Discovering Time Management Strategies in Learning Processes Using Process Mining Techniques

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Abstract. This paper reports the findings of a study that proposed a novel learning analytic methodology that combines process mining with cluster analysis to study time management in the context of blended and online learning. The study was conducted with first-year students (N = 241) who were enrolled in blended learning of a health science course. The study identified four distinct time management tactics and three strategies. The tactics and strategies were interpreted according to the established theoretical framework of self-regulated learning in terms of student decisions about what to study, how long to study, and how to study. The study also identified significant differences in academic performance among students who followed different time management strategies.

Keywords: Blended learning · Learning analytics · Self-Regulated Learning · Time management strategies

1 Introduction

In higher education, blended learning is a well-recognized learning mode that combines online and face-to-face interaction among teachers and learners. It offers learners flexibility to control their own learning experiences and opportunity to extend their learning time from in-class instruction to out-of-class study time. However, flexibility comes with a great responsibility for learners to define learning tasks and set goals; plan and manage resources, time, and environment; and apply effective learning tactics and strategies with the aim of achieving desired academic outcomes [1].

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It has been well-established that self-regulation is linked to a significant improvement in learners' time management, which, in turn, can contribute to learners' success in blended learning [2]. However, only a few empirical studies have examined the link between self-regulated learning (SRL) and actual time management practices in blended learning settings. To bridge this gap, the current study aims to provide evidence and solid understanding of how learners enact specific time management tactics and strategies while progressing in a blended course.

The paper proposes a learning analytic methodology to analyse time management within blended and online learning. The application of the proposed methodology identified four distinct tactics and three strategies of time management in a blended course in health sciences; the use of different strategies was associated with achievement. The results were interrogated against an established theoretical model of SRL to understand how student make decisions about what to study, how long to study, and how to study.

2 Background

2.1 Time Management Strategies and Self-regulated Learning

Time management is commonly linked to self-regulated learning, since it is closely related to learners' decision about what to study, how long to study, and how to study [3–5] with instructors' minimal intervention. In line with the self-regulation viewpoint, time management has been recognized as learners' effort to effectively use their time while progressing toward set learning goals. To define time management tactics and strategies, we borrow from the literature on study tactics and study strategies. In the literature, study tactics are described as cognitive routines that include several actions done in a sequence for performing specified tasks, while study strategies are made-up from a set of enacted tactics by means of selecting, combining, or redesigning these cognitive routines, directed by a learning goal [6–8]. Time management tactics and strategies refer to how timely students manage their study tactics and strategies.

Most models of SRL emphasize three kinds of strategies focused on planning, monitoring, and regulating [9]. In the context of this study, planning involves preparation at the cognitive level; for instance, learners decide to access certain course material in advance, before it was scheduled (*ahead*) or complete a learning task just in time before the relevant face-to-face session (*preparing*) rather than delay task engagement till later in the course (*catching-up*). Meanwhile, monitoring allows learners to evaluate the differences between their current condition (e.g., learning progress) and standards (e.g., predefined learning goals), which, in turn, activates control processes to reduce discrepancies (e.g., engaging more intensively in a certain topic) [10]. Finally, regulation strategies refer to deliberate acts of learners evaluating their comprehension in a specific learning context, such as re-studying learning materials after they have completed it as a part of preparation (*revisiting*). Obviously, all kinds of SRL strategies are inextricably associated with time management, as all include a temporal aspect and a need to plan and manage one's time to put the strategies in practice.

Students' decisions about learning are not random choices; they are driven by learning goals [4]. The current study builds on the work presented in [5] to unveil the students' decision made on their time management strategies, what tactics to use (e.g., how to modify their tactics to support their learning goal), frequency of tactics use (e.g., deciding how long to persist to master a concept) and timing of tactic use (e.g., how to space their learning).

