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Completed Research Paper

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Abstract

This study discusses how students' temporal, adaptive processes, and learning regulation can be understood using multi-channel data. We analyzed the behaviors of 189 students to identify a range of self-regulated learning (SRL) profiles that lead to different achievement in a large-scale undergraduate course seeing how students' SRL unfold during the course, which helps understand the complicated cyclical nature of SRL. We identified three SRL profiles by administrating and analyzing the Motivated Strategies for Learning Questionnaire (MSLQ) three times. We looked at how students adopt different SRL profiles as the course progressed through process mining and clustering techniques to clarify the cyclical nature of SRL. We demonstrated how process mining was used to identify process patterns in self-regulated learning events as captured. Analyzing sequential patterns indicated differences in students' process models. It showed the added value of taking the order of learning activities into account, contributing to theory and practice.

Keywords: Self-regulated learning, learning analytics, process mining, students' motivation, students' strategy use

Introduction

In a world where learning happens beyond the education context, it is essential to produce lifelong learners who can self-regulate their learning. It is widely acknowledged that self-regulation is critical for online learning and Blended Learning (BL) formats as students have more responsibilities for their learning (Ifenthaler 2012; Steffens 2006). Recent studies in the self-regulated learning (SRL) field have moved to more of a process-orientated or event-based view. They mainly investigate how learning processes unfold over time and how scaffolds influence the dynamic nature of regulatory activities. Studies such as (Järvelä et al. 2019a; Molenaar and Järvelä 2014a) emphasized the importance of investigating the sequential and temporal patterns in learning processes. This led to new methodological contributions for analyzing time and order in learning activities. We have focused on process data and investigated the differences among learners to gain insights from students learning process. The overarching research question that guides our study is:

What is the cyclical process of self-regulation that students adopt through a course to achieve their academic goals?

In this study, we investigated the temporal and sequential SRL process in an undergraduate blended learning course in the business school. While different versions of SRL are available, this study focuses on Winne et al.'s (2006) work. Winne (2019) looks at SRL as a cyclical, complex metacognitive and social process that involves adapting cognition and metacognition, motivation, emotion, and behavior. In his view, self-regulation is neither static nor a state and involves cyclical adaptation. It consists of a series of contingencies over time. However, we are not sure when those actions occur, how they influence each other, and how they refer to the learning outcome. As Winne et al. (2019) stated, the data used in learning analytics rarely provides a clear signal of the learning process. In this regard, Gašević et al. (2015a) described that data needs to be collected to describe the learning process in terms of events in a learning episode. They suggested using Winne (1982) characterization of traces and his COPES model (Conditions–Operations–Products–Evaluations–Standards). Therefore, this study built its discussion based on Winne's (2006) version of SRL and looked at the motivational and strategy use constructs longitudinally. For measuring motivational and strategy use, we administered the Motivated Strategies for Learning Questionnaire (MSLQ) (Pintrich 1991) three times in a BL course (N=189).

Through running the study and researching the sequential and temporal structure of SRL processes, we provided knowledge for the development of SRL theories on the micro-level. Analyzing sequential patterns indicated differences in students' process models and demonstrated the added value of taking the order of learning activities into account by discovering regulatory patterns. The paper's contribution is to reveal and understand the details of the complex nature of SRL as an event that unfolds over time. This study took a step forward in understanding the cyclical nature of SRL in learning analytics by recognizing the complexity of how and when students' motivation, cognitive, and metacognitive self-regulation unfold over time. The practical contribution of this study is for educators to early update the instructional design and apply early interventions based on students' level of SRL. This study also had a methodological contribution by collecting longitudinal data.

The organization of the rest of this paper is as follows. The preceding introduction provides a contextual background. This is followed by an overview of the theoretical framework that guides the study and its cyclical nature of self-regulated learning. Next, we present the methodology, how we collected data, and how we analyzed it. Finally, we discuss our findings and present the conclusions.

Theoretical Background

Self-regulated Learning

For the last thirty years, self-regulated learning has emerged as an important topic in education and psychology (Azevedo and Gašević 2019; Greene and Schunk 2017; Winne 2019). It is acknowledged that self-regulation is essential for learning, especially in a blended learning environment where there is limited interaction between the lecturer and students. Zimmerman (2000) defined SRL as "self-generated thoughts, feelings and actions that are planned and cyclically adapted to the attainment of personal learning goals".

There are different definitions available for self-regulated learning; however, they all agree that there are cycles in SRL that consist of different phases and subprocesses. Models are different in terms of phases and subprocesses. All different variations of self-regulated learning have been categorized into two groups; goal-oriented and meta-cognitively weighted.

Goal-oriented: In terms of background, Boekaerts' model of SRL follows Action Control Theory and Transactional Stress Theory (Boekaerts 1995), Pintrich (2000) has a background in social cognitive approaches and Zimmermann (2000) also has a background in social cognitive theory, but all of them follow a goal-oriented approach. In this model, the constructive or self-generated nature of SRL is considered, and it is agreed that the process of monitoring, regulating and controlling the learning includes cognition. Moreover, other factors such as motivation, emotions, and society are also important.

Meta-cognitively weighted: In terms of background Borkowski's model of SRL follows 'Meta' theorists, information-processing perspective and the metacognitive research (Borkowski 1996). Winne and

Hadwin's model of SRL has the most heterogeneous theoretical background by adopting the use of cognitive tactics and strategies for tasks that stressed the learners' meta-cognitively governed process (Winne and Hadwin 1998). While they do not have a goal orientation aspect in their definition, they stressed that self-regulated learners have intrinsic motivation and are goal orientated.

