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A Process Mining Approach to Understand Self Regulated- Learning In Moodle Environment

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ABSTRACT

This paper proposes the use of Fuzzy Miner, a process mining technique to map the student-regulated learning (SRL) behaviour on Moodle online learning environment. The activity logs from 90 undergraduate students was extracted using the process mining technique. Finding shows process mining was able not only to identify the SRL patterns but also able to highlight the students' SRL behaviour. Understanding the cyclical nature in SRL and the students' SRL behavior online as outlined in this study would help the educational stakeholders in motivating the students' efforts to learn.

Key words : Fuzzy Miner, Learning Analytics, Moodle, Process Mining, Self-Regulated Learning.

1. INTRODUCTION

With the flexibility that online learning offers, it also imposes a new challenge to learners. Learners tend to work alone because the time and place boundaries do not exist as in traditional learning environment. Adapting to online learning environment requires learners to take responsibility for their own learning. Learners have to manage time for learning, seek information or help related to their learning. They need to self-regulate their learning.

As much said about the importance of self-regulated learning (SRL), very little effort is shown to know, understand or even measure the activities made by learners over the online learning environment, with regards to proving that SRL truly exists online as much as it does offline. Self-regulated learning is postulated as predictor of academic achievement [1], [27], hence the need to spend time to understand the SRL patterns over online learning environment, such as learning management system, Moodle and Blackboard, to name a few. This would benefit the learners themselves, the academicians, and the academic management of an institute of higher learning (i.e. stakeholders), in ensuring that the quality of education and online learning platform could facilitate in producing good graduates and independent lifelong learners.

As quoted from [2], "Self-regulation is important because a major function of education is the development of lifelong learning skills." With such intention, this research aims to identify the SRL patterns through process mining on data and information retrieved from an online learning environment. Since Moodle is the common environment in current implementation at institutes of higher learning, the research questions that guide this research are:

- What are the type of data captured from logs that can be used to identify the SRL patterns performed by learners?
- How do the data reflect the SRL process based on SRL model commonly cited in literature?

2. RELATED WORKS

This section summarizes the previous research related to this study. In general, the related works are divided into two: self-regulated learning, and process mining in learning analytics

2.1. Self-Regulated Learning (SRL)

One of the most cited self-regulated learning models is Zimmerman's Model of Self-regulated Learning [3]. Zimmerman defines self-regulated learning as "self-generated thoughts, feeling and actions that are planned and cyclically adapted to the attainment of personal goals" [4]. Zimmerman model is found suitable for this research because it focuses on the interaction between three phases of self-regulated learning, i.e. forethought, monitoring and reflection (as shown in Figure 1). This model is used to design a process model to support SRL in online learning environment, as it is found fit to be the theoretical framework for this purpose.

The SRL in process terms was further defined as "the self-directive process by which learners transform their mental abilities into academic skills", in which learning is an activity that learners do proactively instead of as a reaction to teaching. One of the processes often found among SRL learners is "monitoring their behavior in terms of their goals and self-reflect on their increasing effectiveness" [2], which is possibly made by consistently checking on the online learning environment and taking action online even before being instructed by the teachers or lecturer.

Referring to Figure 1, learners set goals to achieve based on certain criteria and choose appropriate learning method to achieve them, in the forethought phase. These goal settings are done based on their beliefs that motivate them to plan ahead. These self-motivation beliefs are stated as self-efficacy (i.e. the learners' belief on their capabilities to perform the task), outcome expectations (e.g. monetary rewards, good marks, future skill possessed, high income when graduate), intrinsic interest or value (i.e. perceive the task to be useful and related to personal goal), and learning goal orientation (i.e. the purpose of learning to the learners).