2.2 Temporal Analysis of SRL

Research on SRL has emphasized the use of trace data as artifacts of students' learning [4] recorded over a given period of time in an authentic educational setting. Trace data captures fine-grained learning events and dynamics of learning sessions [11]. As such, trace data are used to unveil latent behavior of learners, indicative of how learners regulate their effort to achieve their learning goals. The SRL literature also stressed the importance of temporal and sequential dimensions of learning [12–16] with the objective of uncovering how patterns and processes of SRL unfold over time [14]. According to Chen et al. [17], the temporal dimension relates to the passage of time (e.g., how long and how often learners engage), whereas the sequential relates to the order in which learning tasks take place. Both dimensions are closely related to the research on time management. Thus, a combined temporal and sequential analysis promises to provide new perspectives into time management and ways to improve SRL as a whole.

Process mining has been used by several scholars in the field of learning sciences to investigate regulatory patterns of groups and individual learners [22]. For instance, Sonnenberg and Bannert [18] used process mining techniques to analyze coded think aloud data about SRL processes of students who studied with hypermedia. Similarly, Bannert et al. [16] employed process mining to detect differences in frequencies of SRL events between most and least successful groups of students with respect to post-test scores. Process mining models of the two groups detected a substantial temporal difference between the groups and more regulation activities in the group of high performing students. A novel approach that combines process mining and clustering to detect learning tactics and strategies from trace data has recently been proposed [19]. This approach was applied for the analysis of trace data about students' online activities in a flipped classroom. The findings showed five learning tactics that were combined in three different learning strategies. The identified learning strategies could explain (a) how the students enacted the learning tactics over course timeline and (b) academic performance in the course. The learning strategies were well aligned with approaches to learning [20], with high engagement students following a deep learning approach and having high academic performance, while low engagement students employed a surface approach to learning and had relatively low performance.

In line with the previous works, the current study aimed to explore meaningful time management tactics and strategies by combining process mining and clustering techniques to shed some light on this notable resource of learning within online spaces. Specifically, the study addressed the following three research questions:

(1) What time management tactics and strategies can be detected from the students' interactions with online learning activities within a blended learning course?
(2) How do students in different strategy groups enact time management tactics throughout the course timeline?
(3) To what extent do the way students enact the tactics improve their self-regulated learning and course performance?

3 Methodology

3.1 Study Context

This study was conducted in a first year undergraduate course at an Australian university. The trace data were collected from 241 students enrolled in a Health Science course that ran for 13 weeks (1 semester). The course adopted a blended learning model which required students to complete online learning exercises provided via the university's LMS (Moodle) prior to face-to-face classroom activities. Two components of the online learning task were available to the students to prepare for the class in each week: tutorials and pre-laboratory exercises. Although the tutorials and pre-laboratory exercises were not mandatory to complete during the preparatory stage, they were beneficial for developing a strong foundation in the topics taught in the course. In the face-to-face setting, students were required to attend two weekly sessions: a 3 h lecture and a 1 h tutorial. The students were also required to attend 7 practical sessions (3 h each) and 3 laboratory sessions (2 h each).

3.2 Data Sources

Digital Traces. This study relied on digital traces from students' interactions with the online course activities in the period from February to June 2017, covering 13 weeks of the course. In total, there were 5,993 online learning sessions performed by the students throughout the entire course. The data were derived from LMS records which comprised every event's timestamp, unique user ID, event context, event name, IP address, and a description of the learning action. Time management was analysed by looking at times when the students performed online activities (out-of-class study), as evidenced in the trace data (timestamps) and validated against the course schedule provided by the course instructor. Note that the students were recommended to study one topic per week and complete pre-laboratory exercises during the assigned week. Each learning action was labelled with an appropriate ***mode of study*** based on its timing with respect to the week's topic as: (i) *preparing* - if the learning action was related to the topic the students were supposed to study in the given week, (ii) *ahead* - if the learning action was advance of the schedule, (iii) *revisiting* - if the learning action was related to a behind-the-schedule topic that the student had already studied at some earlier point in time, and (iv) *catching-up* – if the student had never accessed activities related to the behind-the-schedule topic. Successive learning actions between any two consecutive events that were within 30 min of one another were grouped into a learning session [21]. Learning sessions served as the unit of analysis when identifying patterns indicative of students' time management tactics.

Academic Performance. The second data source was derived from the overall course score in the 0–100 range. The assessments contributing to the final course mark included 2 quizzes (contributing 20%), practical marks (25%), and the final exam (55%). Quiz 1 and Quiz 2 were administered in Week 7 and Week 13, respectively. Both quizzes were conducted in a conventional setting.

