Analytics of Temporal Patterns of Self-regulated Learners: A Time Series Approach

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Abstract

Temporal patterns play a significant role in understanding dynamic changes in Self-regulated Learning (SRL) engagement over time. Several previous studies have proposed approaches for automated detection of SRL strategies through analysis of temporal patterns. However, these approaches are mostly focused on the analysis of patterns in sequential ordering of SRL processes. This offers a useful yet limited temporal perspective to SRL. As noted in the literature, temporality of SRL has two dimensions – passage of time and ordering of events. To address this gap, this paper specifically proposes a time series approach that can automatically detect SRL strategies by accounting for both dimensions of temporality. Our approach also explores when specific processes occur and how learners engage metacognitively or cognitively with learning tasks. In particular, this study investigated SRL engagement as students composed essays using multiple sources within a 120-minute time frame. The results indicated that five distinct strategies with varying levels of engagement were detected. The correlation between these identified strategies and students' scores was not statistically significant; however, further exploration revealed that students who adopted a specific strategy could outperform other groups based on obtained scores. We also noticed additional factors that had a positive effect on learners' performance.

CCS Concepts

• **Applied computing** → *Computer-assisted instruction*; • **Mathematics of computing** → *Time series analysis.*

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Self-regulated Learning (SRL), Time Series, Clustering, Learning Strategies, Learning Analytics.

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1 Introduction

Self-regulated learning (SRL) has been extensively investigated across multiple educational disciplines. SRL comprises a series of cognitive, metacognitive, affective and motivational processes [1]. Understanding the impact of these SRL processes on academic writing can enhance learning outcomes by fostering desirable learning behaviors and assisting students to successfully achieve their goals [29]. For instance, when writing from multiple sources, learners need to use a set of cognitive and metacognitive skills to increase their success in this learning task [33]. To construct an essay from multiple sources, learners typically follow several steps within a time frame, including reading instructions, comprehending the content of the proposed topics, utilizing supportive tools (e.g., timer and planner), and ultimately drafting their essay [31].

Failing to properly engage with SRL processes in multi-text writing can lead to potential issues, such as affecting the quality of written essay or generating irrelevant information [12, 31, 48]. Several studies, such as [52], have indicated a visible association between the SRL strategies adopted by students and their performance. For example, learners with high performance demonstrated greater self-efficacy and a higher frequency of implementing SRL strategies during their writing tasks [4, 50]. In contrast, low performers were less likely to engage in such strategies [4, 50]. Understanding learning behavioral patterns can benefit education in several ways, including aiding instructors in course design, illustrating student behaviors and measuring learning outcomes [58]. Although previous studies have indicated that SRL behaviors typically correlate with students' performance, analyzing the temporal patterns of SRL can provide additional insights into how engagement with specific processes can impact learning outcomes. For example, learners who evaluate their progress 20 minutes before task completion may achieve higher scores.

Although SRL processes are crucial for successful learning, measuring these processes can be challenging [21]. For example, higher granularity in captured data can make it difficult to interpret SRL processes [2]. To tackle this issue, numerous studies have compiled various approaches, including process mining (PM), machine learning, and statistical techniques, to extract meaningful strategies of how learners self-regulated their learning by making use of trace data [23, 37, 39, 46]. These studies have employed frequencies, event duration, and temporal patterns to comprehend students' behaviors during their interaction with SRL. For instance, Srivastava et al. (2022) applied multiple techniques to extract meaningful strategies, such as clustering approaches and the First-Order Markov Model (FOMM); however, these techniques have limitations in identifying the real-time occurrence of SRL processes [46]. Specifically, the researchers analyzed the temporal distribution, including the duration and frequencies within each group, without explicitly indicating the exact time at which students engaged with these detected strategies (e.g., the minute a group of students began monitoring their writing task) [46]. A further study has explored the use of smart devices to record students' emotional signals (e.g., eye gaze) during their writing activities, aiming to understand metacognitive and cognitive events using time series prediction [32]. The trace data generated by these devices was used as input for the proposed analytic models to estimate SRL processes in the next time windows [32]. To date, research studies primarily have adopted universal techniques (e.g., process mining) to detect SRL strategies while each technique has its strength and weakness[23, 36]. For instance, a First-Order Markov Model (FOMM) can measure the transition probabilities among SRL events [46], but it does not account for the specific timing of these transitions. However, time series approaches can address this issue by providing deeper insights into processes' occurrences during critical learning periods.