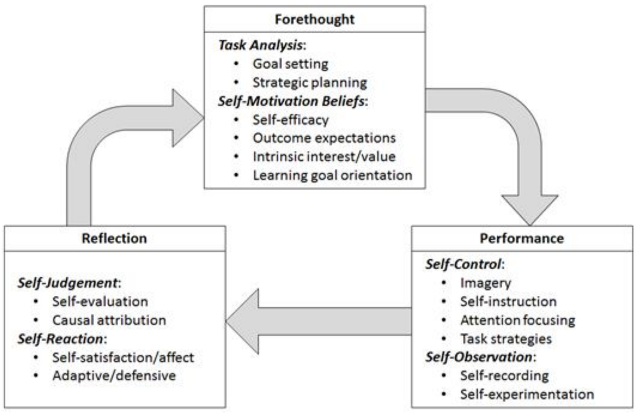

Figure 1: Zimmerman's SRL Model (2000)

Goal orientation, according to Elliot, McGregor and Gable and Panadero [5], [26], is categorised into two types: mastery goal and performance approach goal. Learners are motivated with the idea of mastering the material of learning in mastery goal, whereas the motivation source comes from comparing with other peers in performance approach goal.

Regardless of the positive impact in forethought phase, the result of the process could be negative. For example, learners may feel that they are not capable of performing tasks perceived required to attain their goals, which may result in demotivation in learning instead of full self-motivation. This is intrinsically unique for each learner, and may be a challenge in identifying them in this research.

The second phase in SRL model shown in Figure 1, i.e. performance phase (or sometimes called monitoring phase), in which two major strategies are applied by the learners: self-control; and self-observation. According to Ley and Young[6], self-regulated learners view learning as a controllable process, as they constantly plan, organise, monitor, and evaluate their learning during this process[1]. Hence, the purpose is to monitor task progress and maintain the motivation towards the task.

Self-control used by learners can be a task-specific strategy (i.e. a systematic process that needs to be followed to complete a task), or general strategies (i.e. not exclusive for a specific task, like imagery, time management, environment structuring, help-seeking method, interest incentives, and self-consequence)[2]. On the other hand, self-observation strategy happens when learners apply metacognition control and self-recording, by mentally tracking their performance and outcome to external criteria. Nevertheless, learners could still create formal records of their learning processes, such as daily journals or diaries, and records on external factors that impact their learning. Tracking performance is a complex process if it involves complex learning materials, especially when learners tend to record the perceived activity instead of actual ones. This is among the reasons that motivate this research into investigating the log data retrieved directly from the back-end of the online learning platform, in which the data could not lie on what actually happened during the learners' learning activities online.

The final phase of the Zimmerman[4] SRL model is the self-reflection phase (as shown in Figure 1). Learners in this stage will judge their work and react to the result of their work. This reaction can be in positive emotion form or negative emotion form. Self-reflection phase consists of self-judgement (i.e. learners evaluate their results to one or more of the standards: prior level of performance, mastery of all component of skill and/or social comparison with others like classmates and peers) and self-reaction (i.e. the positive or negative reaction of learners towards their self-judgement).

Despite the detailed explanation on SRL processes, research has shown that learners are lacking in the skill of regulating their learning. Learners tend to procrastinate [7], stop before mastering skills[8], feel overconfident with their skills[9] and cram the work at one specific time[10]. It is important for to measure SRL because it allows reflection for improvement in teaching and learning as well as in academic performance.

Schraw[11] has summarised how existing strategies can be used to measure SRL, both for offline and online measures. In order to capture and study the actual online activities and to be "unobtrusive" in doing so (i.e. not disturbing the on-going activities that is going on over the online learning environment), Schraw[11] recommended four unobtrusive measures: trace logs, hyperlinks, palette choices, and inserted beliefs. Activity logs in Moodle can be traced to provide the opportunity to measure SRL in real-time or online and in an unobtrusive way. It allows the mining of processes going on in Moodle, in the quest of identifying the SRL patterns online. Modular Object-oriented Dynamic Learning Environment (Moodle), featuring some web 2.0 technologies, is built on a social constructivist pedagogical approach, encompasses in the problem-based learning (PBL) approach[12]. Moodle captures detailed interactions between students and lecturers that are useful to understand online behaviour of students[13]. Moodle keeps detailed logs of individual detailed use sessions of the students and the instructors, and get user reports from that, in which they can be obtained according to, students, time, and fixed activities, to name a few[14]. Hence, the processes of learning could be analysed through these records.