3.3 Data Analysis

Time Management Tactics. Initially, time management tactics were detected from sequences of study modes. In particular, First Order Markov Model (FOMM), implemented in the pMineR R package [22], was used to compute and visualize the process model from learning sessions. By inspecting the overall process model, potential time management tactics were inferred based on the density of connections among events (i.e., modes of study). To move from observations to automated detection of tactics, we used the matrix of transition probabilities between events, produced by the FOMM, as the input to the Expectation Maximization (EM) algorithm [19] to identify clusters of sequences. The identified clusters reflect patterns in the sequences of study modes and can be considered manifestation of students' time management tactics.

Time Management Strategy Groups. Time management strategies were inferred from the way a student employed time management tactics; i.e., strategies were characterized by one or more tactics [23]. Agglomerative Hierarchical Clustering based on Ward's algorithm [24] was used to identify time management strategies by grouping students with similar usage patterns of time management tactics. To identify such student groups, we represented each student as a vector of the following variables: (a) counts of instances of the identified time management tactics followed by the student (one variable per time management tactic); and (b) the total number of instances of time management tactics. The distance between students, required for the Ward algorithm, was computed as the Euclidean distance of the corresponding vectors. The optimal number of clusters was determined by inspecting dendrograms.

Time Management Tactics Use Across Strategy Group. To further explore the temporal data, we used another process mining technique implemented in the bupaR R-package [25]. The unique features introduced in bupaR assure that the time frame is relevant enough to bring insight into the learning process and has a great potential to inform and enhance understanding of how students make complex learning decisions. In our analysis, we considered event logs that recorded each student's active learning process from the beginning (Week 1) to the end (Week 13) of the course. Each event belonged to a case. A case, in general, is an instance of the process; in this study, a case is an individual student enrolled in the course. In addition, each event relates to a coarser concept of activity. In this study, activities are the tactics adopted by a student while progressing in their learning. For this analysis, we combined the identified time management tactics with online learning resources (e.g., tutorials and pre-lab exercise) to provide meaningful representations of time management (e.g., *ahead_tutorial* and *prepare_tutorial*). When an activity is performed, an activity instance (occurrence) is recorded. For a given case (user_id), we would obtain, from the event logs, a set of execution traces. We denote the traces as a sequence of activities ordered by their time of occurrences in the course timeline (see Table 1).

Table 1. An example of a sequence of activities (trace) for each student obtained from event logs

user_id	trace_length	start_timestamp	complete_timestamp	trace
8	1	2017-06-08 09:56:00	2017-06-08 09:56:00	Prepare_Tutorial
14	2	2017-03-28 08:21:00	2017-04-28 15:37:00	Prepare_Tutorial,Catch.up_Prelab
212	2	2017-03-08 09:09:00	2017-04-06 22:55:00	Ahead_Tutorial,Prepare_Tutorial
12	3	2017-02-28 08:41:00	2017-03-17 08:19:00	Ahead_Tutorial,Mixed_Tutorial,Prepare_Tutorial
19	3	2017-03-06 22:07:00	2017-03-27 22:39:00	Prepare_Tutorial,Mixed_Tutorial,Prepare_Tutorial
35	3	2017-03-22 01:26:00	2017-04-27 12:20:00	Catch.up_Tutorial,Catch.up_Tutorial,Ahead_Tutorial
41	3	2017-03-15 15:01:00	2017-06-08 11:39:00	Catch.up_Tutorial,Prepare_Tutorial,Prepare_Tutorial
52	4	2017-03-15 19:57:00	2017-06-10 07:15:00	Catch.up_Tutorial,Catch.up_Tutorial,Catch.up_Tutorial,Prepare_Tutorial
77	4	2017-03-14 09:16:00	2017-03-19 21:31:00	Prepare_Tutorial,Prepare_Tutorial,Catch.up_Tutorial,Prepare_Tutorial

Process models were then generated based on the identified traces. A process model consisted of a set of nodes and a set of arcs, where the nodes were the process activities and the arcs were the order of the activities. The discovered models were often "spaghetti-like" showing all details of a process. To make the models usable for interpretation, 80% of the most frequent activities were kept for each time management strategy group. This allowed us to study temporal characteristics of different strategy groups.