As SRL involves both metacognitive and cognitive processes, numerous studies, such as that by Rakovic et al. [30], have emphasized the influence of metacognitive processes on students' writing, particularly in relation to time characteristics. Metacognitive processes are a central component of SRL. For instance, high-performing students have tended to engage more actively in monitoring tasks, including time management [30]. The Rakovic et al. discussed how metacognitive events are measured in multi-text writing [30]. The measurements included the time students spent on reading task instructions, planning, and engaging with the reading materials [30]. In contrast, the temporal features of cognitive processes have been extensively studied in text writing as well [43]. Specifically, Schilperoord and Joost investigated text production in real-time by analyzing pause patterns, which reflect how writers think and produce content during the writing process [43]. Although these studies [30, 43] have discussed the temporal attributes of metacognitive and cognitive processes independently in writing, further investigation is needed to articulate how writers temporally engage with both SRL categories simultaneously. For example, writers typically read from source materials to compose information into a written product that meets the requirements [30]. Nath et al. studied the temporality of both cognitive and metacognitive events using multiple techniques, such as raincloud visualization, which provided a comprehensive understanding of temporal writing behaviors [23]. However, this combined approach did not capturing the timing and sequence of SRL processes from a time series perspective [23]. Specifically, this study was unable to identify when and how learning strategies occurred [23]. Finally, analyzing the time series of both metacognitive and cognitive processes can provide a holistic view of how students engage with learning tasks while preserving the dynamics of these processes over time.

Although temporality in SRL encompasses two dimensions, certain research studies have mainly concentrated on one of them [23]. These two dimensions include: 1) the sequentiality of events occurrence (e.g., order of events), and 2) the passage of time, which can be measured by event duration, event frequency, or specific points in time [13, 22, 23]. Numerous studies have investigated the sequential patterns of SRL where each study focus on different aspects and methods [7, 17, 55]. He et al. examined how SRL behaviors can change after formative assessment [7]. The analysis of this study focused on the temporal features of SRL behaviors including the frequency and transitions among processes [7]. Additional study classified students into different groups based on their similar SRL temporal behaviours [55]. Specifically, this study applied clustering techniques to categorize students using SRL frequency and then examined the transitions among these processes in each detected group [55]. Although these studies provided insights into the temporality of SRL processes, exploring both temporal dimensions using time series analysis to identify when and how SRL strategies occur over time remains crucial [23].

Time Series (TS) analysis has recently attracted significant attention from researchers due to the growing use of temporal data [9] in educational contexts. The primary objective of TS is to comprehend and monitor the dynamic changes in learning behaviors over time, as learners often alter their strategies throughout the learning period [11, 45]. This is highlighted in several studies that have explored the temporality of learning activities in higher education environments over extended periods using Learning Management Systems (LMS) trace data[9, 11, 41, 45]. These projects aim to analyze temporal features from various perspectives, such as assessing learning consistency, identifying at-risk learners and detecting unique learning tactics [9, 11, 41, 45]. Other research studies offered deeper insights into adopting TS techniques in association with SRL, aiming to investigate how students regulate their learning activities over time [49, 57, 58]. The three mentioned studies offer valuable insights into adopting time series techniques in SRL, including the analysis of students' reflective writing behaviours over time [49], identifying behavioural patterns across multiple course stages [57], and analysing students' micro-level behavioural patterns [58]. However, this study leverages time series analysis to detect SRL temporal strategies, offering insights into how learners dynamically regulate their learning processes.

As per our literature review, this study draws inspiration from existing research demonstrating that learners who engage deeply with SRL are more likely to succeed in their writing endeavors [49].

Temporality in SRL involves more than just calculating duration and frequency or examining transitions among processes through various techniques. The temporality also encompasses the sequences of these critical processes, providing a deeper understanding of how SRL processes unfold over time[23, 36]. The main limitations in prior research studies include: 1) the need to explore SRL temporality from a time series perspective (e.g., when and how processes occur) in various learning tasks, 2) the shortage of research to extract temporally meaningful strategies of both metacognitive and cognitive processes and how these strategies affect learners' performance, and 3) the necessity of employing techniques (i.e., TS) that can handle both dimensions of temporality (passage of time and ordering of events) for detecting SRL behaviours.

To address the above gaps, the current study aimed to investigate how students interact with SRL and detect meaningful strategies by analyzing their temporal behaviors in multi-text writing. We employed a time series approach to analyse learners' SRL events over a two-hour session. Our time series approach resulted in identifying five distinct SRL strategies across seven metacognitive and cognitive processes. These strategies were classified according to students level of engagement, ranging from low to high. Furthermore, the relationship between these identified learning strategies and student performance was interpreted. The key contribution of the present study lies in observing the temporality of SRL processes, which promises to offer deeper insights into writing analytics.

2 Background and Related Work

2.1 SRL Theoretical Framework that Guides this Study

SRL encompasses a set of processes where learners intentionally regulate their learning tasks or problem-solving strategies to reach their set goals [17]. The theoretical framework of SRL describes multiple cognitive, metacognitive, affective, motivational, and behavioral processes learners engage in as they work in a particular learning environment [7, 26]. Zimmerman's SRL model [59, 60] comprises three primary phases: 1) forethought, which occurs prior to learning (e.g., planning a learning task), 2) performance, which occurs during the learning activity (e.g., monitoring performance), and 3) self-reflection, which follows the learning task (e.g., self-assessment). The Zimmerman's model shows that SRL is a dynamic operation which can be explained by a series of events occurrence [55]. Based on the Zimmerman's theoretical framework, Bannert developed a detailed operationalisation scheme for SRL processes, as shown in Appendix A [1]. The Bannert's framework categorizes SRL processes into three main categories: metacognitive, cognitive, and other processes [2, 31]. The metacognitive events consist of four sub-processes: 1) orientation, 2) planning, 3) evaluation, and 4) monitoring [2, 31]. Additionally, the cognitive operations are classified into two levels, high and low, which include three sub-events: 1) first reading, 2) re-reading, and 3) elaboration/organization [2, 31]. Finally, the category of 'other processes' includes motivational and procedural activities, such as expressing feelings (positive or negative) about the learning task [2, 31].