2.2. Process Mining in Learning Analytics

Learning analytics is an emerging field in education technology that uses the learners' digital trace to improve learners' and teachers' activities online. As quoted by

Siemens and Gasevic[15], the Society for Learning Analytics Research defined learning analytics (LA) as the "measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs". The domain of LA sits between technical and social learning theory fields, in which the algorithms that form recommender systems, personalisation models and network analysis are covered under the technical side, whereas the impacts of these algorithms are covered in the social system of learning, i.e. the non-technical side[15]. Efforts have been made to prove that LA is a field with potential for improving teaching and learning.

Having said this, this research focuses on the process mining analysis technique for data analysis purpose. Based on existing research, process mining techniques analyse process data and produce process model, presentable in visualisation format named process models, such as Petri-net, Heuristic Net, and Fuzzy Model. Visualisation in process mining technique enables communication on important information in a very limited space resources, which is a display screen. According to Roll and Winne[16], the challenge of visualisation in learning analytics is how to represent the information without causing information overload and at the same time do not leave behind the important information.

Visualisation techniques in process mining show the relationships between each process and how these processes are related to each other. One of the issues in process mining visualisation are representational bias, in which its importance of representational bias based on process mining techniques and the characteristics of underlining the processes not based on graphical representations is emphasised by van der Aalst[17].

With the growth of education technology like Moodle, Massive Open Online Course (MOOC) and learning management system (LMS), a digital trace of learners are now possible to be gathered and thus allow it to be analysed to enhance learning and teaching. Other than online learning platforms, data of learners' digital traces are also available in the academic systems, such as attendance system, academic management system, learning outcome attainment management system, to name a few. Learning analytics uses digital trace to focus on empowering learners and teachers making decisions, instead of automating the decision making, making it one of the promising techniques developed to make use of these data. The systems provide learners and teachers with the crucial data that can be translated to understanding learning behaviour in a real learning setting.

Learning Analytics is an iterative process that consists of three main steps[18]: data collection and pre-processing; analytics and action; and post-processing. Out of these three processes, the analytics and action is the main focus of adoption in this research, in which the data is analysed based on the objective of analytics to discover hidden patterns that would be used to support SRL activities.

Most of the current research focuses on static data, such total number of downloaded materials, logins or forum posts, to understand how learners self-regulate their learning in online learning platforms. The latest development is an attempt to study the self-regulated learning from temporal data[19], using techniques like sequential analysis and process mining. This strengthens the reason for adopting process mining as the analysis method in this research.

Process mining is a data mining technique focusing on extracting process-related knowledge from event logs[20]. Winnie[21] mentioned that process mining is a powerful tool for identifying a pattern of self-regulated learning, citing the three main categories of process mining techniques from van der Aalst[20]: process discovery; conformance; and enhancement. Process discovery technique takes the event log and produces a model of the process without prior information of the model; conformance technique compares the existing process model to the event log whether the process model fits the reality captured by the event logs or not; and enhancement technique is used to enhance or improve an existing process model based on the actual reality recorded in event logs[20]

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In order to perform process mining, algorithms are needed to produce a suitable type of model that meets the purpose of this research. Sample of algorithms widely used are Alpha Algorithm, Heuristic Miner, Multiphase Miner and Fuzzy Miner. Each of these algorithms produce a different type of model, such as Petri net (by Alpha Algorithm), Heuristic net (by Heuristic Miner), Event-driven Process Chain (by Multiphase Miner), and Fuzzy Model (by Fuzzy Miner). This research uses Fuzzy Miner due to it robustness to spaghetti like processes and highly unstructured process[22], [28]. Other than its robustness, Fuzzy Miner produces a Fuzzy Model visualisation that is easy to be interpreted (as shown in the Results and Findings) and allows animation of the process, leading to better understand of the model.
paper.