While there are different versions of SRL available, all the versions of SRL follow the same three phases of preparatory, performance, and appraisal. Among all the variations of self-regulated learning, this study focuses on Winne's work which is metacognitive and has been influenced by Bandura (1986a) and Zimmermann (2000) who present a social cognitive theory. Winne examined SRL as a recursive process. In metacognitive monitoring, the feedback can be given in any phase. In other words, monitoring happens in the performance phase and feedback in the appraisal phase. Winnes' work is more strategy-oriented, it is then helpful to the effectiveness of different strategies used by the students to be compared with each other. For this reason, the students' self-report has been used to understand the strategies that students used. Winne used a trace methodology to find out about students' self-reports and the strategies they used.

Winne (1996) looks at self-regulated learning as an inherent part of learning. He defines self-regulated learning as meta-cognitively guided behaviour that could enable students to adaptively regulate their use of cognitive tactics and strategies in the face of a task. Winne and Hadwin (1998) define SRL as a four-stage process. 1) task definition, 2) goal setting and planning, 3) enacting tactics and strategies planned in the previous stage, and 4) adopting study techniques meta-cognitively. SRL sets out five facets of tasks that can happen in the four phases of SRL. These five facets are referred to as the COPES (i.e. Conditions–Operations–Products–Evaluations–Standards). These five elements of COPES collectively influence the self-regulatory process of learning (Winne 1997). Conditions are all the resources that are available to the students and the constraints that the student has inherited from the task and environment (context and time constraints are examples of this category).

Operations are the strategies, tactics, and cognitive processes employed by the students to achieve their goals. In this stage, the students will do the planning to achieve their goals, referred to as SMART - Searching, Monitoring, Assembling, Rehearsing and Translating. Products are the results of the operation (creating new knowledge would be an example of products). Evaluations are the feedback generated by the students, other peers or their teacher and fit between the product and the available standards. Standards are the criteria by which products will be evaluated. The COPE model describes learning as a cyclical process. When learners engage in the process of learning, they go through the stages we just mentioned. It starts with task perception, goal setting and planning, and translating plans into strategies based on the goals they set for themselves, and after that, they go through an evaluation of what they have done and reflect on themselves. These different phases we recall are not linearly sequenced, and they are loosely ordered. Each of the phases cycled through COPE by metacognitive monitoring. Based on the monitoring they adopted, their perception of the task changes and the goals, strategies and therefore, the shifts between the phases would happen. The learning process is active, and it is constantly changing when that is not proceeding according to the goals.

Even though learners' level of self-regulation is considered to be relevant for successful learning, its measurement is difficult (Boekaerts and Corno 2005). Two frameworks that use different self-reports for measuring students' motivation are student approaches to learning (SAL) and SRL. The SAL framework theorises learning as a composition of motives and strategies. SAL describes deep (meaningful learning) and surface (rote learning) approaches to learning (Entwistle and Ramsden 2015). The SRL framework is categorised by specific cognitive, motivational, and behavioural constructs (Zimmerman 2008). The MSLQ (Pintrich et al. 1993b) and the Learning and Study Strategies Inventory (LASSI) (Weinstein and Palmer 1987) are the two most commonly used questionnaires developed under the SRL framework for measuring motivation and strategy use. We used the MSLQ in this study as it is the most used instrument in SRL measurement and its validity has been checked a lot in the literature (Roth et al. 2016).

The cyclical nature of self-regulated learning

From the social cognitive perspective, self-regulated learning is the development of skills and strategies as a function of the bidirectional interaction of personal, behavioral, and environmental factors, which takes the form of triadic reciprocal causation (Bandura 1986b; Schunk 1989). Schunk (1989) stated that the development of self-regulated learning skills and strategies and bidirectional interactions of the factors appear to be cyclical. McCardle and Hadwin (2015) also stated that there are multiple cycles of phases in self-regulation. Phases such as planning and goal setting, enacting strategies, and evaluating the progress of learning through metacognitive monitoring. It is also possible that students' success in regulation may be varied across cycles (Sobocinski et al. 2017).

Järvelä et al. (2019b) also identified that SRL is not a linear means, and it involves cyclical adaptation. They mentioned that SRL is not a state, and it involves a series of contingencies over time (Molenaar and Järvelä 2014b). In this process, students use metacognitive monitoring and control to strategically adapt their learning whenever it is required (Zimmerman 2013). Ben-Eliyahu and Bernacki (2015) suggested that in order to understand the complexity of the phenomena and capturing cognitive, metacognitive, motivational, and emotional processes in the collaborative learning context, it is required to trace students' behavior over time. Ally (2004) stated that investigating self-regulated learning in the online learning environment is more important. Because in this environment, individuals are required to be more autonomous to be able to be self-regulated. Therefore, we addressed the gap by collecting students' data longitudinally and looking at temporal and sequential analysis over time.

Since Schunk (2005, p. 85) stated that "self-regulated learning is seen as a mechanism to help explain achievement differences among students and as a means to improve achievement", we investigate to understand how different SRL profiles are achieved differently and how changes in SRL affect performance. We looked at the issue iteratively, as it is suggested by Järvelä et al. (2019b). Even though self-report instruments, such as (Pintrich 1995), were successful in identifying students' general beliefs about their learning, motivation, cognitive and metacognitive, and resource management, they did not consider how they happened and how they affect each other. This was very important to identify the changes that happened in the regulatory process. Thus, this study dives into the gap in the methodology on how to capture the evolving process by running the questionnaire three times in the course. As suggested by Ally (2004) we chose the online learning context as an important learning environment that has been getting attention. The advantage of the study reveals to us how sequences of regulated learning unfold over time, which contributes to the SRL literature.