2.2 SRL Strategies and Learning Performance

Self-regulated learners are typically strategic about their learning. They can plan their learning approach and make adjustments as needed throughout the learning process [53]. The concept of a learning strategy refers to the set of activities that learners execute during their learning cycle [15]. Selecting the right learning strategy is a crucial part of effective self-regulated learning [3]. For instance, learners need to be aware of which learning strategy is appropriate when using technological systems to achieve their learning goals [3]. Exploring the SRL strategies enacted during the learning cycle is pivotal for learning success. To contribute to this field, Srivastava et al. [46] explored the impact of internal and external learning conditions (e.g., prior knowledge and scaffolding) on SRL strategies to identify meaningful strategies that students employ when writing from multiple sources. The authors combined first order Markov models with expectation-maximization clustering to extract SRL strategies [46]. This study revealed three distinctive strategies: (1) Read First, Write Next, (2) Read and Write Simultaneously, and (3) Write Intensively, Read Selectively [46]. Although the Srivastava et al. [46] study makes a significant contribution to the research field by identifying theoretically meaningful SRL strategies using trace data, clustering students based on their SRL temporal behaviors using time series techniques can provide solid insights into how students' metacognitive and cognitive engagement can be changed overtime. In other words, the analytical approach proposed by researchers in the previous study [46] has a limitation in capturing the actual time or temporal dynamics when each SRL process occurs. This limits the ability to examine the fine-grained temporal evolution of SRL strategies.

Further research has illuminated the extraction of learning strategies utilizing trace data. Gašević et al. investigated the association among learning strategies, self-report measures and academic performance [3]. The authors implemented optimal matching sequence analysis in combination with hierarchical clustering to identify learning strategies [3, 14]. The results uncovered four learning strategies characterized by the level of students' learning (e.g., surface or deep learning) [3]. In line with previous research, another study analyzed the engagement of students while performing online tasks based on a specific pedagogical setting [15]. This study conducted an exploratory experiment to observe students' behaviors across different courses utilizing their logs data [15]. The study followed the method proposed by Matcha et al. [19, 20], which detected learning strategies by combining First-Order Markov Models (FOMM) with the Expectation-Maximization (EM) clustering technique [15]. The approach applied by Lahza et al. [15] identified four distinct learning strategies, each demonstrating varying levels of interaction, ranging from inactive to intensive. These studies demonstrated that meaningful strategies can be extracted by applying appropriate clustering approaches utilizing trace data. However, analyzing the temporality of SRL during writing tasks remains under study.

Analyzing the influence of SRL processes on student performance is a common objective across numerous studies in learning analytics field. Various studies have investigated the influence of SRL processes on students' performance from different perspectives, such as examining the association between SRL strategies and learning outcomes [3, 23, 37, 39, 46]. Further studies have explored the impact of SRL processes on both high and low performance groups [8, 17, 31]. Comparisons between high and low achievers can illustrate how SRL events are influenced by factors such as prior academic achievement [8]. Additionally, another study investigated how SRL features (e.g., reading processes) can predict students' scores in writing from multiple sources [31]. In particular, the Rakovic et al. examined four characteristics and their impact on high and low performers [31]. For example, the results indicated that learners who created a plan using available tools tended to achieve higher scores compared to those who did not [31]. Li et al. investigated the sequentiality of SRL temporal behaviors with the aim of comparing low and high achievers [17]. This study revealed that students with high performance levels had a higher probability of transitions among SRL processes [17]. Informed by these studies, classifying learners into high and low performance groups can help illustrate the distinct characteristics of each group in terms of their SRL behaviors, which will be beneficial for both theoretical and practical applications. For example, Hirt et al. [8] found that high achievers used cognitive and metacognitive strategies more frequently than low achievers. While the previous studies have provided valuable insights into how SRL affects learner performance, there is still a need to explore the relationship between SRL temporal strategies and learning outcomes using time-series analysis. To contribute to this filed, the current study seeks to analyse students SRL behaviours in the context of multi-text writing, employing time series approach. In other words, we aim to explore whether engaging with SRL events at a specific time can affect students' performance. For instance, monitoring the learning task early could have a positive impact on students' performance compared to doing so later or closer to a deadline.

2.3 Temporal Analytics and SRL

An increasing number of studies have shed light on the concept of temporality in SRL [36]. The temporality in learning encompasses not only time related factors such as duration but also the sequence in which events occur [34, 35]. Additional definitions of SRL have been described based on the probability of processes transformation and the non-linearity of events occurrence [27, 39]. The main advantage of analyzing temporal patterns in SRL is to provide deeper insights into how to enhance the learning cycle [27, 36].

