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How Much Support is Necessary for Self-Regulated Learning?

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Abstract: Self-regulated learning is crucial for learning success, and is even of greater importance for online learning as there is less support and feedback available to students. We describe a simple intervention designed to support self-regulated learning in the context of SQL-Tutor, a mature intelligent tutoring system. SQL-Tutor logged data about all interactions students performed, including interactions with the SRL support. Frequency-based analyses did not identify any differences in behaviors of low or high scoring students. However, epistemic network analysis identified significant differences in how students use help available from SQL-Tutor. Students who scored low on the SQL test asked for high-level help (in the form of partial or full solution), copied the provided solutions and submitted them as their own. We conclude that additional support is necessary for students with weak self-regulation skills.

Keywords: self-regulated learning, intelligent tutoring systems, epistemic network analysis

1. Introduction

Self-regulated learning (SRL) is widely acknowledged as being crucial for learning success, and especially so in less structured environments such as higher education and online learning (Davis et al. 2018, Schumacher & Ifenthaler, 2021). In recent years, especially since the COVID-19 pandemic started, much learning is happening in digital learning environments, which provide less structured learning, limited interactions with teachers and other students, and require additional efforts from students for success in learning. High drop-out ratios are found in many studies investigating MOOCs and other self-directed learning environments (Koller et al., 2013; Kizilcec et al., 2015), pointing out the need for support for SRL skills.

Self-regulated learning is defined as an “active, constructive process whereby learners set goals for their learning and then attempt to monitor, regulate, and control their cognition, motivation and behavior guided and constrained by their goals and the contextual features in the environment” (Pintrich, 2000). SRL encompasses not only cognitive and metacognitive skills, but also motivational and affective aspects of learning (Panadero, 2017). Many students have weak SRL skills and do not engage in SRL spontaneously (Sonnenberg & Bannet, 2016). However, research shows that students can develop SRL skills (Kizilcec et al., 2017), leading to new studies on how SRL can be supported.

Digital learning environments log fine-grained information about students’ interactions, and allow for new types of interventions in order to improve learning. Several recent papers discuss support for SRL in MOOCs (Davis et al., 2018; Pérez-Álvarez et al., 2020), blended learning and flipped classroom (Moos & Bonde, 2016). There have also been approaches to support SRL skills in open-ended learning environments (Azevedo et al., 2009; Carpenter et al., 2021).

Despite a lot of research on how to support SRL in MOOCs and blended learning, there is limited literature on how to support SRL in Intelligent Tutoring Systems (ITSs). Our paper addresses that gap: we describe a simple intervention to support SRL skills in SQL-Tutor (Mitrovic & Ohlsson, 1999), a mature ITS. Our main research question is to identify how much students would engage with our SRL support. We start by providing a brief literature review on self-regulated learning, and discuss some approaches for supporting SRL skills in online learning. Section 3 presents our intervention and the experiment design. We then present our findings in Sections 4 and 5, followed by the conclusion and limitations of the current work.

2. Related Work

There are several theories of self-regulated learning (Boekaerts, 1999; Zimmerman, 1986, Winne & Hadwin, 1998; Pintrich, 2000), which focus on various processes students use to plan, monitor and manage their learning. These theories agree that the student's ability to regulate learning is of crucial importance for learning effectiveness. Zimmerman (2022) specifies a cyclical SRL model with three phases: forethought, performance and self-reflection. In the forethought phase, the learner engages in goal setting and strategic planning, identifying actions that will enable goal attainment. In the performance phase, while learning, the student uses various learning strategies and monitors progress. In the self-reflection phase, the student reflects upon their learning and regulates the strategies used. Zimmermann (1986) identifies 14 SRL strategies: self-evaluation, organizing and transforming, goal setting and planning, seeking information, keeping records and self-monitoring, environmental structuring, self-consequences, rehearsing and memorizing, seeking peer/teacher/adult assistance, and reviewing. Zimmerman (2002) studied the relationship between SRL and academic achievement, and reported that students who set precise and actionable goals for themselves often reported higher self-awareness and had higher achievements.