Association Between Strategy Group and Academic Performance. To examine if there was a significant difference between the identified strategy groups on academic performance, we used Kruskal Wallis tests followed by pairwise Mann Whitney U tests.

4 Results

4.1 Time Management Tactics

By examining density of connections among events of the overall process model resulting from FOMM, a solution of four clusters was identified. Figure 1 illustrates a temporal distribution plot of study modes in each cluster indicative of time management tactics. Each point on the X-axis corresponds to one event (mode of study), whereas the position on the Y-axis represents the probability of study modes.

The characteristics of the identified clusters could be described as follows: (i) Tactic 1 – *Mixed* (N = 1511, 25.21% of all sequences). This tactic was comprised of ahead, preparing, and revisiting modes of study. Sequences in this tactic were focused on revisiting learning materials in a future week after they has been completed in advance or during the week when those activities were scheduled, (ii) Tactic 2 – *Catching-up* (N = 128, 2.14%). It was the least used tactic and consisted predominantly of the catching-up behavior apart from revisiting and preparing modes, (iii) Tactic 3 – *Preparing* (N = 2441, 40.73%). This is the most widely applied tactic and had the highest frequency of preparation activities compared to the other tactics, and (iv) Tactic 4 – *Ahead* (N = 1913, 31.92%) consisted predominantly of ahead activities.

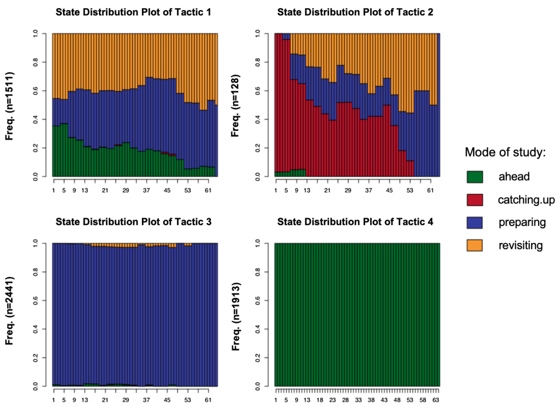


Fig. 1. Temporal distribution of study modes within the detected clusters (manifestations of the students' time management tactics).

4.2 Time Management Strategy Groups

By inspecting the dendrogram resulting from the applied agglomerative hierarchical clustering, a three cluster solution was chosen as the optimal one. To better understand the identified clusters as manifestations of the students' time management strategies, we examined, for each cluster (strategy), how the use of time management tactics changed throughout the course. Figure 2 shows, for each detected strategy, median number of different tactics applied in each week of the course.

Strategy 1 – Active (N = 74, 30.71% of all students) was the most active and dynamic group. This group was consistent in the use of the *Preparing* tactic throughout the course, but also applied different tactics (ahead, preparing and mixed) interchangeably along the course timeline. *Strategy 2 – Passive* (N = 101, 41.91%) had the highest number of students who adopted it. The students were averse towards spending time for studying online with low use of all tactics. Their activity level declined rapidly right after Week 2; in Week 4 they were back on track by adopting the *Preparing* tactic, but failed to maintain the momentum for the rest of the course. *Strategy 3 – Selective* (N = 66, 27.39%) included the students who were highly focused on the

Preparing tactic beginning from Week 3. Their effort dropped in Week 7, but they were able to get back on track and maintained the *Preparing* tactic until the end of the course.