Various studies have employed multiple analytical approaches to yield a deeper understanding of the dynamic and complex temporal patterns inherent in SRL [23, 37, 39, 42]. A recent study introduced a comprehensive approach including raincloud visualization, Order Network Analysis (ONA) and process mining to explore the temporality of SRL and how these patterns affect learning outcomes [23]. An additional study examined the relationships and variances among SRL processes, illustrating how these events can be classified and associated with each other by adopting multiple approaches, while also discussing the longitudinal timeline of SRL processes [42]. Saint et al. [37, 39] adopted a combined methodological framework to uncover the micro-level aspects of SRL processes, aiming to comprehend how students regulate their learning tasks. The SRL micro-level concept refers to sub-categories that involve series of detailed activities, with each sub-category belonging to one of the main SRL framework categories [39]. For example, the record of learners' clicks to perform a specific task can be considered micro-level processes [37]. The combined approach involved temporal process analysis, measuring both the median time spent on each activity and the lag time between process transitions [37]. While previous techniques have limitations in capturing the dynamics of SRL temporality (i.e., when and how SRL processes evolve over time), time-series approaches can address these challenges. For instance, the Dynamic Time Warping (DTW) technique can capture the continuous temporal trends and track how SRL behaviors occur during the actual learning process.

2.4 The Present Study Research Questions

The existing literature review has revealed that analyzing temporality in SRL is still an area under active study [36]. In particular, previous studies have highlighted the need to explore how and when SRL processes occur, the shortage of research detecting temporally meaningful SRL strategies, and the necessity for efficient approaches to handle the dynamics of temporal patterns. Although time series approaches have been employed in various educational contexts [9, 45, 49, 57, 58], demonstrating their effectiveness in categorizing students based on similar behaviors [9], studying both temporal dimensions of SRL, and detecting temporarily-based learning strategies, can triangulate the insights into students' engagement with SRL. Specifically, understanding the sequential nature of SRL operations can provide insights into how engaging with SRL processes at specific times impacts student performance. For instance, a group of students who evaluate their learning progress at the 90th minute of a 120-minute session may outperform other groups. To contribute to this field, we formulate our first research question:

RQ1: What are the learning strategies, and what are the temporal sequences of those strategies, that students enact as they engage in a learning task?

Analyzing students' temporal behaviors without linking them to their learning performance does not provide sufficient information to effectively support students. Research in this field has clearly indicated that the detected strategies can be utilised to explain differences in learners' learning outcomes [46]. Therefore, we have formulated the second research question:

RQ2: To what extent are the learning strategies that learners enact during a task associated with their achievement?

3 Methods

3.1 Participants

This study involved 135 undergraduate students at a Chinese university who consented to participate in the essay writing task using multiple sources. Due to a technical issue, the data about one participant were removed from our analysis, reducing the final sample size to 134 (65% female and 35% male). The participants come from diverse academic disciplines, including science, technology, engineering, medicine, and other fields. All participants were native Mandarin speakers. The mean age of the students was 22.60 (SD = 3.39). Prior to data collection, ethics approval was obtained.

3.2 Study Context

In this lab-based experiment, participants were required to write an essay of 200-400 words on three topics: 1) Artificial Intelligence (AI), 2) scaffolding to optimize learning, and 3) differentiation practices in the classroom. The total duration of the experiment was 120 minutes. During task time, students were able to read the materials and write their essays applying several skills such as organization (e.g., a learner writes down an overview about the essay topic). Additionally, students took an extra hour for revision with the help from various facilitators (e.g., GPT). Those revision activities were outside the scope of the current study. We also conducted a pre-test to collect basic demographic information about students and assess prior-knowledge of the participants.

3.3 Learning Environment

The learning environment utilized in this study was a specially developed web-based system equipped with various functions to meet the study's objectives. This environment was designed to integrate seamlessly with SRL theory, allowing participants to use a range of customized tools that afforded the engagement in different SRL processes, including orientation, planning, evaluation, monitoring, first-reading, re-reading and elaboration/organization. For instance, the planner tool assists learners in planning their writing tasks by enabling them to select one of the available strategies (e.g., read selectively, write intensively). The environment also includes a navigation bar, allowing users to browse through reading materials, general instructions and the rubric. In the writing space, students can compose their essays by integrating information from the provided reading content, utilizing an editing toolbar. Additionally, there is a list of important supporting instruments, including a timer, search box and notes tool, which can be utilized during the learning task.

3.4 Measurement

3.4.1 Trace Data Based on SRL. We prepared the dataset by converting raw trace data into meaningful SRL processes, following the theoretical framework described in [1], as shown in Appendix A. Metacognitive processes primarily focus on how learners manage their learning activities. For instance, students typically begin a given task by checking the specifications and setting a plan for how to complete it. Subsequently, they spend more time evaluating and monitoring their work. Cognitive processes occur when a student engages with reading activities, including first reading and re-reading, or when they write down information and generate new ideas about the essay topic.

