrano-Iglesias, 2018). Since regulation is unlikely to emerge without scaffolding or support (Järvelä et. al, 2016), we decided to reflect the regulation phases in the learning design of the activity. By doing so, we expected: i) to foster SSRL during the collaborative learning activity; ii) to make SSRL more visible, since the learning design pointed at moments in which shared regulation was more likely to happen. Therefore, we followed a twofold approach. On the one hand, the groups were offered the opportunity to complete two additional Google Docs documents related to the SSRL phases: a task understanding quiz, so that they could detect misconceptions and reach a common view of the task; and ii) a laboratory diary, in which they could write down their session goals and plans, monitor their progress, take notes about the ongoing task, and decide what to do in the next session (adaptation). On the other hand, we set up the Moodle support in a similar way as described in (Salehian Kia, 2021), where the descriptions of the lab assignment tasks were located in different resources. This way, Moodle logs might be more informative about the specific learning tasks the students are engaged in at every moment.

Data sources and coding

As indicated in the introduction, the study is based on the collection and analysis of data from two sources:

1) We collected process data from the learning tools set up in the environment of the activity: logs from Moodle (who accesses which resource and when), Google Docs (who writes and when, what is written, in which position of the document it is written), and DNSE3 (who sets up a simulation and when, when results are downloaded, when simulations are stopped, …). After collecting the data, we fused the different datasets provided by each tool ordered by timestamps.
2) We also recorded the audio of the conversations that students had while collaborating face to face with the aim of providing evidence of where and when SSRL processes occur in relation to elements of the design of the task and environment.

In this first exploratory study, we only used process data generated by three groups (two high performing groups, and one low performing group) thus generating what we call *Dataset_TRACE*. Similarly, we transcribed and coded the conversations of those same three groups, considering the turns of the speakers as the unit of analysis, using the schema proposed by (Winne & Hadwin, 1998) that identified four main regulatory phases: task understanding, planning & setting goals, task enactment (with focus on monitoring), and adaptation. Then, two raters independently coded one of the high performing groups and, according to the Gwet's AC1 measure, they reached an almost perfect agreement level of 0.86. The remaining two group conversations were coded by either one or the other rater. Once the three conversations were coded, one of the researchers identified the episodes of SSRL (meaningful moments in the conversations in which the groups are involved in SSRL processes) thus generating what we call *Dataset_AUDIO*.

Thanks to *Dataset_AUDIO* (coded conversations among group members where SSRL episodes are identified) we expect to better understand where and when SSRL processes become visible in the trace data (*Dataset_TRACE*), and what they look like, which is the main goal of this study.

Results and conclusions

To achieve our goal, first we should check whether SSRL processes emerge during the collaborative activity. Table 1 shows the relative frequency of SSRL codes found in the conversations of the different groups (*Dataset_AUDIO*). It reveals that all groups engaged more in the *task understanding* phase, which has been identified as a critical phase of regulation, as it emphasizes the importance of a common understanding of the task as a key aspect for reaching good collaboration (Miller & Hadwin, 2015). Also, the *adaptation* phase is the least detected for all groups. We should further explore the reasons why this happened. Looking at the differences between groups, it is worth noting that the low performing group (LP1) differs in the percentage of time that they *monitor* with respect to the high performing groups (HP1 y HP2). This finding is consistent with the literature of self-regulation of learning that suggests that low performers are more engaged in metacognitive monitoring (Saint et. al, 2020), looking for the right strategy to help them progress with their learning process. This higher metacognitive monitoring may increase cognitive load and reduce opportunities for successful learning (Saint et. al, 2020). The other remarkable difference is the underuse of *planning & setting goals* processes. This is also consistent with the SSRL literature, where we can find works in which it is shown that low performing groups tend to engage less in planning processes in contrast with high performing groups (Zheng et. al, 2019).