Methods

Participations

We had 189 students from a large scale entry-level business school course. We collected 189, 173, and 153 viable surveys (N=515). We collected students' motivation and self-regulatory strategies by administrating the Motivated Strategies for Learning Questionnaire (MSLQ) three times in weeks 3, 7, and 11 of a 12 week semester.

Data collection

Instrument

We used the MSLQ questionnaire, which was developed by Pintrich et al. (1993a). The questionnaire measures motivation, cognitive and metacognitive strategies, and resource management through 31 items in the motivation section and 50 items in the learning strategies section (Figure 1).

MSLQ follows a cognitive perspective when students' beliefs and cognition are the instructional input for being an active processor of information in class. The validity and reliability of the instrument had been already checked in the literature (Büyüköztürk et al. 2004; Pintrich et al. 1993a).

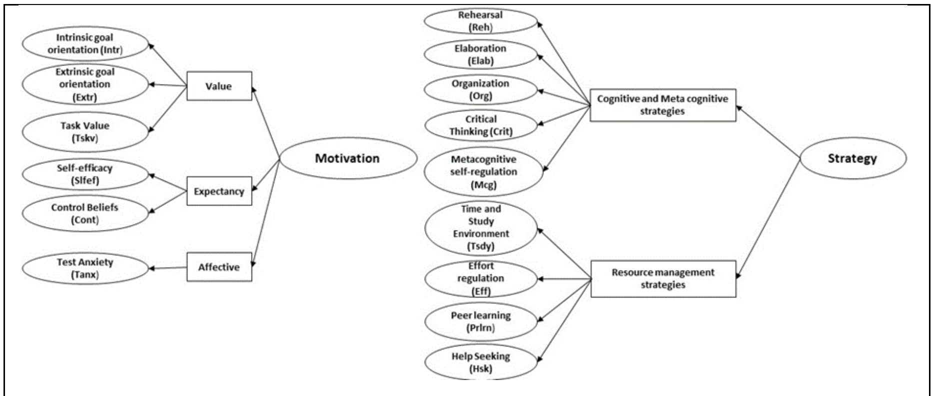

Figure 1. MSLQ concept map

Procedure

The research procedure is depicted in Table 1. We ran MSLQ three times in Week 3, Week 7, and Week 11 of a 12 week semester. The students needed to hand in two assignments before (Week 6) and after midterm (Week7, 10, 12), as is shown in Table1. P1 is the result of assignment 1 and test 1, and P2 is the result of assignments 2A and 2B. They also needed to take part in midterm and final exams as well in order to be able to meet the requirements of the course. We also presented the weight for each assignment and test in Table 1.

WK 1	Wk 2	Wk 3	Wk 4	Wk 5	Wk 6	Wk 7		Wk 8	Wk 9	Wk 10	Wk 11	Wk 12	Wk 13	Wk1 4
		MS LQ 1 g			P1- Ass ign 1	MS LQ 2	P1- Tes t			P2- Ass ign 2A	MS LQ 3	P2- Ass ign 2B		P3- final exam
		7% /3			5%	7% /3	23 %			15 %	7% /3	5%		45%

Table1: Research Procedure

Context and setting

This study took place in a large-scale introductory course for undergraduate students in a business and economics school, with a study load of 20 hours per week, for a period of twelve weeks. This was a compulsory course for the department. The course was designed based on a blended learning methodology. The lecturer's approach to blended learning involved purpose-made online lectures in lieu of traditional face-to-face delivery. His online lectures were supplemented with short, face-to-face weekly tutorials. Each lecture video featured a short quiz at the end that tested students' understanding of the material just covered. Prior to each tutorial, the lecturer analyzed the embedded quiz results and determined which course material had proven most challenging. He then prepared a set of review questions in Top Hat (some copied from the quizzes, others entirely new) and presented these to students at the tutorial. The questions were a mix of multiple-choice, true/false, and fill-in-the-blank types. He discussed the students' collective answers to each Top Hat question and then proceeded to give a mini-lecture on the topic. After he finished going through the review questions, he launched the first of two Top Hat tournaments, which primarily contained the same embedded quiz questions featured in that week's online lectures. Top Hat tournaments were round-robin style competitions where students competed head-to-head and won if they were the first to answer correctly. The tournaments typically consisted of eight time-limited rounds of questions. During the competition, a leaderboard was populated, showing the top students and their scores. At the conclusion of the tournament, the top five or six students were awarded an individually wrapped candy as a prize. Students were incentivized to watch each week's online lectures and participated in the weekly in-class tutorial by means of awarding participation marks.

Data analysis

Over three rounds of surveying of a population of 189 students, a set of 515 (189, 173, and 153) viable surveys were collected. We cleaned the data first. We handled missing data. For this reason, we needed to test if we had missing values at random or not. Therefore, we ran Little's Missing Completely at Random (MCAR) test for each iteration of each class. Our results showed that the data was missed at random. There were different approaches for handling the missing data, for example, listwise deletion, pairwise deletion, mean imputation, and regression imputation. We replaced missing values with maximum likelihood. We considered the rule of thumb by preplacing less than 10 percent of the data. In the analysis section, we first looked at the correlation between the constructs, their assignments and test results and the final score. We also checked how these constructs and their relations changed as the course progressed. Then, we applied the K-Means clustering algorithm in SPSS to see how students were different based on their motivation and self-regulation profiles. The number of clusters has been identified with checking through two step cluster algorithm and elbow method. We compared the profiles based on students' level of motivation and strategy use and considered what they achieved differently in their final. Furthermore, we also considered how students' profiles unfolded as the course progressed. We used SPSS V26 to cluster.