3. METHODOLOGY

The main research inquiry of this study is to identify online students' SRL pattern by using Fuzzy Miner. Specifically, we aim to answer the following research questions:

- What are the type of data captured from logs that can be used to identify the SRL patterns performed by learners?
- How do the data reflect the SRL process based on SRL model commonly cited in literature?

3.1. Participation and case selection

Moodle activities performed by third-year students in a Malaysian university were selected for this study. Third year students were selected as they would have prior technical experience with Moodle environment as Moodle serves the platform for the university's LMS. The Moodle activities of 90 registered students for Networking course were collected between January 2016 and June 2016. A technical course is selected for this study due to the nature of the course that demands the students to be highly self-regulate their learning.

SRL was investigated at course level as it was proven that students will use different SRL strategies for different courses[16].

For each course offered by the university, the lecturers need to provide online learning materials, and perform assessments in terms of online quizzes, forum discussions and assignment submissions online. Moodle keeps detailed logs of the students' activities performed online and captures students' navigation to online content, such as forums, quizzes and learning materials (i.e. documents and videos).
An example of activity logs generated from Moodle database is as shown in Figure 2.

log_id	username	ACTIVITY_SIMPLE	TheTime
776629	ZZZBBBBAA	viewed course NA	30-01-16 23:58
776661	ZZZBBBBAA	viewed course_module quiz	30-01-16 23:58
776663	ZZZBBBBAA	viewed course NA	30-01-16 23:58
861725	ZZZBBBBAA	viewed course NA	01-02-16 19:03
867669	AAABBBCCC	viewed course NA	01-02-16 20:42
867772	AAABBBCCC	viewed course_module resource	01-02-16 20:43
873364	AAABBBCCC	viewed course NA	01-02-16 21:55

Figure 2: Sample activity logs captured in Moodle

A total of 40 types of online activities were extracted from Moodle, however, only 21 activities were found relevant to this study, as listed in Table 1 below.
From the log descriptions shown in Table 1, "view course" is an indicator that the student is viewing overview of the course structure. Actions such as "view link", "view quiz", "view resource", "view forum", "view folder", "view page", "view grade report" and "view discussion forum" show that the student is accessing materials provided or created by the lecturer. These are the simplest log records that could be retrieved from the online system, which are the first indicators on students' commitment and practice of SRL.

Table 1: Moodle Logs Activities

Log Name	Log Description
viewed course NA	View course
viewed course_module URL	View link
viewed course_module quiz	View quiz
viewed course_module resource	View resource
viewed course_module forum	View forum
viewed course_module folder	View folder
viewed course_module page	View page
viewed grade_report NA	View grade report or marks
viewed submission_status NA	View submission status
viewed submission_form NA	View submission form
uploaded assessable assign_submission	Upload assignment
created submission assignsubmission_file	Create assignment submission file
submitted assessable assign_submission	Submit assignment
updated submission assignsubmission_file	Update assignment submission file
started attempt quiz_attempts	Start attempting quiz
viewed attempt quiz_attempts	View quiz attempt
viewed attempt_summary quiz_attempts	View summary of quiz attempts
graded user grade_grades	View grades
submitted attempt quiz_attempts	Submit quiz attempt
reviewed attempt quiz_attempts	Review quiz attempt
viewed discussion forum_discussions	View discussion forum

In addition to that, activities recorded during an online quiz, such as "start attempting quiz", "view quiz attempt", "view summary of quiz attempts", "submit quiz attempt" and "review quiz attempt" hold as proof on the effort made by the student in practicing SRL during the completion of the quiz. "View submission status", "view submission form", "upload assignment", "create assignment submission file", "submit assignment" and "update assignment submission file" activities show that students are engaging in SRL for the completion and submission of the assignment in Moodle.