Other SRL theories include similar concepts and processes, which students use to select goals and plan learning, monitor and self-reflect on their progress, and regulate their behaviour, motivation and metacognition in order to achieve the goals. Winne and Hadwin's model (1998) consists of four linked phases: task definition, goal setting and planning, enacting study tactics and strategies, and metacognitively adapting studying. Pintrich (2000) model contains four phases: 1) forethought, planning and activation; 2) monitoring; 3) control; and 4) reaction and reflection.

In traditional learning, SRL is supported by actions teachers perform, and also by asking students to write reflective journals and self-assess. The popularity of MOOCs and flipped classroom in recent years has also resulted in a lot of research investigating different learner features and their relationships to learning outcomes. A big problem in MOOCs is disengagement, with typically large percentages of students not engaging with learning materials. Research shows that the lack of SRL skills is a big factor for disengagement in MOOCs (Kizilcec & Halawa, 2015).

Various approaches have been proposed to engage students more. Moos and Bonde (2016) added SRL prompts to videos in the context of flipped classrooms. The planning prompts were questions added at the start of the video, which aimed to support the planning phase of SRL. The monitoring questions were added in the middle of the video, while self-reflection prompts were added at the end of the video. The authors found that students who received the prompts learnt more and also used more SRL strategies in comparison to the control group. Wong et al. (2019) also used prompts to support SRL. In addition to prompts, when learning from videos students may be required to write annotations and answer questions (Mirriahi et al., 2021). In some cases, adaptive nudges are provided to students to make them reflect on their past experiences and plan their future actions (Dimitrova & Mitrovic, 2021; Mohammadhassan et al., 2022). Other approaches include the use of visualizations in order to draw students' attention to important parts of the video, for example in forms of heatmaps (Chatti et al., 2016). Visualizations can be used to present the summary of the student's activities as a learning dashboard (Matcha et al., 2019) or an open learner model (Hooshyar et al., 2020; Bodily et al., 2018), and also to support social comparison by providing a summary of the activities done by the class (Brusilovsky et al., 2015).

Several research projects investigated the effect purpose-built tools added to MOOCs (Pérez-Álvarez et al., 2020). Davis et al. (2018) developed SRLx, a personalized tool for supporting SRL skills for the edX MOOC platform. The tool supports learners in planning their goals weekly, and provides feedback on realization of the plans via a dashboard. The use of the tool was voluntary. The authors found that only 32% of students used SRLx at least once, but those students engaged with various elements of the MOOC significantly more than their peers.

SRL skills have also been supported in hypermedia learning and games. MetaTutor (Azevedo et al., 2009) incorporates four animated agents, which explicitly support the SRL phases. Crystal Island (Carptenter et al., 2021) requires students to write self-reflections while solving open-ended problems.

3. Experimental Design

The study reported in this paper was conducted as a natural field experiment (Dunning, 2012). We observed learning of students in an existing database course at the University of Canterbury. The students had several lectures on relational databases and SQL before they were introduced to SQL-Tutor in a scheduled lab. They were free to interact with the system as much as they wanted over a period of four weeks, in preparation for a course SQL test on October 7, 2021. The post-test was administered within the system on October 6, 2021.

Figure 1. Experimental phases

The overall design of the experiment is shown in Figure 1. At the start of the first session with SQL-Tutor, students received a short pre-test, after which they were asked to specify their overall goal for using SQL-Tutor (Figure 2). There were no restrictions on how to specify the goal. The next step was to set the goal for the current week (Figure 3), which required students to specify how much time they wanted to spend in SQL-Tutor that week, how many problems they planned to solve, and what level they would like to achieve. The student level in SQL-Tutor ranges from 1 (the minimum) to 9, and depends on the student's progress on specifying queries. For more information about how SQL-Tutor models students' knowledge, please see the paper by Mitrovic (2003).