We developed a trace parser to extract SRL processes from the raw trace data, following the protocol defined in Fan's et al. study [2]. The technique that we followed to capture SRL processes include two phases [2]. The first phase, we label the raw trace data into eighteen meaningful actions. For example, if a learner use the planner tool during the learning task, this action will be labeled as PLANNER. The second phase, we create a map to link the mentioned 18 actions with the main seven SRL processes. For instance, when a student reads the content using the navigation bar, this sequence of actions (READING ->NAVIGATION ->READING) will be labeled as first reading operation (LC.F).

3.4.2 Essay Score. The rubric for evaluating each essay involved four global criteria: 1) a word count of 200 to 400 words, 2) basic writing skills, which assess clarity and the level of writing (e.g., minimal spelling and grammatical errors), 3) academic writing skills, which adhere to the norms of academic writing (e.g., using appropriate logical structures, academic verbs and tenses), and 4) originality, which involves using the writer's own words and avoiding copied text. The full score of essay was 25 points based on the designed standards. Two human researchers initially evaluated the essays using the specified rubric. To do this, both evaluators independently marked 12 essays based on each part of the scoring rubric. Subsequently, after confirming that the inter-rater reliability was adequate (ICCs > 0.85), one rater continued marking the remaining essays.

3.5 Data Analysis

The main objective of this study is to investigate the hidden temporal patterns of SRL processes enacted by learners as they worked on the multi-text writing. In particular, we sought to distinguish strategies that participants adopt to solve their learning problem based on the temporal behaviours. Additionally, we explored the correlation between the captured patterns and learning outcomes (essay scores) as a part of this project scope. To achieve this, we conducted time series analysis (TSA) and applied statistical techniques, detailed in the subsequent sections.

3.5.1 Learning Strategies and Time Series. To answer our first research question (RQ1), we initiated our analysis by encoding the seven SRL processes (MC.O, MC.P, MC.E, MC.M, LC.F, LC.R, and HC.E/O) into numerical codes to be eligible for our proposed algorithm. Beside the SRL actions data, our lab environment generated some blank values between labeled processes, reflecting the start and end times of these processes. To handle this, we calculated the duration for each pair of consecutive mapped processes by subtracting the start time of the next process from the current process time. We then used the duration for each SRL process of each user as input features for our clustering method.

As we intended to examine the students' SRL temporal behaviours over time, we applied Dynamic Time Warping (DTW) technique, which has been adopted by various studies [44, 45, 56]. These studies have applied the DTW technique for various purposes, such as studying the consistency of learning activities and identifying students' profiles (e.g., at-risk learners) [44, 45, 56]. The main functionality of DTW algorithm is to determine the optimal path between two-time sequences (e.g., two participants), facilitating the categorization of their temporal similarities [45]. We used K-Means as a clustering method with DTW, the approach that allowed us to measure the similarity of students' SRL temporal patterns and cluster them into distinct groups. Our method involved a function that first generated 7 SRL features per time window for each user, creating a 12-window time series. Before applying the time series approach, we have scaled the data using a Python function called TimeSeriesScalerMeanVariance(mu=0., std=1.). This function normalizes time series data so that each time series in the dataset has a specified mean (mu) and standard deviation (std), which enhances the quality of the clustering algorithm. Additionally, we tested the

DTW algorithm on the data both before and after removing outliers, and observed similar behaviors when varying the seed values. To enhance the efficiency of our analytical approach, we set time windows, each encompassing SRL actions captured within a certain interval. Although the selection of the number of time windows may require expert opinion or domain knowledge [10], we used both our domain knowledge and empirical testing to determine the optimal time window size. We found that a 10-minute window aligns with the duration of many SRL events and provides transparent visualization of the detected clusters. Additionally, we used barycenter (centroid) to represent the interactions with SRL in each cluster, minimizing the DTW distance between sequences.

After plotting the engagement level of each cluster across all seven SRL processes, we labeled each cluster and defined its characteristics based on the temporal and dominant traits of cognitive and metacognitive patterns. The detected five clusters reflected the learning strategies that learners adopted to solve the problem of writing using multiple resources.

3.5.2 Association Between Determined Patterns and Essay Scores. To address our RQ2, we implemented the analysis of variance (ANOVA) test to determine if there were statistically significant differences in the mean scores across the identified clusters [45, 46]. For further analysis, we divided students into two groups (high / low performance) based on their scores where the maximum score was 25 points. Additionally, an Analysis of Covariance (ANCOVA) was conducted to investigate whether other factors were associated with student performance, a method that has been implemented in many studies such as [51]. As the study was conducted at a foreign university, we considered student English language competency as a factor that may influence the relationship between SRL processes and outcomes. To assess language competency, participants took the College English Test Band 6 (CET6), which is considered a national exam in China [47].