3.2. Data collection

The activity logs were extracted directly from Moodle database. Although Moodle provides an interface to extract the activity logs, the database extraction were preferred due to the detail data it provides, such as activity timestamp up to the seconds.
Clean-up process was performed by ensuring that only students' activity logs were kept in the log. This process was done by removing system-generated activities and lecturer-generated activities from the activity logs. Removing the system- and lecturer- generated activities will show only the activities that the students engaged.
The remaining data was then analysed via process mining. Process mining requires three minimum data for it to work, which are listed in Table 2 below.

Table 2: Data Requirement

Data Requirement	Moodle Data Mapping
Case ID	Student ID
Activity	Activity_Simple
Timestamp	TheTime

Referring to Table 2, *Case ID* was a unique process instance identity. In this study the *Case ID* was mapped to the *Student ID* as the scope was only on the students' online activities. An *Activity* was the process that were performed by each process instance. It is only useful if multiple entries (multiple rows) of the activities were available in order to understand a process instance behaviour (student SRL). *Timestamp* was used to identify the order of the process activities, delay and bottleneck.

The Fuzzy Miner was the mining algorithm to introduce the "map metaphor" to process mining, including advanced features like seamless process simplification and highlighting of frequent activities and paths[23]. In this study, the software used to adapt the Fuzzy Miner was the Disco software. Disco software provides more intuitive and easy to configure for analysis where the main paths of the process flows were easily identified and wasteful rework loops are quickly discovered.

The activity logs of the participants' online activities for the course was extracted at the end of June 2017. The total activities for the students' activities on Moodle (refer to Table 1) was 13,328. In this study, discovery process mining via Fuzzy Miner was applied where the activity logs were extracted. Fuzzy Miner was used due to it robustness to spaghetti-like processes and highly unstructured process[17,20]. Moreover, Fuzzy Miner produced a Fuzzy Model visualisation that is easy to be interpreted and allows animation of the process, which further leads to better understanding of the model.

The configuration of the model was set to default, where *Activities* parameter was set to 75 percent (75%) and the path to zero percent (0%). Adjustment to this parameter will produce different Fuzzy Model.

4. RESULTS AND FINDINGS

The results and findings for this study are divided into two parts: the fuzzy model map, and the fuzzy model animation.

4.1. Fuzzy Model Map

In the overall process model, it was found that "viewed course NA" and "viewed course_module resource" were the most used activities for students. As shown in Table 3, "viewed course NA" received the highest frequency of 4,379 times (32.86%) and "viewed course_module resource" received 3,760 times (28.21%). In general, 90 students registered for the selected technical course have viewed the course 4,379 times and viewed the module resource 3,760 times.

Table 3: Top Four Activities

Activity	Frequency	Relative Frequency
viewed course NA	4,379	32.86%
viewed course_module resource	3,760	28.21%
viewed course_module URL	1,127	8.46%
viewed discussion forum_discussions	600	4.50%

Figure 3, 4 and 5 show parts of the Fuzzy Model Map for overall students' activities for selected cases. Figure 3 shows how students visited forum through "view course_module forum" and "viewed discussion forum_discussions" activity. According to Cheng, Liang, and Tsai[23], visiting forum is and indicator of help-seeking strategies which perceived performance phase happen.

