# Analytics of Planning Behaviours in Self-Regulated Learning: Links with Strategy Use and Prior Knowledge

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## ABSTRACT

A sophisticated grasp of self-regulated learning (SRL) skills has become essential for learners in computer-based learning environment (CBLE). One aspect of SRL is the plan-making process, which, although emphasized in many SRL theoretical frameworks, has attracted little research attention. Few studies have investigated the extent to which learners complied with their planned strategies, and whether making a strategic plan is associated with actual strategy use. Limited studies have examined the role of prior knowledge in predicting planned and actual strategy use. In this study, we developed a CBLE to collect trace data, which were analyzed to investigate learners' plan-making process and its association with planned and actual strategy use. Analysis of prior knowledge and trace data of 202 participants indicated that 1) learners tended to adopt strategies that significantly deviated from their planned strategies, 2) the level of prior knowledge was associated with planned strategies, and 3) neither the act of plan-making nor prior knowledge predicted actual strategy use. These insights bear implications for educators and educational technologists to recognise the dynamic nature of strategy adoption and to devise approaches that inspire students to continually revise and adjust their plans, thereby strengthening SRL.

## CCS CONCEPTS

• **Applied computing → Interactive learning environments**.


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## KEYWORDS

self-regulated learning, strategic planning, learning strategies, learning analytics

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## 1 INTRODUCTION

The emergence of computer and information technology has facilitated a shift in educational contexts, transitioning from conventional classroom settings to online learning environments [17]. Over the past decade, a number of CBLE has been developed [4, 5, 29, 39]. These CBLEs offer significant advantages; not only do they enable learning and teaching at scale but also offer opportunities to design and implement timely support for learners' learning process [20]. Furthermore, CBLEs afford a high degree of autonomy to learners, allowing them to exercise considerable discretion in determining how to learn, what to learn, and when to learn [22]. Consequently, the inherent characteristics of CBLEs imposed increased expectations on learners to be adept at self-regulating their learning.

Self-regulated learning (SRL) is a multi-dimensional theoretical construct that encompasses the cognitive, metacognitive, motivational, and emotional dimensions through which learners engage with learning tasks [35]. Although various conceptual frameworks of SRL exist, they commonly incorporate a macro-level cyclical process consisting of forethought, performance, and reflection phases [15, 49]. For instance, Winne and Hadwin's model [49] proposed four stages of SRL: 1) task definition, which involves understanding the task as shaped by both internal and external conditions;

2) goal-setting, which involves setting goals and planning the detailed approaches towards the goal; 3) enactment, the execution of planned learning strategies and tactics; and 4) adaptation, which entails reflecting on previous learning experiences to make appropriate adjustments. In the context of CBLEs, Azevedo et al. [6] developed a model that identified a range of SRL processes, including both macro-level processes – namely planning, monitoring, strategy use, task difficulty assessment, and interest – as well as 35 micro-level processes. While a substantial body of research has explored SRL processes during the performance phase, less attention has been paid to the forethought phase and how to support learners' SRL processes during the forethought phase [21]. In particular, the planning process, which is defined as an individual's intention to perform a given behavior and which requires cognitive self-regulation, is a critical component of the forethought phase of SRL [2, 19]. Prior studies indicate that learners who formulate comprehensive plans prior to initiating the learning process are more likely to succeed [52]. Furthermore, the introduction of planning prompts, which nudge learners to formulate learning plans, has been shown to increase course completion rate and encourage a productive learning mindset which predicts learning success [52].

Existing research primarily employs pre-task surveys and interviews to capture the planning process. However, given that SRL is inherently dynamic and deeply rooted in the learning context, traditional offline self-report measures fall short in encapsulating the fluid nature of SRL processes [30, 38]. Learners may report a plan inaccurately given that they lack comprehensive vision of the learning task before they start learning [38]. To overcome these limitations, learning analytics (LA) offers the opportunity to capture and analyze learners' planning processes through the collection of online data (i.e., trace data). Recently, an interview study was conducted to understand the learners' expectation of using LA to support their SRL process on CBLEs, and found that learners expressed great interests in having tools that can support them in planning and scheduling their learning process [3]. However, to date, few studies have considered capturing learning plans during the learning process [23, 38]. Development of analytics and tools that capture the planning process could potentially inform stakeholders in providing more adaptive support to learners' SRL [11, 48]. Lastly, learners' level of prior knowledge could affect how they approach the task [32, 36], while limited studies have considered the predictability of prior knowledge on learners' planned and actual adoption of learning strategies.

To address the aforementioned limitations, the current study designed a CBLE in which a novel planner tool was dedicated to capture learners' learning plan during the learning process. Then, LA techniques were implemented to capture trace data about the SRL processes and to analyze (a) the extent to which learners would follow their planned learning strategies, (b) whether prior knowledge was predictive to their planned strategies, and (c) the extent to which learners adopted learning strategies varied if they made plans or not. By capturing trace data and adopting a combination of cluster and temporal analysis, we identified three adopted learning strategies and made comparison with the strategies they planned. Learners' level of prior knowledge was examined to evaluate the association with planned and actual strategy use. The results indicate that the learners adopted different learning strategies from those they planned, and while prior knowledge was found predictive of their planned strategies, plan-making process did not lead to differences in adoption of strategies.