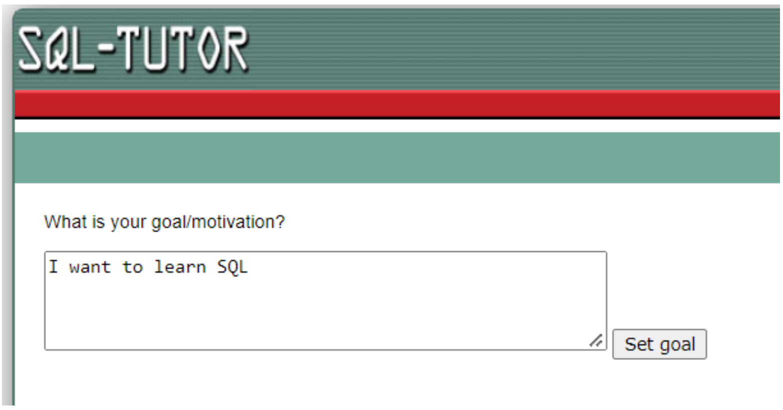

Figure 2. Setting the overall goal

After specifying the weekly goals, the dashboard was shown (Figure 4). The dashboard contains the overall goal, the visualizations showing the progress on the weekly goals, and the open learner model (OLM). From the dashboard, the student could change the overall goal, or go to the workspace and commence with tutored problem solving (Figure 4). At the start of each week, students set the goals for the week and get the dashboard.

Our intervention for supporting SRL skills (Figures 2-4) covers all three phases of Zimmerman's model. The forethought phase is supported by specifying the overall goal as well as the weekly goals. The dashboard supports the performance/reflection phases, as it allows the student to reflect on their progress towards goals, as well as self-assess/reflect on their knowledge using the OLM. Please note that the OLM was a part of the standard version of SQL-Tutor (Mitrovic & Martin, 2007). The OLM is shown to students in SQL-Tutor when they select problems to work on.

The intervention we developed is similar to the one used by Davis and colleagues (2018), with several differences. Davis et al. added support to a MOOC, while in our case the students interacted with an intelligent tutoring system. In addition to the differences based on the type of learning resources (watching videos in the case of MOOC, and solving problems in the case of SQL-Tutor), there are differences in how the dashboard is utilized. The dashboard used in (Davis et al.) was only available by request, while in our case, the dashboard was shown to the student at the start of each week (after specifying the weekly goals), and also at the start of each session. Additionally, students could explicitly request to see the dashboard using the button in the SQL-Tutor workspace. Therefore, our students had more opportunities to see the dashboard. Finally, our dashboard does not only provide feedback on the realization of the goals, but also includes the OLM, thus allowing students to reflect on their knowledge.

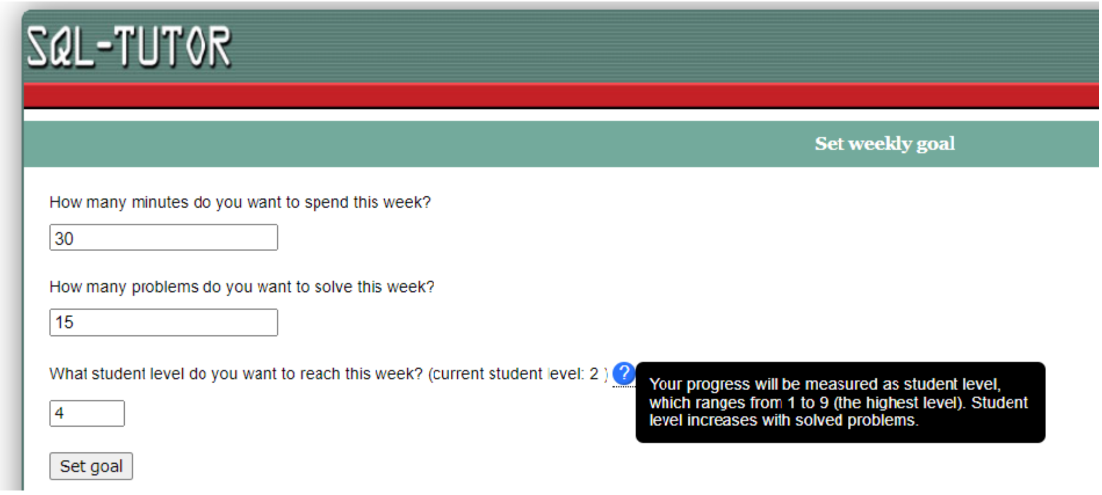

Figure 3. Setting the weekly goal

4. Findings

There were two versions of the test (versions A and B) which were counterbalanced as pre/post-test. Both tests had four questions of similar nature. At the pre-test time, 47 students took test A, and their mean score was 2.17 (sd = .99), while 62 students completed test B with the mean score of 2.16 (sd = 1.05). There was no significant difference ($p = .97$) between the pre-test scores, showing that they were of similar complexity. The difference in the numbers of students who completed tests A and B is due to the fact that pre-test completion was optional, so some students did not submit their answers.