We used person-center modelling instead of variable-center modelling approaches as variable-centered modelling approaches are helpful in providing evidence or the opposite case to falsify educational theories (Malcom-Piqueux 2015; Masyn 2013; Morin et al. 2018). Person centric modelling approach helps us to group individuals that have similarities and have differences from other groups. In the educational context, we have heterogeneous students, and the variable center approach's assumption is not compatible with having multiple subpopulations. We also investigated the differences between clusters with ANOVA. We identified that there were significant differences between clusters in terms of motivation and strategy use. This study also employed a process mining technique to explore the temporal structure of motivation, cognitive, and metacognitive events during the students' SRL process. We aimed to see if the learning process is similar among students in their classes. Studies such as Sonnenberg and Bannert (2015) stated that process mining could be very helpful in analyzing and visualizing the SRL process. In their recent study, Sonnenberg and Bannert (2019) stated that process mining in education is in its infancy and needs more. We used Disco® software from Fluxicom for applying process mining.

Results and Findings

In this study, we use a combination of educational data mining and process mining to give an advanced insight into the SRL process. Through this analysis, we give a detailed picture of the self-regulated process events. Educational data mining, especially process mining, has been defined as an emerging approach to investigating learning processes (Bannert et al. 2015). Through correlation and its significance, we show the importance of each factor and its relationship with each other. We provided clustering to identify groups of participants based on the similarity of scores on their motivation and strategy use. Through process mining, we showed the sequence and changes in the SRL adaptation process.

Correlation

First, we explored and summarized the correlation between motivational, strategy use constructs, results of the test, results of assignments, and the final score. The correlation between motivational and strategy use constructs with the final course outcome has been depicted in Table 2. Motivation from three iterations has a significant correlation with the final course outcome. In terms of strategy use, this construct has a higher correlation with the final course outcome in the second and third iterations. The correlation between motivation and final score and the correlation between strategy and the final score increased as the course progressed. The correlation of P1 (assignment result before break) and P2 (assignment result after the break) with the final score is significantly higher compared to the correlation of other constructs and the final score. There was always a high correlation between motivation and strategy use in all three measurements, which shows that highly motivated students applied more strategies. Strategy use 1 is the only construct that did not have a high correlation with the final. Students in our study were joint the university from high school, they might have lower strategy skills, or for example, the strategies they used in high school were different. We also had the same correlation pattern for all the constructs with the final score for P1 and P2. Motivation 1 had a high correlation with P1, but strategy 1 did not have a high correlation with P1. P1 had a high correlation with motivation 1 but did not have a high correlation with strategy 1. However, P1 had a high correlation with motivation 2 and strategy 2. P2 also had a high correlation with motivation 3 and strategy 3. The correlation of MSLQ3 and P3 and MSLQ2 and P2 are high, but the correlation of MSLQ1 and P1 is high for the motivation but is not significant for strategy use.

Motivation (M) Strategy (S)	M1	S1	M2	S2	M3	S3	P1	P2	Final Score
M1	1								
S1	.320**	1							
M2	.631**	.256**	1						
S2	.281**	.671**	.433**	1					
M3	.604**	.275**	.762**	.449**	1				
S3	.263**	.630**	.289**	.735**	.490**	1			
P1	.255**	0.119	.367**	.208**	.421**	.207*	1		
P2	.159*	.182*	.196*	.209**	.192*	.180*	.529**	1	
Final Score	.163*	0.092	.261**	.208**	.281**	.271**	.631**	.620**	1

Table 2. Correlation at a Component Level

Clustering

In this section of our analysis, we looked to identify different SRL profiles of students and see how they are distinct. We applied the K-Means clustering algorithm to answer this question and looked at the issue longitudinally. Each time, we clustered the students based on one iteration of MSLQ data (Table 3). We identified three SRL profiles in each iteration.

Minimally self-regulated learners profile (Cluster 1)

They are students in cluster 1 who had the minimum motivational and strategy use (Minimum SRL). There were 69 students in this cluster at the beginning. This is the largest cluster at the beginning of the course, and as time passed, the number of students in this cluster dropped to the point that we had just one student in this cluster at the end of the course. This cluster is the minimum achievers in the first two iterations and is average achievers in iteration 3.

Average self-regulated learners profile (Cluster 2)

They are students in cluster 2, who had an average amount of score in motivation and strategy use (average SRL). There were 65 students in this cluster, and they achieved 69.07 in their final course outcome on average. This is the second-largest cluster at the beginning. As time passed, the number of students in this cluster increased to the point that at the end of the course, this cluster had the highest number of students (N=90) in the third iteration.

	Iteration 1			Iteration 2			Iteration 3		
Cluster (C)	C1	C2	C3	C1	C2	C3	C1	C2	C3
Motivation	4.27	5.281	5.29	4.15	4.89	5.30	1.96	4.53	5.30
Strategy Use	3.94	3.99	4.88	3.58	4.14	4.94	1.81	3.94	4.90
Numbers per cluster	69	65	55	48	77	48	1	90	62
Final	62.77	69.09	69.86	62.48	69.90	74.84	67.68	66.97	74.67

Table 3. Clustering at the component level

Competent self-regulated learners profile (Cluster 3)

They are students in cluster 3, who had the highest motivation and strategy use (high SRL). Those are the highest motivated students who always use the maximum strategies. The students in this cluster achieved the maximum in their final course outcome. There were 55 students in this cluster. This is the smallest cluster at the beginning, and as time passes, the number of students in this cluster increases.

When we had three different clusters of students, we understood that clusters were significantly different from each other through the one-way ANOVA analysis. It shows that three groups of competent, average and minimally self-regulated learners had different perceived SRL and motivation.