# 2 LITERATURE REVIEW

## 2.1 Compliance with strategic plans

Self-regulated learners set specific learning goals and plan the subsequent learning process to fulfill goals [8, 46]. For example, strategic planning is the process wherein learners make plans concerning the sequence, timing, and effort relating to the utilization of cognitive and metacognitive processes to attain a specified learning goal [8, 23]. Despite the fact that numerous theoretical frameworks of SRL have been proposed, the importance of strategic planning process has been commonly emphasized. For instance, Winne and Hadwin [49] proposed the four-stage COPES model, which emphasizes SRL as a recursive process among different stages – task definition, goal-setting, enactment, and adaptation – with each stage comprises five aspects of learning – condition (C), operation (O), product(P), evaluation (E), and standard (S). As described in the COPES model, in stage two, learners make their plans for coordinating learning tactics according to the task condition (i.e., internal and external condition) and their perception to the conditions. For instance, a learning task that involves reading the topic of artificial intelligence (stage 1, condition) may sound interesting to a learner (stage 1, product), and the learner subsequently plans to engage in deep learning by careful reading and taking notes (stage 2, product). Extant studies have underscored the advantages and benefits derived from plan-making behaviors. For instance, in MOOC context, Kizilcec et al. [23] conducted an empirical study exploring the predictability of various SRL strategies in attaining specific learning goals, discovering that learners engaging in goal setting and strategic planning were more likely to achieve their personalized course goals.

Given the positive impact of planning and goal-setting in learning, previous research has integrated SRL scaffolding to aid learners in their plan-making and goal-setting processes [6, 8, 12, 40]. For instance, Bannert and Reimann [8] utilized prompts to support various aspects of the SRL process, discovering that prompts fostering goal-setting and plan-making had the most significant impact compared to other SRL processes. In a similar vein, Davis et al. [12] conducted a study in the MOOC environment, encouraging learners to actively establish weekly learning plans and reflect on their progress. Results showed that the learners exposed to planning prompts exhibited significantly higher learning performance (i.e., course grades) compared to those who were exposed to the planning prompts but did not make plans and those in the control condition (i.e., no prompts condition). However, two primary limitations exist within these studies. Firstly, there is a prevailing lack of comprehension within the current literature regarding how learners execute their planned activities – it remains unknown whether learners merely set goals and plans but proceed with different route to what they planned, or whether their learning processes align consistently with their plans. Addressing this gap can enrich the literature by examining the connection between what is planned and what is actually performed, thereby guiding future design of prompts to support effective learning processes. For example, if students employ learning strategies consistently as planned, such plans could serve as invaluable data to inform interventions when students planned sub-optimal strategies. Here, learning strategy is defined as the systematic arrangements of learning tactics (e.g., read and write simultaneously), whereas learning tactics are single cognitive operations (e.g., highlighting) [48]. Secondly, previous studies have commonly prompted learners to make plans prior to commencing learning tasks. However, planning is an ongoing process, and capturing plans prior to the task makes it hard to understand the dynamic process of planning [38, 48]. One way to address this limitation is to provide planner tools embedded in the context of CBLE and allow learners to interact with the tool throughout the task [45]. Such instrumentation tools that capture interaction with learning information have been proven effective in capturing high cognitive and metacognitive SRL processes (e.g., planning) [45]. To date, limited studies have embedded instrumentation tools in capturing planning process in CBLEs [13]. Aamong those that have implemented planning tools, the design complexity has often made the tools difficult for learners to use, leading to their infrequent use for plan-making process [9, 26, 45].

To address these limitations, we (a) designed and implemented a novel and easy-to-use planner tool which allowed learners to report their strategic plans while engaging with the learning task, and (b) investigated whether learners actually performed strategies that are consistent with the strategies that they planned to use. So, our first research question (**RQ1**) was: *To what extent do learners adopt learning strategies that are consistent with their planned strategies?*

## 2.2 Association between prior knowledge and planned strategies

Learners' prior knowledge describes the level of domain knowledge to the targeted learning content. Based on the COPES model of SRL, prior knowledge is one of the internal condition within the COPES construct that affect how learners plan to operate on learning content [49]. The literature offers some empirical evidence to support this relationship. For example, Moos and Azevedo [32] found that learners with higher prior knowledge tended to plan their learning by frequently activating their relevant domain knowledge and revising their learning goals compared to those with lower prior knowledge. Moreover, the Moos and Azevedo [32] study also found that, in a 40-minute single reading and writing task, high prior knowledge learners tended to plan to use fewer learning tactics because they did not need to construct basic domain knowledge though comprehensive reading, which normally requires a variety of tactics including note-taking, highlighting, and memorization. However, one of the main limitation in the current literature is that most studies have been focused on the extent to which prior knowledge can predict the frequency of occurrence of different cognitive or metacognitive processes, rather than investigating the association of prior knowledge and learners' plans about strategy use. As such, we proposed our second research question (**RQ2**) as: *To what extent is learners' prior knowledge associated with the planned strategies?*