We collected data from 136 students and eliminated the data about ten students who did not complete the pre-test, two students who did not take the mid-term test, and also data about 16 students who used SQL-Tutor for less than 10 minutes. That leaves data about 108 students. Both pre- and post-tests were optional, so not all students completed them. There were 71 students who completed both tests. Table 1 reports the basic statistics of the system usage. The students interacted a lot with the system, with the average time of over 4 hours. More than half of the students (55%) explicitly requested to see the dashboard (that is in addition to seeing the dashboard automatically at the start of the session/week), which is higher than the rate reported by (Davies et al. 2018).

Table 1. *Summary of interactions with SQL-Tutor*

	Min	Max	Median	Mean (sd)
Pre-test	0	4	2	2.17 (1.02)
Time (min)	13	1,007	188	267.11 (248.80)
Sessions	2	33	7.5	9.23 (6.65)
Solved Problems	0	266	26.5	37.81 (43.97)
Attempts	1	926	114	164.67 (169.40)
Level achieved	1	9	3	3.12 (1.90)
Post-test (71 students)	0	4	2	2.28 (0.92)
Dashboard requests (60 students)	1	28	2	4.52 (6.10)
SQL test (%)	7	100	58	54.76 (21.66)

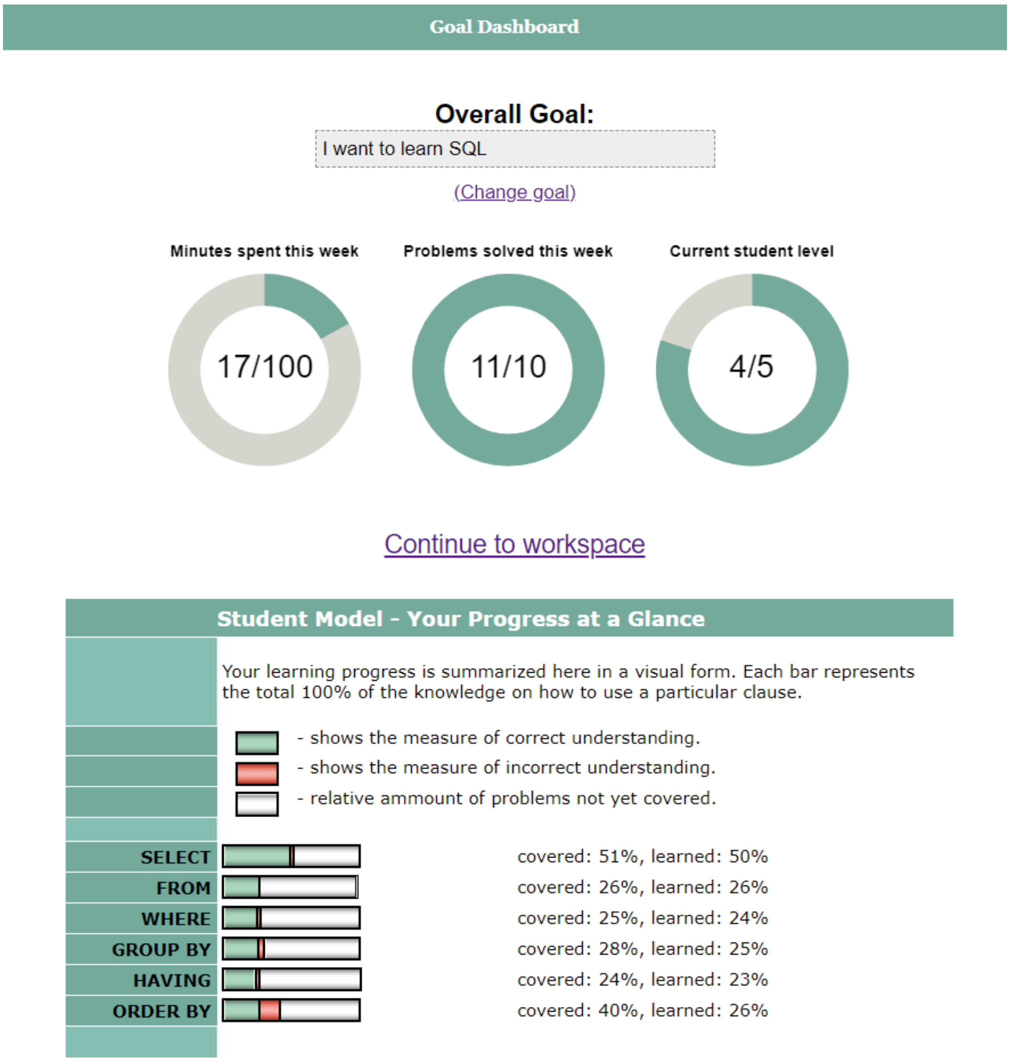

Figure 4. Dashboard

Of 108 students, 92 (85.2%) specified meaningful goals, which ranged in length from a single word to the maximum of 15 words (median = 4, avg = 4.69, sd = 3.16). Table 2 shows several example goal statements. The five most frequently occurring words in the stated goals are: *SQL* (49 times), *Learn* (29), *pass* (14), *get* (12) and *good* (11). Although students had the opportunity to change the overall goal at the start of each week, only two of them did so.

Table 2. *A random sample of short, medium and long submissions for the overall goal*

Overall Goal	Classified as
Learn sql	Intrinsic
To gather a good understanding of SQL	Intrinsic
To become familiar and comfortable with using SQL	Intrinsic
To pass this course with at least an A-	Extrinsic
To pass my course	Extrinsic
Pass tomorrows test	Extrinsic
Achieve high grades	Extrinsic