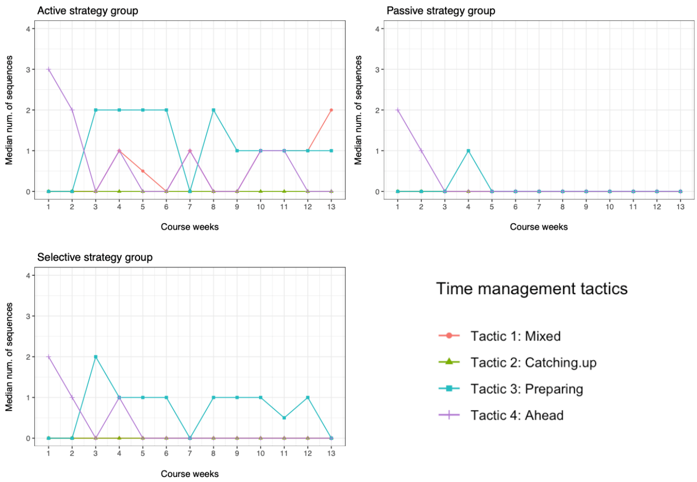
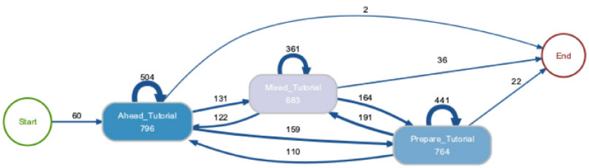


Fig. 2. The dynamics of time management tactics for each identified strategy group

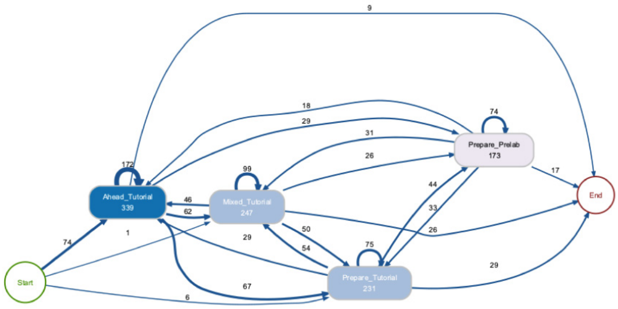
4.3 Time Management Tactic Use Across Strategy Groups

Three process models were created to represent each identified strategy. Figure 3 illustrates the learning processes performed by the students (by enacting several tactics) in each strategy group. The course design permitted the students to decide which tactic to start with and they could change the tactics at any time. Clear differences in the temporal pattern can be identified between the groups, as explained below.

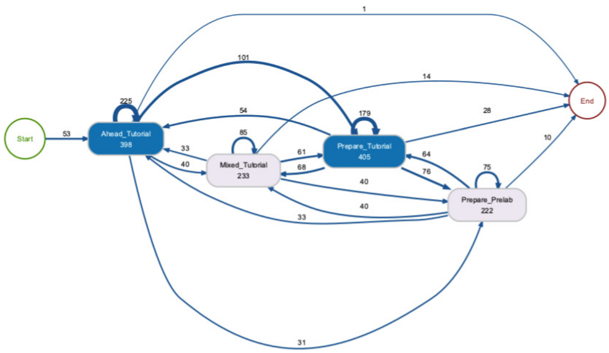
The total duration of time spent to complete the course (in days) was Mdn = 99.62, Q1 = 97.82, Q3 = 101.81 for the *Active* strategy group (Fig. 3(a)) had. This group was characterized by *Ahead_Tutorial* → *Prepare_Tutorial* → *Mixed_Tutorial* as a common activities sequence; that is, a path of transitions with high certainty in activity instances. The frequency of activity instances was relatively equally distributed among the tactics; i.e., all tactics are equally important. The students in this group tended to stay long in the same mode of study (loops around ahead, preparing, and revisiting). The transition often occurred between two tactics (based on the high frequency of activity instances); i.e., *prepare_tutorial* to *mixed_tutorial* (191 instances) and *mixed_tutorial* to *prepare_tutorial* (164 instances). The students in this group showed careful choices between cognitive, metacognitive, and regulation activities while progressing in their learning. This is evidenced by repeated efforts in preparing and reviewing course materials and the regularity in applying various tactics.