4 Results

4.1 Detected Clusters Based on SRL Engagement (RQ1)

This section presents the clustering results addressing our first research question, alongside a qualitative analysis of each identified group, as depicted in Figure 1 (from **a** to **g**). In these sub-figures, the x-axis represents the distribution of 12-time windows, while the y-axis illustrates the levels of SRL engagement. To ascertain the optimal number of clusters, we applied the Elbow method, which suggested five as the ideal number. The five detected clusters described learning strategies based on metacognitive and cognitive temporal engagement. The specifications of these learning strategies are as follows:

Cluster 1 – Incremental Metacognitive Engagement: This cluster involved (n = 11) students who started their engagement in early stage by highly interacting with several SRL processes including orientation, planning in the first 10 minutes followed by first reading towards minute 20, as illustrated in Figure 1 (a), (b) and (e). The predominant behavior among these learners includes moderate and consistent monitoring of their performance, with a notable increase in evaluation towards the end of learning session, as depicted in Figure 1 (c) and (d). This group began their moderate writing activity within the first 30 minutes of their participation, with increased interaction around minute 110. Based on the generated plots, it is evident that these learners had relative interaction with cognitive activities, with concurrent reviewing of their work.

Cluster 2 -– Transitional Cognitive Engagement: This group involved the largest number of participants (n = 42) who began their writing session by exceedingly orienting and planning their task in the first 10 minutes similar to group 1, then they intensively evaluated and monitored their progress about minute 80, as shown in Figure 1 (a), (b), (c) and (d). Throughout the first hour, these learners intensively engaged in the first-time reading, and they continued their moderate re-reading in the second hour, as shown in Figure 1 (e) and (f). There was remarkable reduction in reading efforts towards minute 70 and shifting their focus on writing.

Cluster 3 -– Inactive Metacognitive and Occasional Cognitive Engagement: In this group, learners (n = 24) mainly engaged in orientation during the first 10 minutes and monitoring during the last 10 minutes of the session. Their interaction pattern was marked by unpredictable spikes in first reading during the mid-session and initiation of writing tasks towards the session's end, as observed in Figure 1 (e) and (g). The members of this group seem to be unaware of effective SRL strategies, as indicated by their lack of active engagement across all processes.

Cluster 4 — High Cognitive Engagement: Members of this group (n = 24) demonstrated a medium level of engagement in planning tasks within the first 10 minutes. Subsequently, they engaged highly with metacognitive processes, including evaluation and monitoring, by the 80th minute, as illustrated in Figure 1 (b), (c) and (d). Although they exhibited similar behaviors to the learners in cluster 2, they showed high and consecutive engagement during at least one time window with cognitive processes between minute 20 to minute 110, as illustrated in Figure 1 (e), (f) and (g). This group demonstrated the highest level of re-reading activities compared to the other clusters, as shown in Figure 1 (f).

Cluster 5 — Consistent Cognitive Engagement: The learners (n = 33) assigned to this group began their participation with high orientation and low level of planning, as displayed in Figure 1 (a) and (b). Afterward, they intensively engaged with the first reading activity within the first 40 minutes, and they greatly evaluated and monitored their performance in the mid-session time, as illustrated in Figure 1 (c), (d) and (e). This cluster affiliates appeared to intensively engage with writing task in the second hour (minute 60 - 110), as depicted in Figure 1 (g). Learners in this cluster expressed a low level of re-reading, with a slight of this process increase in the second hour.

4.2 Correlation Between Clusters and Essay Scores (RQ2)

This section presents the results of our conducted statistical tests. A one-way ANOVA was conducted to compare the effect of the five detected clusters on essay scores. The analysis revealed that there was no statistically significant difference in mean essay scores between the five clusters ($F(4, 129) = 0.820, p = 0.514, \eta^2 = 0.025$). For further investigation, an ANCOVA was performed to assess the effect of the CET6 English test on essay scores, while controlling for the influence of the five detected clusters. The analysis revealed

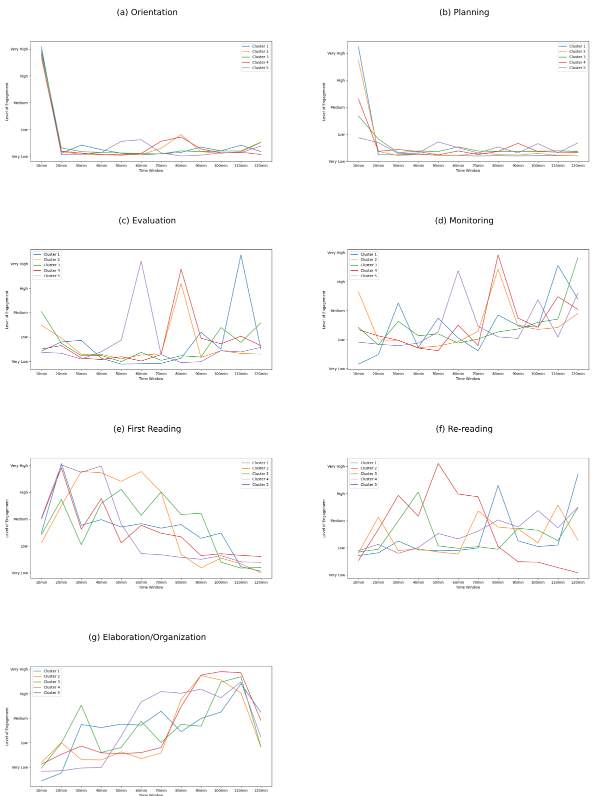

Figure 1: Level of engagement for each detected cluster (1 to 5) across all 7 SRL processes. The engagement levels are categorized from very low to very high, illustrating how student engagement fluctuates across 12 time windows, with a total participation time of 120 minutes. The clusters are represented by different colored lines to distinguish the engagement patterns among the five groups.

that the CET6 English test scores had a statistically significant effect on essay scores ($F(1, 87) = 8.116, p = 0.005$, partial $\eta^2 = 0.085$). In other words, we harnessed two variables including CET6 exam and cluster no to estimate the essay score using ANCOVA. Additionally, the variance between the pre-test and the determined clusters were examined implementing ANOVA test. The result revealed that cluster 3 was found to be significantly different from the reference group, with a p-value of 0.016. The descriptive statistics for the five detected clusters presents in Table 1, and Table 2.