The overall goal statements were classified by the first author of this paper as intrinsic or extrinsic (as in Table 2). When analyzing the behavior and learning of the students who specified the two types of goals (Table 3), we did not find significant difference on most variables, but there was a significant difference on the SQL test scores and also on dashboard requests. The students who specified intrinsic goals explicitly requested to see the dashboard more often and achieved higher scores on the SQL test.

Table 3. *Comparing students who specified intrinsic/extrinsic goals*

	Intrinsic (59)	Extrinsic (33)	
Pre-test	2.20 (1.08)	2.15 (.91)	
Time (min)	272.90 (265.83)	255.85 (235.26)	
Sessions	9.64 (7.00)	9.27 (6.91)	
Solved Problems	42.64 (54.17)	31.85 (25.46)	
Level achieved	3.08 (2.17)	3.48 (1.58)	
Post-test	N = 39, 2.26 (.94)	N = 21, 2.19 (.81)	
Dashboard requests	**N = 36, 3.81 (4.77)**	**N = 12, 2.92 (2.15)**	t = 2.24, p < .05
SQL test (%)	**57.76 (19.97)**	**47.83 (21.16)**	U = 1202.5, p < .05

As SQL-Tutor is provided to students on a voluntary basis, not all students started interacting with it in week 1. Table 4 specifies the number of students who used the system in a particular week of the study (the *Active* row), as well as the number of students who used it for the first time that week (the *Started* row). Not surprisingly, the number of active students increased in the last week, due to the SQL test.

Table 4. *Numbers of students interacting with SQL-Tutor in different weeks*

	Week 1	Week 2	Week 3	Week 4
Active	33	32	31	98
Started	33	15	17	43

We also analyzed the weekly goals, in order to examine whether students were ambitious in setting their goals and whether they were able to fulfil their plans. We were interested in seeing whether their planning tendencies changed over time. The data is illustrated in Figure 5. Students' goals for the time, problems and student level increased over time. The actual time spent in the system and the number of solved problems were above the goals in the final week, as students were preparing for the test. However, the achieved student levels were constantly below the goals.