Process Mining

In figure 2, by applying process mining, we present how the cyclical nature of SRL works in our course. It shows how the temporal patterns of students change in a sequence of time. Process mining adds meaning to the learning events through aggregation and preparing the shape of process models. The starting point in figure 2 represents the start of our study. It shows how students divided to three clusters at the beginning of the class (65 students in Cluster1, 55 students in Cluster 2, and 69 students in Cluster3). Next line shows how many students in each cluster achieved differently. Each of the arrows show the learning path for a group of students. In this figure we are following students and investigating their unfolding process as the course progressed. Students had specific motivation and strategy use at the beginning of the course as we measured in our first iteration of data collection and clustered them into three (the first row of rectangle in figure 2). As we explained before, Cluster 1 students are those with minimum SRL, Cluster 2 is those with Average level SRL, and Cluster 3 is those with Maximum SRL. After making profiles of students based on their level of motivation and self-regulation, we investigated how their level of motivation affects their performance and how they change or unfold clusters. In terms of students' achievement, we categorized students' achievement in their assignments into four categories P1, P2, P3, and P4. Scores between 80 and 100 were categorized into category 1. Scores between 65 and 79 to category 2. Scores between 50 and 64 to category 3. Scores between 0 and 49 to category 4.

We used HeuristicsMiner algorithm (Weijters et al. 2006) from Disco software for applying process mining to our students' data. We chose the HeuristicsMiner algorithm based on a comparison of seven process discovery algorithms on the dimensions of accuracy and comprehensibility suggested by De Weerdt et al. (2012). The algorithm is well applicable to educational data and easily takes care of the noises in data. The output model induced by the HeuristicsMiner algorithm is displayed in Figure 2. In figure2, we have boxes representing the motivation, cognitive and metacognitive self-regulation events and the results of tests and assignments. Arrows represent links between events and show the number of links between two events.

As we explained before, we had the results of administrating MSLQ three times and three evaluations throughout the course (P1, P2, P3). In order, we had first, MSLQ1 in week 3, P1 in week 6 and week 7, MSLQ2 in week 7, P2 in week 10 and week 12, MSLQ3 in Week 11, and then P3 in week 14. Our goal was to check the cyclical nature of students' SRL, how students' SRL profiles changed as the course progressed, and see how students used the test and assignments as evaluation tools and how they reflected on their learning based on their performance monitoring. We were interested to understand how the results of tests and assignments affect students' motivation and strategy use.

Based on Winne (2019), we investigated the cyclical adaptation of regulation. We were looking to explain regulation as a series of contingencies over time. We looked at how the results of tests and assignments that students received affect their self-regulation process. How their motivation level affects or relates to their performance in the course. We talked about them in our process mining analysis and the correlation and clustering analysis results we presented in the first section of our analysis.

Iteration 1

Cluster 1 students who are minimal SRL, for the P1 test achieved from category 4, category 3, and category 2. None of them achieved from category 1 (high achievers). Cluster 3 students who are high SRL, achieved from category 1 and category 2 in P1 (which are the highest two categories of achievement). Interestingly cluster 2 students (average SRL) always achieved from Category 1 in P1 (highest achievers). This is against what we expected to see. We expected the highest SRL to achieve the highest and the same order for other clusters, but this was not what we observed. When we looked at the correlation between motivation and self-regulation and P1, we observed that motivation has a significant correlation with P1 but not strategy 1.

Students who are in category 1 achievement (P1) and they were from cluster 1 and cluster 2 were able to either maintain their level of SRL or increase it and moved to Cluster 2 and cluster 3 (average and maximum SRL profiles). This is what we expected high self-regulated learners being able to reflect on their SRL skills based on how they perform in the tests and assignments and try to maintain the same level or adopt a higher profile. Most of the students who are in categories 1, 2, and 3 in P1 moved to cluster 2. This is promising as our goal was to produce lifelong learners through increasing students' motivation and teaching them new strategies. Students who are in categories 2, and 4 in P1, moved to cluster 1 (Minimum SRL). Moving from Cluster 2 to category 1 is dropping, so it shows some students dropped in their level of motivation but only very few. Not all students were able to use the tests as evaluation tools and update their SRL skills. All students in category 4 in P1 moved to Cluster 1(Minimum SRL). Here we observed how low achievement affects students' motivation and self-regulation, especially for our low achievers. This is where the lecture adopts new techniques to help students who are in need. All students in category 3 in P1 moved to Cluster 2 (Average SRL). Average achievement led to average SRL. Then again, we looked to see how the level of motivation and self-regulation in the second iteration affected their test and assignments (P2). From correlation analysis, we understood that motivation and self-regulation learning have a high correlation with P2.

Iteration 2

Cluster 3, the highest SRL students, are divided into 3 different categories in terms of their achievement for P2. Most students belong to categories 1 and 2, but 8 of them in this cluster achieved from category 3 scores in their P2 (which is the second lowest category). We always expected to have the highest score for the students with the highest SRL. We expected to see students being able to maintain their level of motivation and strategy use. Even though it is well documented that students' level of motivation always drops as the course progress, considering our special instructional design, we expected to see movements to the highest self-regulated learning profiles. So we had dropped in terms of students' motivation and strategy use at our second iteration, but as we see in the next iteration, they increased again as the course progressed towards the end. High SRL students ended up with different achievements, but mostly, they were higher achievers.

Cluster 2 (Average SRL) students still kept the same achievement level. They all belong to categories 1 and 2 in P2(The highest and second achivers group). Cluster 1 students (Minimum SRL) improved and achieved from both category 4 and category 2. Even though they have a minimum SRL, this is promising, but they tried hard to achieve from Category 2.