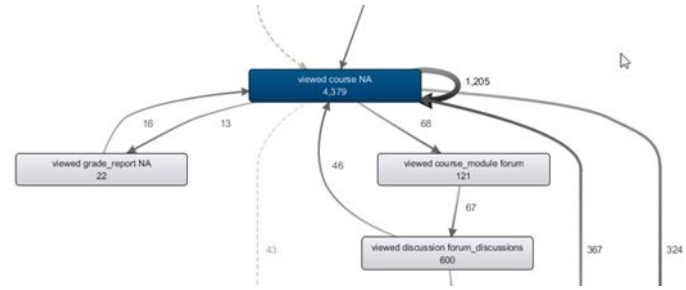

Figure 3: Sample activity logs captured in Moodle

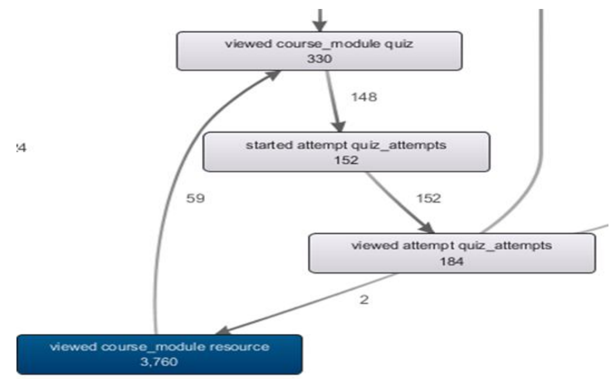

Figure 4: Fuzzy model (Part 2)

Figure 4 shows that, which we believe also, a sample of reflection phase of Zimmerman SRL model through activity of "view course_module resources" just after "view attempt quiz_attempts". This flow of activities is perceived as students revisiting the course resources after attempting a quiz and redo the quiz with the expectation to improve their result. Figure 5 shows how students resubmitted assignment files through "updated submission assignsubmission_file" activity. It is perceived that by updating their assignment submission, the students have gone through self-reflection phase as stated in the Zimmerman's SRL Model, hence proved that the self-reflection phase occurred.

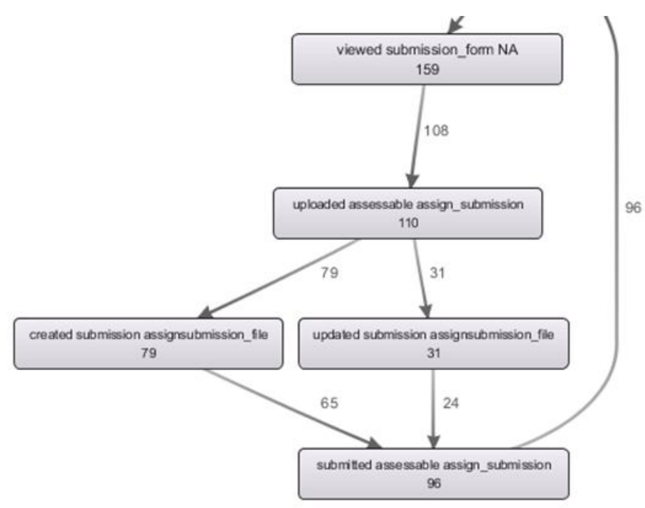

Figure 5: Fuzzy model (Part 3)

4.2. Fuzzy Model Animation

In animation mode of Fuzzy model as shown in Figure 6, it is observed that students do reread material shared in Moodle as they were answering quizzes. This behaviour indicates that the students studied before attempting to answer the quiz.

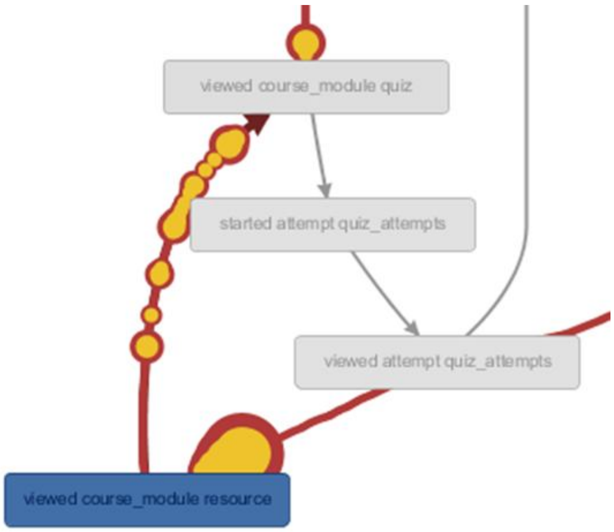

Figure 6: Fuzzy model animation.