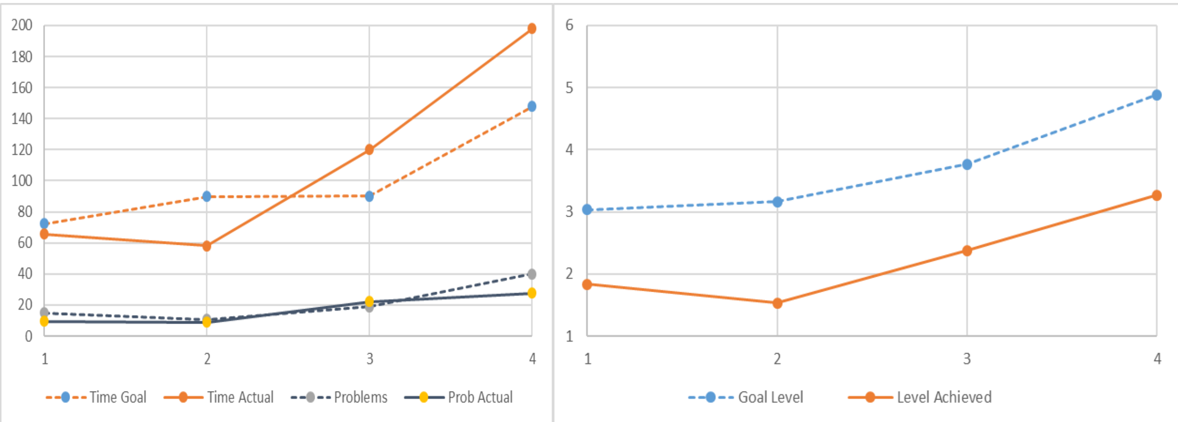

Figure 5. Planned vs achieved time, problems and student level

5. Analyzing Behavioral Differences

Intrinsic or extrinsic motivation is something students came in with and is not due to the SRL support. For that reason, we also analyzed the data collected from the 21 students scoring high on the SQL test (i.e., more than 75%) compared to those who achieved low marks, i.e., less than 35% (Table 5). Apart from the significant difference on the SQL test score, the only other significant difference we observed was on the post-test score ($t = 3.49$, $p < .001$).

Table 5. *Comparing Low and High groups*

	Low (22)	High (21)
Pre-test	1.95 (.99)	2.24 (1.09)
Time (min)	246.41 (250.13)	255.48 (238.61)
Sessions	10.41 (8.84)	7.81 (5.09)
Solved Problems	28.27 (27.29)	38.76 (38.51)
Level achieved	2.95 (1.62)	3.33 (1.83)
Post-test	**1.81 (.91)**	**2.88 (.81)**
Dashboard requests	1.73 (2.25)	3.10 (5.42)
SQL test (%)	**24.15 (7.40)**	**85.43 (6.97)**

As the frequency analyses did not discover any differences in students' interactions with SQL-Tutor, we used Epistemic Network Analysis (ENA) to identify behavioral differences. ENA is a quantitative ethnographic method for identifying connections in interactions, which could be conversations between multiple people, but can also be applied to interactions with software systems (Shaffer et al., 2009). ENA provides visualizations for qualitative interpretation along with statistical tests (Shaffer et al., 2016). Epistemic networks model co-occurrence of coded data, where codes represent relevant actions or events. The coded data is analyzed by identifying codes within a moving window which defines the temporal context. The resulting network is aggregated across all lines for each unit of analysis, and visualized as graphs, where codes are represented as nodes, and edges represent relative frequency of co-occurrence between the codes.

We used the ENA1.7.0 Web tool (Marquart et al., 2018) for investigating the interactions. From SQL-Tutor logs, we extracted data about the following actions which are of relevance for SRL, and used them as codes for ENA:

- *Start* (of a session),
- *DashboardRequest* (explicit request by a student),
- *NewDatabase* (when student requests a new database to practise on),
- *StudentProblemChoice* (the student selects the next problem to work on on their own),
- *NewProblem* (request for a new problem),
- *ProblemSolved* (correctly solved problem),
- *ProblemAttempt* (the submitted solution has some errors),
- *ProblemAttemptHint* (incorrect solution, and hint was provided),
- *ProblemAttemptAllErrors* (incorrect solution, and the student requested to see all errors),
- *ProblemAttemptPartialSolution* (incorrect solution; the student requested to see a partial solution),
- *ProblemAttemptFullSolution* (incorrect solution; the student requested to see the full solution).

For the students in the Low/High groups, there was a total of 5,619/6,503 selected events from the logs. When generating epistemic networks, we defined units as the group (Low vs High) subsetted by the student. The unit of conversation was set to include all actions performed by a single student. Figure 6 shows the networks for the Low (left) and High (right) groups. The width of a line connecting two nodes is proportional to the frequency of those two codes co-occuring in interactions.