Then we looked at the effect of P2 on MSLQ3 (effect of achievement in test on motivation and strategy use). Looking at the correlation table, we understood that p2 had a significant correlation with motivation and strategy use. Students from Category 1 achievement in P2 (Highest achievement) moved to clusters 2 and 3 (Average and maximum SRL). Students from Category 1, 2, and 4 achievements moved to cluster 2 (Average SRL). Cluster 3 became almost empty; just one student from category 2 achievement moved to cluster 1, which is the lowest SRL level. But even that one student who dropped in motivation and self-regulatory skills achieved from category 2 in P3 (the second-highest category). All students except one student moved to clusters 2 and 3, which is the best result we could hope for, being able to move students to the highest achievers categories. This is a good achievement for us as our design aimed to produce lifelong learners who could take control of their learning. All students except one moved to average and high SRL profiles. Students who are from category 1, category2, and category 3 in P2, moved to Cluster 3 (highest SRL).

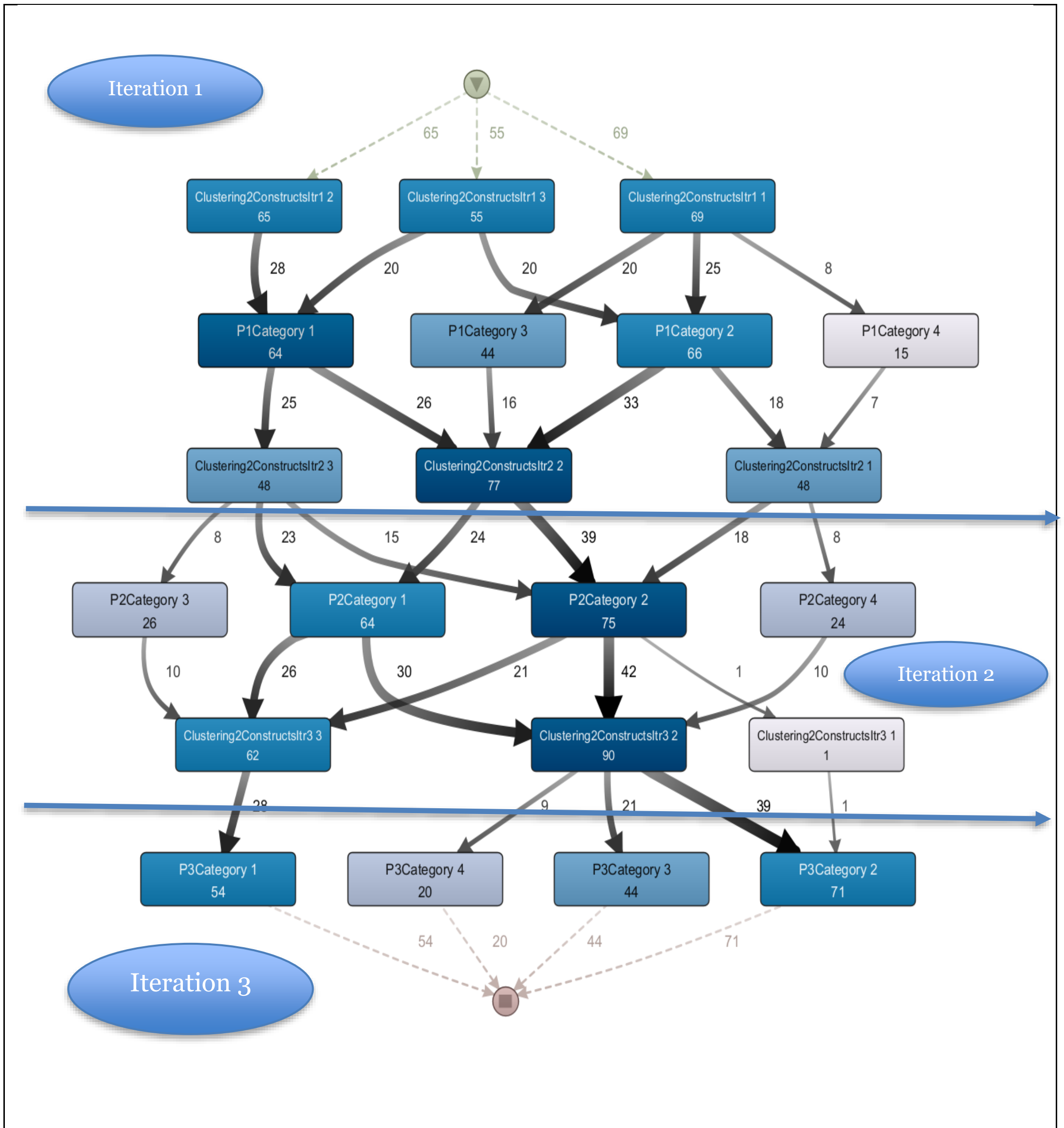

Figure 2. Process Model of students

Iteration 3

We had the best movement among the clusters at the end. We just had 9 students from category 4 achievement (the lowest achievers) in P3. 39 students achieved from category 2, 28 from category 1, and 21 from category 3. Even though only students that remained in the lowest SRL cluster still managed to achieve from Category 2 (second highest) in P3.

The only students who could achieve from the first category belong to the highest SRL cluster (Cluster 3). In another language, all the highest SRL profile students achieved the highest at the end. And students in Cluster 2 (average SRL) achieved scores from all three categories of 2, 3, and 4. And luckily, just 9 students achieved from category 4. We just had 1 student in our lowest SRL profile in this iteration.