5 Discussion

5.1 Interpretation of Results

The exploration of SRL temporal patterns can offer novel insights into how students change their learning behaviors over time. Numerous researchers have investigated the significance of temporality in SRL, implementing various methods such as calculating duration, aggregating frequencies and visualizing the relationships among SRL elements [23, 37, 39]. However, there is limited research exploring the temporality of SRL processes, particularly in understanding when and how these processes dynamically unfold throughout the entire learning process.

In the current study, we applied a time series approach to explore the strategies that learners adopted during their multi-text writing assignment. The findings of this study provide a novel contribution to the current field by addressing the dimension of SRL events temporality. This aligns with prior research demonstrating that temporal behaviors can be significantly associated with students achievement comparing to interactions frequency [40]. For example, the timing of students' engagement with specific activities could have a greater impact on their learning outcomes than calculating the frequency of their interactions [40].

The results of RQ1 provided an empirical evidence that meaningful learning strategies can be extracted based on temporal SRL patterns and demonstrated how these strategies unfolded over time. The existing literature has shown a shortage of investigations into when and how SRL temporal behaviors occur. Additionally, certain approaches have exhibited limitations in the direct extraction of learning strategies using both dimensions of temporality, including the order of events and the passage of time [23]. To address these gaps, we applied a time series approach capable of detecting distinctive strategies using both dimensions of temporality and determining when and how these strategies occur within an identified time frame. Specifically, we applied the DTW algorithm to measure the similarity of SRL engagement between two sequences (i.e., two students). Although our results corroborate findings from other studies, showing that learning strategies can be detected using temporal features [38], our time series approach has provided novel insights into when and how SRL temporal strategies occur, and how learners engaged metacognitively and cognitively with SRL processes over time. For example, we found a group of students (i.e., Cluster 5) who engaged intensively with cognitive processes throughout the writing session, with peaks in metacognitive engagement occurring midway. Upon observation, we noted variances in the level of engagement with SRL processes among the five determined groups, ranging from very low to extremely high. Additionally, we observed notable transitions between metacognitive and cognitive categories that participants enacted to achieve their learning goal. However, the majority of students across all groups tended to engage heavily with cognitive processes such as elaboration/organisation, with intermittent interactions with metacognitive activities. This finding aligns with a previous study that demonstrated learners typically prioritize cognitive efficiency (i.e., employing cognitive strategies to maximize learning) in their tasks [16]. For instance, learners may adopt cognitive strategies to manage time constraints or task demands(e.g., reading to write) in order to achieve their goals. Moreover, our observations of temporal engagement revealed that certain groups, which adopted specific strategies at particular times, outperformed other groups (e.g., 85% of Cluster 5 members exhibited high performance). This finding suggests that the timing of SRL engagement can influence learners' performance.

Three of the detected clusters (2, 4, and 5) exhibited various levels of engagement with cognitive SRL processes including first-reading, re-reading and elaboration/organization. All detected groups exhibited noticeable engagement with orientation activity during the first 10 minutes. This finding resonates with prior research indicating

Table 1: Descriptive statistics of means and standard deviations (SD) for essay scores, pre-test scores, SRL frequency and SRL duration across the five clusters.

Cluster No.	Average Essay Score	Pre-test Average Score	Average SRL Frequency	Average Duration (Seconds)
1	14.55 (SD 3.08)	8.18 (SD 2.04)	1395.00 (SD 317.71)	6727.85 (SD 503.23)
2	14.26 (SD 2.74)	7.29 (SD 2.22)	1417.07 (SD 377.59)	6631.84 (SD 530.51)
3	13.92 (SD 3.37)	6.33 (SD 1.95)	1469.71 (SD 551.84)	6534.83 (SD 742.58)
4	13.63 (SD 3.15)	6.79 (SD 1.79)	1385.92 (SD 349.30)	6570.47 (SD 342.92)
5	14.94 (SD 2.69)	7.03 (SD 2.17)	1314.24 (SD 358.83)	6359.39 (SD 546.62)

Table 2: Distribution of students across clusters, including high and low performers.