In animation mode, the Fuzzy Miner via Disco software shows movement of each process instance using a circle shape. Paths that the process instance travels frequently is shown through the thickness of the line. As shown in Figure 6, the line thickness between process "view course_module resource" and "view course_module quiz" is thicker than process between "view course_module quiz" and "started attempt quiz_attempts", which shows that the former process happens more frequent than the latter one.

5. DISCUSSION

The purpose of this study is to examine the students' SRL pattern with process mining technique, using the activity logs extracted from the course's Moodle platform. The Fuzzy Model shows that the activity logs from Moodle can be mapped to Zimmerman's SRL model, hence, can be used to observe students' SRL. The top four activities performed by students (refer to Table 3) indicated that learners do set goals to achieve, based on certain criteria in the *forethought* phase. This agrees with previous research that self-regulated learners create strategies to guide the cognition, have control of the effect and perform the execution[25].

The process mining result also shows that there were lack of activities during the *performance* phase but most students revisited their activities (as depicted in Figure 3, 4 and 5). This shows that the self-reflection phase produces positive reactions for most students with regards to their effort to learn. This reaction in *self-reflection* phase will in turn influences forethought phase in terms of goal setting, planning and further efforts to learn.

The result of this study is useful for lecturers, students and instructional designers as the cyclical nature of SRL affects all of these stakeholders. Process mining provides an effective way to analyse the vast amount of complex information in an online learning platform, such as Moodle which was rarely being used before[19].

6. CONCLUSION

This study shows that the process mining technique provides new opportunities to better understand self-regulating learning behaviours in online learning. Through process map, such as Fuzzy model and animation, we can see how students adopt SRL throughout the course. Future works include SRL evaluation for a few semesters and the SRL comparison between high performing and low performing students. In terms of process mining, the future work could include using trace log files that was saved in other online learning platforms with regards to identifying SRL.

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REFERENCES

1. C. Mega, L. Ronconi, D.R. Beni, **What makes a good student? How emotions, self-regulated learning, and motivation contribute to academic achievement.** *Journal of Educational Psychology*, 106 (1) (2014) 121-131. https://doi.org/10.1037/a0033546
2. B.J. Zimmerman, **Becoming a self-regulated learner: An overview. *Theory into practice*,** 41(2) (2002) 64-70. https://doi.org/10.1207/s15430421tip4102_2
3. B.J. Zimmerman, A.R. Moylan, Self-regulation: **Where metacognition and motivation intersect**. *Handbook of metacognition in education* (2009) 299-315.
4. B.J. Zimmerman, Self-efficacy: **An essential motive to learn**. *Contemporary educational psychology*, 25(1) (2000) 82-91. https://doi.org/10.1006/ceps.1999.1016
5. A.J. Elliot, H.A. McGregor, S. Gable, **Achievement goals, study strategies, and exam performance**: A mediational analysis. *Journal of educational psychology*, 91(3) (1999) 549-563. https://doi.org/10.1037//0022-0663.91.3.549
6. K. Ley, D.B. **Young, Self-regulation behaviors in underprepared (developmental) and regular admission college students**. *Contemporary Educational Psychology*, 23(1) (1998) 42-64. https://doi.org/10.1006/ceps.1997.0956
7. P. Steel, **The nature of procrastination: a meta-analytic and theoretical review of quintessential self-regulatory failure.** Psychol. Bull., 133(1) (2007) 65–94. https://doi.org/10.1037/0033-2909.133.1.65
8. R. Isaacson, F. Fujita, **Metacognitive knowledge monitoring and self-regulated learning: *Academic***

success and reflections on learning. J. Scholarsh. Scholarsh. Teach. Learn, 6(1) (2006) 39–55.