(a) Active Strategy Group



(b) Passive Strategy Group



(c) Selective Strategy Group

Fig. 3. Process models for the learning processes of the three identified strategy groups. The number in the box represents the absolute frequency of occurrences of events (activity instances), while the numbers associated with edges represent absolute frequency of transitions between consecutive activities. Darker node colour represents higher frequency of activities. (Color figure online)

The median time spent by the *Passive* group (Fig. 3(b)) to complete the course (in days) was 86.68 days (Q1 = 70.06, Q3 = 97.89). The most common path of transition displayed by this group was *Ahead_Tutorial* → *Mixed_Tutorial* → *Prepare_Tutorial* → *Prepare_Prelab*. In contrast to the *Active* group, this group demonstrated high transitions from *ahead_tutorial* to *prepare_tutorial* (67 instances) and *ahead_tutorial* to *mixed_tutorial* (62 instances), while, *prepare_tutorial* showed low connection with *mixed_tutorial* (54 instances). The *Preparing* tactic was connected with both tutorial materials and pre-laboratory exercises and its usage frequency was relatively low. These results seem to suggest the *Passive* group adopted a surface approach to learning, with low frequencies in all learning tactics.

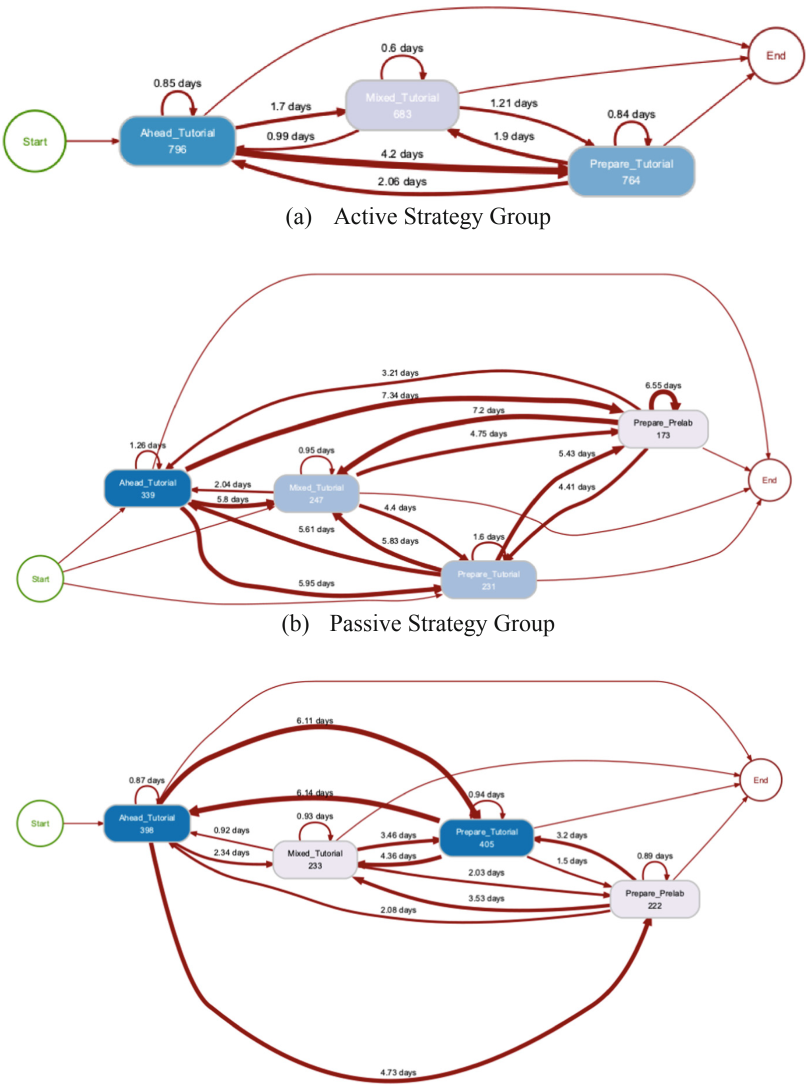
The median time spent by the *Selective* group (Fig. 3(c)) to complete the course was 98.04 days (Q1 = 92.48, Q3 = 99.90). *Prepare_Tutorial* → *Ahead_Tutorial* → *Mixed_Tutorial* → *Prepare_Prelab* was the most common sequence. Like the *Passive* group, this group was focused on preparing for both tutorials and laboratory exercises. Similarly, both groups showed relatively low frequency of re-studying (*mixed tactics).* In comparison to other groups, this group had frequent transitions from *ahead_tutorial* to *prepare_tutorial* (101 instances) and from *prepare_tutorial* to *prepare_prelab* (76 instances). That is, the group predominantly focused on planning (e.g., ahead and preparing), while less frequently on preparing and revising.