The students were able to learn regulation and improve motivation. On top of students trying to improve their motivation and strategy use, the lecturer also tried to improve the motivation of students as well. The lecturer in our study tried it by giving a participation mark and throwing chocolate as ways to enhance students' motivation. Increasing motivation was important in self-regulating. The lecturer also constantly talked about how students can self-regulate their learning. He helped students set a goal for themselves, teach them the strategies to learn and teach them strategies to evaluate themselves to self-reflect. For example, he taught students new learning strategies and resource management and emphasized them through his specific instructional design. For instance, he set a time to watch the videos before the class. Ask students to participate in group activities, answering questions by giving them a small mark.

Discussion and Implications

In this study, we researched students' SRL processes in a BL environment. In a BL environment, students need to have the ability to manage their learning process. As Ifenthaler (2012) mentioned, Self-regulated learning (SRL) is an essential skill in lifelong learning, especially in an online learning environment. Students need to take control of their learning in an online learning environment. Unlike the traditional way of teaching, students had access to the material in our online learning setting, and they needed to prepare for attending the review session. In the traditional class, the lecturer goes through the material, and after that, students can go through the material again after the lectures. However, in a blended learning environment, students had to go through the material before the start of the course. But it was also possible that students did not go through all the materials (Nguyen et al. 2018). Therefore, in our study, the lecturer checks the students' activities to make sure that they are catching up with the materials before the start of the class. He also identified the concept that most of the students had difficulty understanding to prepare the mini lecturers for the review session and make sure that they were able to understand the material. Macfadyen and Dawson (2010) stated that automatic monitoring of students' activities could give insight to the courses' lecturers to prevent low course performance.

The course lecturer prepared purpose-made videos for each week of the course. Each video had a quiz at the end. The students needed to watch the videos (online preparation). They also had to participate in the quizzes at the end of each video. Based on how students performed in the quizzes, the lecturer prepared a mini-lecture for the face to face review sessions. Then students had the option of either physically attending or watching videos streaming. In the review session, the lecturer discussed the stuff that most students got wrong (Discuss formative questions). He also reruns quizzes. He wanted students to reflect on their learning based on weekly quizzes. The students bid other students by answering questions so that their names appear on the leather board. All this happens in the hope that students reflect on their own learning. Therefore, in this study, first, we examined the SRL constructs to understand students' behavior and perception (motivation and strategy use), we ran the MSLQ three times in weeks 3, 7, and 11 to measure their motivation and strategy use. The students needed to hand in two assignments before (Week 6) and after midterm (Week7, 10, 12). P1 is the result of assignment 1 and test 1, and P2 is the result of assignments 2A and 2B. They also needed to take part in midterm and final exams as well to be able to meet the requirements of the course.

Several studies investigated data variables from learning management systems to predict students' final scores. These studies used different indicators for predicting students' achievement to better design the instructions for the courses so that fewer students drop out. For example, they used data from the learning management system from various activities in which students participated (Gašević et al. 2015b; Tempelaar et al. 2015). These studies fail to quantify the impact of emotional, motivational, cognitive–metacognitive factors, and resource management. Barbera et al. (2015) also stated that the investigation of students' temporal patterns had been lost in the previous studies. We needed to get to know the differences between students' temporal patterns and the differences in their self-regulation process. First, we wanted to know whether we could identify high-performance students from the lower performance based on their motivation and strategy use. Perera et al. (2008) stated that based on students' activities, we could differentiate between students' performance based on their pattern of activities. We chose to look at motivation and strategy use as Winne and Jamieson-Noel (2002) stated that motivation and self-efficacy could be factors that helped us understand the differences between students' clusters.

This study also addressed the gap identified by Järvelä et al. (2019b) through researching students' adaptation of SRL profiles throughout the course through process mining and clustering techniques. This helped us better understand the cyclical nature of SRL. We observed how students' reported motivation an and strategy use changed as the course progressed. Then, we identified three SRL profiles and investigated how different SRL profiles could also lead to different achievements. To understand the SRL process, we drew on Winne's model of individuals' SRL cycles involving three axioms at a micro-level with COPES (i.e., Conditions, Operations, Products, Evaluations, and Standards). The application of Axiom 1 is that students use tools to operate on raw materials, to construct a product that is evaluated in a formative or summative way with respect to standards of socio-cultural kinds. As students engage in the learning process, they go through several stages, as mentioned before. It starts with task perception, goal setting and planning, and translating plans into strategies based on the goals they set for themselves. Then they evaluate themselves during the learning process, it is also important to understand how much their evaluation of themselves affects their motivation and strategy use and how much they are willing to interact with learning materials. We observed that each of the phases is cycled through COPES by metacognitive monitoring. Based on the monitoring they adopt, their perception of the task changes and the goals, strategies, and shifts between the phases would happen. It was also important to understand the relationship between students' motivation, strategy use, and achievement. To achieve this, we examined the correlation. We looked at the correlation of constructs, internal test and assignments results and the final score in three iterations. Correlation analysis for the whole class showed that all the constructs had high correlation with the final score except Strategy 1. As the course progressed, the correlation between constructs and the final score increased. We also observed a very high correlation between motivation and strategy use in each iteration, but we cannot conclude whether high motivation led to using high strategies or vice versa. Understanding the constructs that had a high correlation with the final score was very important as the lecturer could teach students and update the instructional design.

In this way, appropriate instruction can be designed for the courses to prevent dropouts. Other studies, such as Nguyen et al. (2017), emphasize the importance of instructional design and its effect on activities students do. Therefore, we also explained the instructional design and the lecturer's requirements in the course.