9. P.H. Winne, D. Jamieson-Noel, **Exploring students' calibration of self -reports about study tactics and achievement.** *Contemporary Educational Psychology*, 27(4) (2002) 551–572. https://doi.org/10.1016/S0361-476X(02)00006-1
10. R. Taraban, W. S. Maki, K. Rynearson, **Measuring study time distributions: Implications for designing computer-based courses.** *Behavior Research Methods, Instruments, & Computers*, 31(2) (1999) 263–269. https://doi.org/10.3758/BF03207718
11. G. Schraw, **Measuring self-regulation in computer-based learning environments**. *Educational Psychologist*, 45(4) (2010) 258-266. https://doi.org/10.1080/00461520.2010.515936
12. L. Buus, Scaffolding **Teachers Integrate Social Media Into a Problem-Based Learning Approach?** *The Electronic Journal of e-Learning*, 10(1) (2012) 13-22.
13. A.D. Aranda, **Moodle for distance education. *Distance Learning***, 8(2) (2011) 25.
14. S. Wallden, E. Makinen, **Educational Data Mining and Problem-based Learning**. Informatics in Education, 13(1) (2014) 141-156.
15. G. Siemens, D. Gasevic, **Guest editorial-Learning and knowledge analytics**. *Educational Technology & Society*, 15(3) (2012) 1-2.
16. I. Roll, P.H. Winne, **Understanding, evaluating, and supporting self-regulated learning using learning analytics**. *Journal of Learning Analytics*, 2(1) (2015) 7-12. https://doi.org/10.18608/jla.2015.21.2
17. W. M. P. van der Aalst, **Process Mining: Discovery, Conformance and Enhancement of Business Processes**. Media, 136 (2011).
18. M.A. Chatti, A.L. Dyckhoff, U. Schroeder, H. Thüs**, A reference model for learning analytics**. *International Journal of Technology Enhanced Learning*, 4(5-6) (2012) 318-331. https://doi.org/10.1504/IJTEL.2012.051815
19. M. Bannert, P. Reimann, C. Sonnenberg, **Process mining techniques for analysing patterns and strategies in students**' self-regulated learning. *Metacognition and learning*, 9(2) (2014) 161-185. https://doi.org/10.1007/s11409-013-9107-6
20. W.M.P. van der Aalst**, On the Representational Bias in Process Mining.** IEEE 21st International Workshop on Enabling Technologies: Infrastructure for Collaborative Enterprises (2012) 2-7.
21. P. H. Winne, **Issues in researching self-regulated learning as patterns of events**. Metacognition and Learning, 9(2) (2014) 229-237. https://doi.org/10.1007/s11409-014-9113-3
22. N. Trcka, M. Pechenizkiy, W. van der Aalst, **Process Mining from Educational Data**. *Handbook of Educational Data Mining*, Boca Raton, Florida: CRC Press, (2010) 123–142. https://doi.org/10.1201/b10274-11
23. C. W. Günther, A. Rozinat, Disco: **Discover Your Processes.** BPM (Demos) 940 (2012) 40-44.
24. K.H. Cheng, J.C. Liang, C.C. Tsai, University students' online academic help seeking: **The role of self-regulation and information commitments**. *Internet and Higher Education*, 16 (2013) 70–77. https://doi.org/10.1016/j.iheduc.2012.02.002
25. B.J. Zimmerman, D.H. Schunk, eds., ***Handbook of self-regulation of learning and performance***, Abingdon, Oxon: Taylor & Francis, (2011).
26. E. Panadero, **A Review of Self-regulated Learning: Six Models and Four Directions for Research**. *Frontiers in Psychology*, 8 (2017) 422. https://doi.org/10.3389/fpsyg.2017.00422
27. T. Honicke, J. Broadbent, **The influence of academic self-efficacy on academic performance: a systematic review**. Educ. Res. Rev. 17 (2016) 63–84. https://doi.org/10.1016/j.edurev.2015.11.002
28. O. Kingsley, A.R.H. Tawil, U.Naeem, S. Islam, E. Lamine, **Using semantic-based approach to manage perspectives of process mining**: Application on improving learning process domain data. 2016 IEEE International Conference on Big Data (Big Data) (2016) 3529–3538