The graphs shown in Fig. 4 depict the discussed process models from the time perspective. The time periods associated with directed edges represent idle time; i.e., time period between two consecutive activities. The *Active* strategy group had the longest idle time between *ahead_tutorial* and *prepare_tutorial* (Mdn = 4.20 days). In comparison with other group, students in this group took less than 2 days to prepare and revisit the topics; i.e., from *prepare_tutorial* to *mixed_tutorial* (Mdn = 1.90) and from *mixed_tutorial* to *prepare_tutorial* (Mdn = 1.21). The *Passive* strategy group had the longest idle time is between *ahead_tutorial* and *prepare_prelab* (Mdn = 7.34) followed by *ahead_tutorial* to *mixed_tutorial* (Mdn = 5.80) and *ahead_tutorial* to *prepare_tutorial* (Mdn = 5.95). That is, this group took at least 5 days to shift from their first activity (*ahead_tutorial*) to other activities. This group took the longest time from *prepare_tutorial* to *mixed_tutorial* (Mdn = 5.83) and from *mixed_tutorial* to *prepare_tutorial* (Mdn = 4.40) comparing to the other two groups. Although the *Selective* strategy group predominantly focused on ahead and preparing tactics, it took them a long time (almost a week) to shift from *prepare_tutorial* to *ahead_tutorial* (Mdn = 6.14) and from *ahead_tutorial* to *prepare_tutorial* (Mdn = 6.11).

4.4 Association Between Strategy Groups and Academic Performance

The results of the Kruskal Wallis test showed a significant association between the identified strategy groups and the students' course performance (p-value < 0.001 for total score). The pairwise tests showed significant difference with effect sizes (r) ranging from small to medium (Table 2).

The *Active* group (Mdn = 78.01, Q1 = 72.57, Q3 = 84.05) was highest performing. The *Passive* group (Mdn = 74.29, Q1 = 59.57, Q3 = 81.28) was lowest performing. The *Selective* group (Mdn = 76.46, Q1 = 73.65, Q3 = 82.66) was mid-performing.



(a) Active Strategy Group

(b) Passive Strategy Group

(c) Selective Strategy Group

Fig. 4. Idle time (in days) between the end of the from-activity and the start of the to-activity across three identified strategy groups. Darker line color represents longer idle time. (Color figure online)

Table 2. Pairwise comparison of strategy groups with respect to the total course score.

Cluster 1	Cluster 2	Z	p	r
Passive	Selective	1.0226	<0.001	0.198
Active	Passive	–0.2921	<0.001	0.203
Selective	Active	–0.6678	<0.001	0.020

5 Discussion

We discuss the findings based on the framework proposed by Kornell and his colleagues [5] on SRL decisions of what to study, how long to study, and how to study. The results showed that the students employed a wide range of tactics and strategies to manage their learning. The study confirmed this proposition by identifying three strategy groups – *Active*, *Passive,* and *Selective*. The profiles of these groups reflect their time management strategies and academic achievement in the course. The *Active* group was the most active and dynamic; the students in it adopted diverse tactics and used them throughout the course. Due to the careful alignment of diverse tactics such as study in advance (*ahead tactics*), prepare learning prior to a face-to-face session (*preparing tactics*), re-studying right after a class and revision during the test weeks (*mixed tactics*), this strategy was recognized as the one of autonomous learners and associated with the highest achievement. In contrast, the *Passive* group, associated with the lowest achievement, used only a few tactics during their learning, and sometimes used tactics in a way not supporting their study. Unlike the *Active* group, the *Selective* and *Passive* groups highly focused on preparation with less revisiting efforts. A possible explanation may be that both groups believed that having already learned a topic, little would be gained from re-studying. However, such a strategy is far from optimal. To sum up, our results indicate that students who were identified as high performing – the *Active* group – put efforts to plan their study (cognitive), modified their learning accordingly (metacognitive), aligned their study tactics with the course structure and maintained their level of motivation (regulation strategies) throughout the course timeline. In line with the SRL theories, the *Active* group demonstrated productive self-regulation [4, 9, 26].