The two networks look similar, but the ENA tool also produces the network showing the differences between the two groups (Figure 7). The color of a connector between two codes shows which group had more co-occurences of the two codes. For example, the connection between *ProblemAttemptFullSolution* and *ProblemSolved* is colored red, which means that those two codes occured more often for the Low group. The model had co-registration correlations of 0.98 (Pearson) and 0.98 (Spearman) for the x-axis, and co-registration correlations of 0.96 (Pearson) and 0.95 (Spearman) for the y-axis, showing a very good fit. There was a significant difference between the two groups on the x-axis: a two sample t-test assuming unequal differences showed that the Low group (mean = .46, sd = .99) was significantly different from the High group (mean = .49, sd - .58), $t = 3.86$, $p < .001$, Cohen's $d = 1.16$, but there was no significant difference on the y-axis. Further exploration of the difference network shows that the low group more often required additional feedback (at the Full Solution and the Partial Solution level), followed by a correct submission. We suspect that some students from the Low group copied the solution provided by the system (partial or full), and then submitted it as their solution.

Such behavior of course does not result in learning, thus explaining significantly lower scores on the post-test and the SQL test for the students from the Low group.

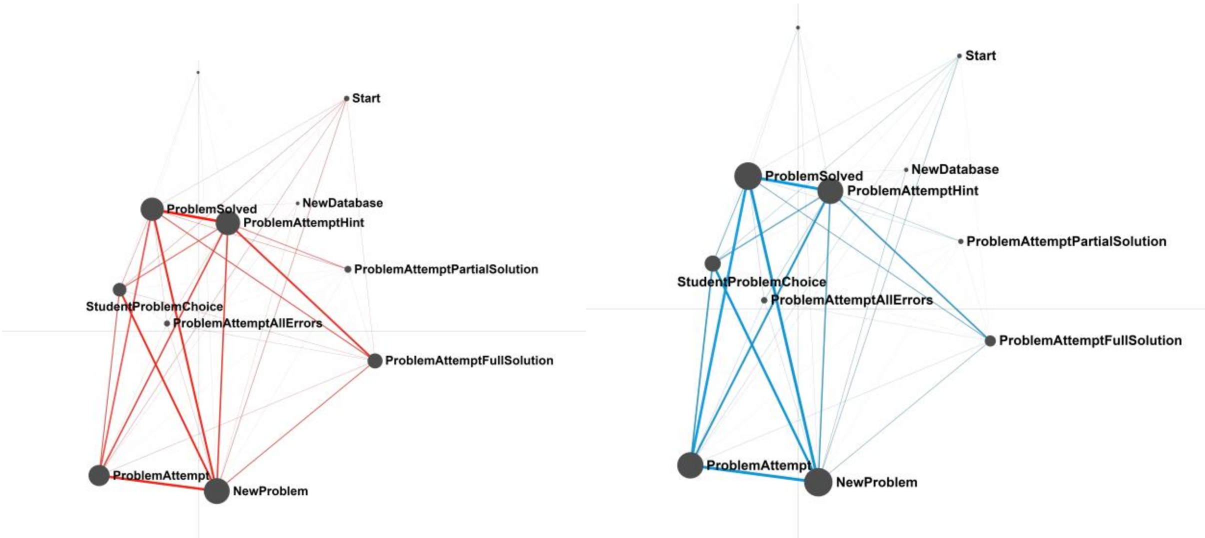

Figure 6. Epistemic networks for the Low (left) and High (right) groups

The percentage of problems solved after seeing the full solution for the Low group is 24.34% (sd = 26.44), while for the High group the average is 16.65% (sd = 13.08). Although the difference between the two groups on just the proportion of problems solved after seeing the complete solution is not statistically significant, ENA provides better insights as it analyzes several measures simultaneously. The locations of codes (i.e., events) in ENAs shows that all codes representing high-level feedback are grouped close to each other (i.e., full solution, partial solution and all errors).

The connection between *NewProblem* and *ProblemAttemptFullSolution* is also more common for the Low group, which shows that some students ask for a full solution immediately, without trying to solve the problem on their own. On the other hand, the connection between *NewProblem* and *StudentProblemChoice* are more frequent for the High group, showing that those students more often select problems for themselves. All these observations indicate stronger SRL skills and learning strategies for the High group.