Table 1
Relative frequencies of SSRL codes (Dataset_AUDIO)

	Task understanding	Planning & Setting Goals	Monitoring	Adaptation
HP1(n=441)	56%	17%	25%	2%
HP2(n=673)	45%	27%	28%	1%
LP1(n=477)	49%	**10%**	**41%**	0.2%

Once we have detected, using *Dataset_AUDIO*, that SSRL episodes are present in all groups (to a certain extent), we want to explore (in *Dataset_TRACE*) how the students are interacting with the learning tools (Moodle, Google Docs, DNSE3) during the time intervals of those SSRL episodes. An example of this alignment between both datasets can be seen in Figure 1, which shows an episode of almost 4 minutes in which one high performing group engaged in different SSRL processes while using the Google Doc with the diary. Figure 1 shows how the group members started doing task understanding, then they planned, then they engaged with the diary and finally they planned again and monitored their activity. This process makes sense when using the diary, since the diary contains one section for each SSRL phase. Thus, a plausible interpretation is that the group was writing down in the diary their understanding and plan of the tasks to be carried out during the lab session.

Looking at all the other episodes for both high performing groups, we have found similar alignments between the use of the tools and the SSRL processes in which they are involved. Specifically, the engagement with the task understanding quiz (another Google Doc) suggests a real task understanding process for both groups.

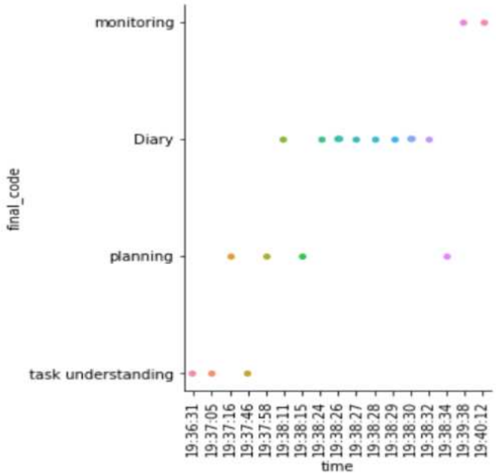
Also, while engaging in the task understanding quiz, sometimes they also look at specific Moodle resources, which also suggests that they are discussing their understanding while deepening in specific learning contents. The use of the diary is also well aligned with the SSRL processes found. While using this tool, both groups engaged in different SSRL processes: task understanding, planning, and monitoring. As mentioned above, the diary contains one section for each SSRL phase, so it makes sense that the use of the diary is related with all the phases individually, but also doing loops (e.g., planning → Diary → planning) or mixing SSRL processes (e.g. planning → Diary → monitoring). As future work, we plan to use the information from the logs to see on what part of the diary they are writing, and thus assess whether this finer-grain engagement data is well aligned with the corresponding SSRL processes. Moreover, we found common patterns regarding the use of Moodle. For both high performing groups, we found the following sequences: “monitoring → Moodle”, “planning → Moodle”, “task understanding → Moodle”. Though the interpretation of these sequences is not so obvious, we will again use finer-grain information from Moodle logs (i.e., which specific resources are accessed) so that, in the light of the Learning Design, we can check the alignment with SSRL processes. Besides, the alignment between SSRL phase and Moodle activity may be mediated by another variable, the moment within the work session (e.g., they may plan and then use Moodle during the first 30 min of the session, but after that they may do monitoring → Moodle in the second half of the session).

However, when it comes to the low performing group, we cannot see any of these patterns, except for “Monitoring → Moodle”. It should be further explored whether this is due to their episodes being too short, because they do not make proper use of the tools (in different ways, either explanation suggest a potential limitation to detect SSRL processes from trace data in low performing groups), or instead because the sample that we have analyzed so far is too small.

All in all, it seems that, at least for the high performing groups, our approach looks promising as a way to deepen our understanding of SSRL processes that the groups follow and see how these processes look like, and thus eventually help to detect them using trace data informed by the Learning Design. It is worth noting that for this study we have only analyzed 3 out of 16 groups. This exploratory sample will be complemented when the rest of the data that we have collected is analyzed. Moreover, as future work, we will also extract meaningful actionable indicators that could be used for automatic or teacher-in-the-loop scaffolding of the groups, in order to improve the quality of their SSRL processes. Finally, this approach opens up the possibility of looking for SSRL strategies based on the trace data collected, as it has been done in the area of SRL (Saint et. al, 2020). All these future directions aim to achieve the overall goal of being able to support real-time SSRL during collaboration by using SSRL analytics.

Figure 1

Sample episode for one high performing group. Each dot is a turn taken by a member of the group



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