Cluster No.	Users Count	High Performance	Low Performance
1	11	8 (73%)	3 (27%)
2	42	33 (79%)	9 (21%)
3	24	18 (75%)	6 (25%)
4	24	14 (58%)	10 (42%)
5	33	28 (85%)	5 (15%)

that metacognitive processes are considered as an interface through which students begin to manage their learning tasks [25, 54]. The common temporal behaviors among these three groups (2, 4 and 5) are that they engaged heavily with reading activities in the first hour and then interacted intensively with the writing process in the second hour, with sporadic peaks of evaluation and monitoring in the middle session time. Although many studies such as [46] have harnessed SRL temporal patterns to capture meaningful strategies, these studies did not explain when and how specific strategies occur in real time. The current study addressed this gap by using a time-series approach to precisely determine when and how SRL strategies are enacted within defined time windows, providing deeper insights into the evolution of learning strategies over time.

The current study revealed how learners engaged with SRL processes during a 120-minute writing task. For example, participants in cluster 2 actively engaged in first reading during the first hour before transitioning to writing in the second hour. This finding underscores the benefits of knowing the actual timing of SRL events for implementing appropriate interventions when a critical event is not adequately addressed [24]. Interestingly, clusters 2 and 4 exhibited similar temporal behaviors, with heightened evaluation and monitoring of their performance towards minute 80. A similar pattern was observed for cluster 5 at minute 60 for both metacognitive activities. As shown in Figure 1 (e) and (g), it is possible that cluster 2 members (represented by the orange line) were adopting a structured strategy (read first, then write) to achieve their learning goal. We speculate that this was reflecting their prior planning activity for this multi-text writing. Lim et al. [18] indicated that monitoring operation had the highest frequency among SRL processes when students wrote essays. However, the current findings revealed that participants showed less engagement with metacognitive events (e.g., monitoring) and greater interactions with cognitive activities.

Clusters 1 and 3 demonstrated different levels of engagement with SRL processes during learners participation. The overall behaviours of cluster 1 members was unstable, as they lacked balanced engagement between metacognitive and cognitive activities. In contrast, members of Cluster 3 appeared to be less aware of their learning tasks, as indicated by their low engagement with metacognitive processes. These behaviors were linked to their fluctuated cognitive engagement throughout the session. Additionally, our analysis revealed that members of Cluster 3 significantly differed from other cluster groups based on prior knowledge test. This finding aligns with prior research introducing that a shortage of prior knowledge can affect the students' capability to compile information [28, 30].

The descriptive statistics for RQ2 demonstrated variances in performance among groups based on their achieved scores. The distribution of high and low performers indicated that the majority (85%) of cluster 5 members (Consistent Cognitive Engagement) exhibited high performance during their participation, as presented in Table 2. These learners appeared to invest most of their time in drafting their essays with minimal initial reading effort. This approach may be attributed to their focus on submitting a complete product by the end of the writing session. This result align with prior research that has indicated that learners who adopt an intensive writing strategy with specified reading tend to utilize their domain knowledge to achieve their goals [46]. Conversely, approximately 42% of participants in cluster 4 (Highly Cognitive Engagement) were classified as low performers, as shown in Table 2. This outcome may be ascribed to these learners' failure to effectively employ metacognitive processes in reviewing their cognitive learning activities. Previous research study has introduced that students with a high level of monitoring tend to be more productive and submit written products that align with the task requirements [6, 30].

5.2 Implications

The present study has several theoretical and practical implications. We demonstrated that SRL temporal behaviors can be utilized to detect distinctive learning strategies. Our time series approach was able to determine when and how various strategies occur by categorizing students into five clusters, each displaying unique characteristics. This provides further evidence that applying time series analysis to study temporality in SRL can significantly benefit future research on SRL. In particular, this analytical teqhnique can trace the dynamic and distinct SRL behaviours that students enact during their problem-solving learning. Furthermore, we were able to explore the internal transitions between the main SRL categories including metacognition and cognition processes, gaining insights into how and when students adopt a particular strategy. Consequently, analyzing both cognitive and metacognitive processes can provide an inclusive view of task regulation, compared to the insights obtained from studying a single part of SRL. Based on the learning strategies detected in this study, further practical enhancements can be achieved by providing learners with real-time interventions as needed, utilizing their temporal behaviors [23]. For instance, learners with low engagement in re-reading activity need to be notified to enhance the quality of their final products.

6 Limitations and Future Work

This study has several limitations that future research could address. The language proficiency can lead to varying outcomes within the same learning task [5, 30]. Future studies could replicate this research study with recruiting native speakers to explore how SRL temporal strategies can be differed to prior research findings. Additionally, our time series approach can be enhanced by including additional input features for a finer-grained analysis. It is also worthwhile to study temporality in SRL implementing different frameworks, to capture the variances in learners' engagement comparing to other models. We acknowledge that we set the time windows to 10 minutes in order to minimize overlap between processes. For instance, a process could begin at the end of one time window and extend into the next. Although this setting did not impact the overall analysis outcomes, future researchers should considered this if they aim to explore temporal events within shorter time windows such as 1 or 5 minutes. Furthermore, prior research indicates that internal and external factors can affect the learning strategies that students adopt [46]. These conditions can be an area of future research to examine their impact on writing tasks using time series approaches.

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Appendix A

The theoretical framework of SRL used to code the trace data in this study: Digital Appendix A **(Link)**.

Appendix B

The complete statistical analysis for RQ2 can be accessed online: Digital Appendix B **(Link)**.