One of the major problems in regulation of learning lies in how much time to put into practice. The current study found that the high performing students (*Active*) were willing to invest more time to study compared to the low performing (*Passive*) and mid-performing students (*Selective*). This is evidenced by the frequency of activity instances that the high performing group allocated for each tactic (Fig. 3(a)) which was two times higher than that of the lowest performing group. The students in the high performing (*Active*) group also devoted to course completion on average 13 days more than the lowest performing (*Passive*) group. This may reflect the *perseverance of effort* exhibited by high performing students to sustain the time and efforts necessary for completing long-term tasks [27]. Furthermore, on average, the *Active* group spent more time revisiting (*mixed_tutorial*) weekly topics ($M = 5.45$, $SD = 10.42$) minutes. The *Passive* and *Selective* groups spent longer time on preparing for pre-laboratory exercises (*prepare_prelab*) ($M = 9.74$, $SD = 13.57$ and $M = 11.81$, $SD = 18.61$ min, respectively). This may be attributed to the students' *judgement of rate of learning* (jROL). Maybe the two groups perceived pre-laboratory exercises as a difficult task and, thus, maintained a high learning rate. Commonly, the students in all three strategy groups spent more time revisiting learning materials (*mixed_tutorial*) after the week to which the materials were assigned. This was almost twice the time they spent using those materials to prepare (*prepare_tutorial*) for the class. These findings suggest that, all students used regulatory processes to some degree, but self-regulated learners were distinguished by their awareness of active decisions between regulatory processes and learning outcomes and their use of these strategies to achieve academic goals [28].

Furthermore, the use of time in learning is often linked to the *spacing effect* [29]. Spacing—defined as separating successive study sessions rather than massing such sessions—has positive effects on long-term memory [30]. The finding of this study indicated that, after preparatory work, the *Active* group took 2 days on average before immediately returning to the course material to review it, whereas the *Passive* and *Selective* groups waited approximately 6 and 4 days, respectively, before returning to the materials to re-study. A possible explanation may be that the *Active* groups established optimal metacognitive judgments that they could forget some items they had previously studied, so they kept coming back to the items immediately as a priority [26] thereby promoting better recall. In contrast, the *Passive* and *Selective* groups were less sensitive to change as they allowed for maladaptive delay between two tactics. Undoubtedly, long idle time did not benefit recall. Students could forget what they have learned before. In summary, the students in the highest performing group (*Active*) showed a clear endorsement of massing over spacing for predicted learning outcomes [31] contrary to consistent findings in the literature of a benefit for spacing [32].

6 Conclusions and Implications

The purpose of this study was to explore the differences in time management tactics and strategies from the perspective of self-regulated learning theories. We present the time management aspects based on study decisions students make on what to study (what tactic to use), how long to study (frequency of tactics used) and how to study (timing of tactic use). From a methodological point of view, we demonstrated how quantitative temporal data about students' online learning activities can be analysed by methods of process mining. Although used in SRL research, the application of this method, as done in the current study, for exploring students' time management tactics and strategies in the context of online and blended learning activities is original.

This study contributes to the literature on time management and SRL by providing empirical evidence on what, how, and how long students enacted their tactics across different strategy groups and academic achievement. Our research reinforced the importance of time management tactics in students' learning that improve their SRL and performance. From an instructor viewpoint, this study has a potential to inform instructors about what tactics students applied to learn, how students spaced out their learning, and how regularly students engaged in online preparatory work. This allows instructors to understand different characteristics of students to make necessary adjustment in their learning approach and feedback to the students. From a student viewpoint, this study can provide awareness and useful guidelines for the students to inform them about the effective tactics and strategies they could employ while studying online and the opportunities to improve their time-management skills as well as their academic success.

This study highly relied on the trace data of students' interactions with online preparatory learning activities. Although this data allowed for examining actual behavior in an authentic online settings, we could not capture activities that occurred offline (e.g., downloading the learning material) nor in-class activities; such activities which take place in a physical context could influence students' decision in learning.

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