Since our goal was to identify the differences among students in their temporal behaviour, we applied clustering algorithm. Because cluster analysis is very sensitive to variable numbers, we used the upper-level constructs as clustering variables. We placed students in three SRL profiles of competent, average, and low SRL. We observed that students with the pattern of lower SRL achieved the lowest and vice versa.

In table 3, we present each cluster and observe how the SRL cyclical change as the course progresses. As the course progressed, the average score in motivation and strategy for cluster 1 (low SRL group) and cluster 2 (moderate SRL group) dropped as the course progressed. The average motivation for cluster 3 increased for iteration 2, but then it decreased in iteration 3. The same pattern happens for strategy use for both clusters 1 and 2; the average strategy score dropped as the course progressed; however, for cluster 3 students, it increased for iteration 2 and then decreased again for iteration 3. So the profiles are changing as the course progresses. The best result that we achieved in this course was helping students to adopt the higher SRL profile at the end of the course, which addressed our aim. We aimed to produce lifelong learners who are able to self-regulate their learning, and as it is shown in Table 3, we ended up with just one student with the lowest SRL profile at the end of the course. We had the largest minimum SRL profile at the start of the course, and then we were able to reduce it to one student in that lowest SRL profile. We observed how the assessment results affected students' feelings regarding the course and their motivation and self-regulation in the second iteration. We repeated the measurement and observed the effect of the second assessment on students' motivation and self-regulation. We observed how each student's profile reflected differently on themselves. This helped us better understand how the temporal, behavioural, and self-regulation processes of the students worked.

	Clusters	Iteration 1				Iteration 2				Iteration 3			
	Motivation: (M) Strategy: (S) Number: (N)	M	S	N	Final	M	S	N	Final	M	S	N	Final
Low SRL	1	Min	Min	69	62.77	Min	Min	48	62.48	Min	Min	1	67.68
Average SRL	2	Avg	Avg	65	69.07	Avg	Avg	77	69.90	Avg	Avg	90	66.97
High SRL	3	Max	Max	55	69.86	Max	Max	48	74.84	Max	Max	62	74.67

Table3. SRL cyclical change

We also investigated the cyclical nature of SRL through process mining to find the pattern in students' learning process and achievements. The model we generated through process mining showed the comprehensive SRL model in the domain of business school course design which connects the generality and domain-specificity of SRL processes. This was a great way of explaining how students self-regulate their learning. How does receiving feedback from their assignments and tests affect their motivation and strategy use? Students had joined the course with a specific motivation at the beginning of the course. We investigated when they went through the tests and received feedback, how they reflected on themselves, and how they changed or unfolded their clusters. In between, we looked at how motivation, self-regulation and test results are correlated. We checked how the level of motivation and learning strategy use affect the performance in the tests and assignments and how the results of tests affect the adaptation of students' SRL profiles.

We expected learners to regulate themselves through observation, evaluation, and reflection. At the beginning of the course, by observing the course, they do the forethought phase. We measured the motivation and strategy used at that point, and we looked at how students valued the task, how they believed in their level of self-efficacy, and how they measured their anxiety. Then we examined what happened to all those constructs when they went through the tests and assignments. Through the results of the tests, the evaluations have been done by the students, which enabled us to measure again how they affect students' motivation and strategy use. We checked the cyclical nature of SRL by measuring motivation, learning strategy use three times and also measuring their improvements through three tests. In our study, almost all the students move to upper clusters. Our goal was to produce lifelong learners who are able to self-regulate their learning. The lecturer of the class successfully motivated students to engage in the activities and regulate their learning to adapt to a higher profile.

Conclusion

This study was critical as there is not enough study examining the self-regulation learning processes of students over time to identify different regulation types. Recent studies such as (Järvelä et al. (2019b) identified the challenge regarding the cyclical nature of SRL. In this study, we addressed the gap by looking at students' behavioral patterns and investigating the blended learning pedagogy through process mining and clustering techniques. We investigated how students adopted different profiles along the way until they reached the end of the course. We highlighted the functional and adaptive roles of motivation and cognition for achieving good grades.Understanding clusters could guide instructional and curricular strategies designers to encourage their students' optimal motivational beliefs and self-regulated learning in particular courses. As we observed, there were different types of regulation over time. This information is necessary to provide targeted support in regulation at an individual in addition to a group learning setting. We were also struck by observing the consistency in the profile of students. Most of the changes were to the upper-level SRL. More adaptive clusters had a higher level of motivational belief, cognition, and metacognition. These were the students who were active self-regulators. Close to the end of the course, we had just two students in the lowest level of motivation cluster. We aimed to produce highly self-regulated learners. Considering the number of high and moderate students in the self-report, and based on their final achievement, we were able to produce learners who could control their learning.

Understanding the stability of the clusters as the course progress contributes to the literature in SRL, which is very important. Looking at the movement among clusters by empirical findings is very important for theoretical contribution and education practice. We had a methodological contribution of collecting longitudinal data on the regulation process to capture evolving process. By looking at SRL as an event, we contribute to the SRL process and its complex nature. It also gives insight into the potential impact of the online experience of teaching on learners' interests, motivation, and strategic processing. It guides instructional design strategies on how to encourage students' motivational beliefs and self-regulated learning in that specific courses. It was evident from our analysis that the lecturer was able to help students adopt new profiles. The timing was also important as the midterm was a reflection time for students. Like other studies, our study has limitations. When we looked at the cyclical nature of SRL through profiling, we had data from one course in business school, it is always good if we could rerun our study in other departments. Also, profiling is not an inferential statistical technique. The interpretation of cluster solutions relies on theoretical grounds and available statistics. Therefore, there is a need for additional research to cross-validate our findings.

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