6. Discussion and Conclusions

We presented a simple support for self-regulated learning added to SQL, and our observations of how students interacted with the support and with the system itself. We extended SQL-Tutor, asking student to i) specify their overall learning goal, ii) specify weekly goals in terms of the time with the system, problems solved, and the level achieved, and iii) a dashboard summarizing their progress on goals, and also providing an open student model. Although we have found that intrinsically motivated students learnt significantly more than their peers and also made significantly more dashboard requests, students' motivation was measured before interacting with SQL-Tutor and could not have been affected by the SRL support. When comparing the interactions of high-scoring students to low-scoring students, frequency analyses did not indicate any significant differences between the numbers of various learning events. However, a comparison of epistemic networks corresponding to the two subgroups of students shows a significant difference. The students who scored low on the SQL tests requested more detailed feedback on their solutions to problems, often asking for a partial or even the full solution. In the case of one student from the Low group, who solved two problems during the total interaction time of 14 minutes, for both of those problems the student first asked for a full solution, then copied and submitted it. Seeing the full solution may result in the illusion of understanding, a phenomenon identified in studies on learning from worked examples (Renal, 2002; Gerjets et al., 2006, Shareghi Najar & Mitrovic, 2013), which may lead to overestimation of competence. Therefore, low-scoring students need to be encouraged to be more active in learning and solve problems on their own. Such students need to improve their SRL and especially help-seeking skills.

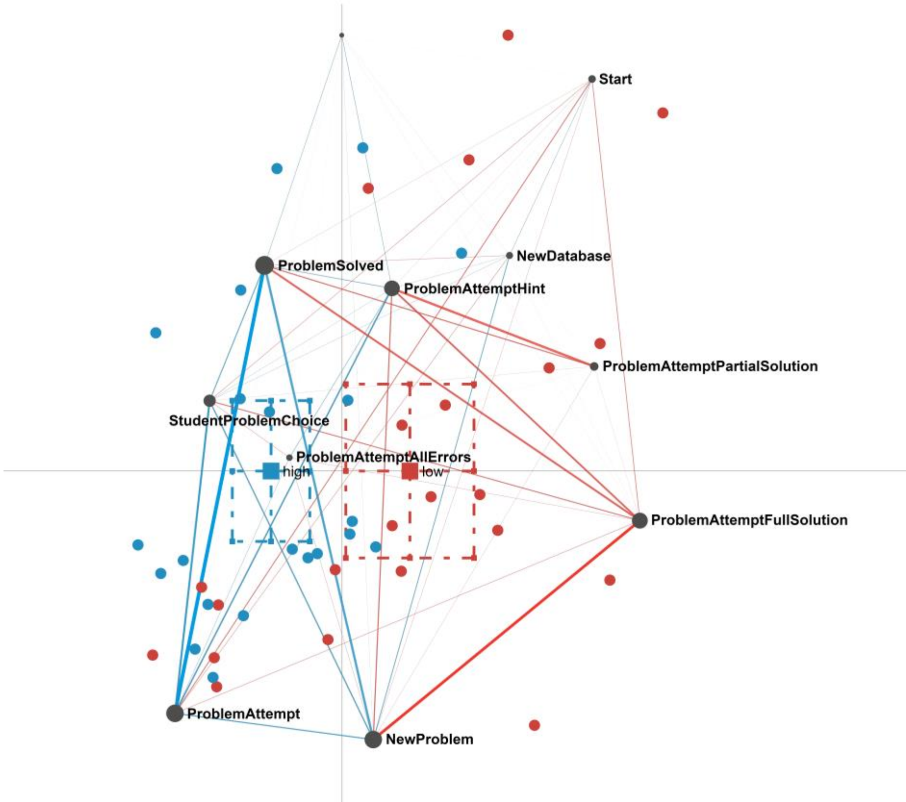

Figure 7. The difference network

There are several limitations of our study. Firstly, our study was only an observational study; we did not compare two groups of students with/without the SRL support. The goal of the reported study was to collect some information about how students interact with the provided SRL support. It is encouraging that more than half of students (55.55%) explicitly requested to see the dashboard, compared to 32% of students engaging with SRLx at least once (Davis et al., 2018). The second limitation is that our SRL support was fixed. In the future, we plan to design adaptive SRL support, and provide different guidance to students with low SRL skills.

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