## 2.3 Association between prior knowledge, plan-making, and adopted strategies

Setting learning goals and making plans to achieve the goals shape learning engagement while working on a task, because plan-making can be seen as offering standards for monitoring the subsequent learning processes and therefore learners are better prepared to explore what the task is about and how to better address the task [46, 48]. Locke and Latham [27] highlighted this connection and explained it from four perspectives: (i) plan-making serves a directive function which encourages learning attention to the task; (ii) it motivates learners, enhancing commitment and effort; (iii) it sustains dedication over time; and (iv) it stimulates the application of prior knowledge and adoption of learning strategies. Empirical evidences can be found to support these propositions regarding plan-making processes. In a MOOC context, it was found that implementing a planner tool that supports the process of making plans about learning strategies to be positively associated with learning engagement and learning performance as measured by the final grades [36, 37]. However, to our knowledge, there is a scarcity in the current literature which investigated whether making plans about learning strategy use is associated with learners' actual adoption of learning strategies.

Not only is prior knowledge potentially associated with how learners plan to operate on the learning task, but is also potentially associated with their actual adoption of learning strategies. Empirical studies have investigated the extent to which learners' prior knowledge about the information studied in the learning task is associated with SRL processes. Some studies found that learners with high prior knowledge demonstrated significantly more frequent monitoring and planning process, and tended to use fewer learning tactics [32, 33]. Moreover, high level of prior knowledge stimulates learners to adopt more advanced tactics (e.g., making inference, as part of their content comprehension process) [31, 32]. Yang et al. [51] found that low- and high- prior knowledge learners demonstrated different learning patterns, with low-prior knowledge learners tended to adopt a local approach (e.g., focus on specific learning content) while their high-prior knowledge counterparts tended to adopt a global approach (e.g., focus on knowledge comprehension combining different parts of learning content). Given that learners' approach to the task can be associated with their level of prior knowledge, it is necessary to control for the influence of prior knowledge when assessing the potential association between making plans about learning strategy use and actual adoption of learning strategies. However, to our knowledge, no study has investigated the association between plan-making about strategy use and actual strategy use when controlling for the level of prior knowledge in CBLEs. So, we proposed our third research question (**RQ3**): *To what extent is plan-making for strategy use associated with the actual strategy use while controlling for prior knowledge?*

# 3 METHODOLOGY

## 3.1 Research design and context

*3.1.1 Participants.* The participants in this study comprised graduate-level university students who were non-native English speakers. They voluntarily enrolled in an academic English writing course designed to teach the principles of scholarly writing composition. As a component of the course curriculum, the students were required to complete a 120-minute reflective writing task, the details of which are elaborated in Section 3.1.4. Of the 245 students who initially participated, valid data was obtained from 202. Specifically, 43 students were excluded from the final data set for the following reasons: 1) 16 were excluded due to insufficient engagement, having spent less than 20 minutes on the writing task; 2) 14 did not provide us with informed consent; 3) five were removed due to technical issues that resulted in the collection of fewer than 1,000 timestamped trace data points; 4) five were removed as they had re-submitted new plans that were different to their first submitted plan; 5) two were removed as they submitted their customized plan (see further explanation in Section 3.1.3; and 6) one was removed as they had no essay data.

*3.1.2 Learning platform.* A snapshot of the CBLE employed in this study is provided in Figure 1. As depicted, the platform interface consisted of several primary functional areas. Reading materials were displayed on the central panel, and the students could navigate through different pages using the navigation bar This navigation bar also allowed access to the general instruction and marking rubric pages, where the students could familiarize themselves with the task requirements and assessment criteria for their essay writing. While engaging with the reading materials, students had the option to utilize annotation tools for text highlighting and note-taking. Furthermore, a variety of instrumentation tools were available on the right-hand side of the interface. Specifically for this study, instrumentation tools offered to the students comprised a search tool, an essay writing tool, a planner tool, a dictionary tool, and a timer tool. These tools were designed to appear as pop-up windows; when a student clicked on an icon, the corresponding tool interface would appear. For instance, as shown in Figure 1, the essay writing pop-up window allowed the students to draft and save their essays. Empirical evidence supports the effectiveness of these instrumentation tools in capturing trace data, which are used to measure students' SRL processes as well as their application of learning strategies and tactics [44, 45].

*3.1.3 Planning tool design.* For this study, a planning tool has been designed to capture data regarding the participants' strategic planning (i.e., the learning strategy and tactics that are planned to use). Figure 2 shows how learners could leverage this tool to plan their overall strategy, time allocation, and specific reading and writing tactics. Firstly, the participants were prompted to select an overall learning strategy from a drop-down list, illustrated in Figure 2 – (a). Following this, the participants could delineate their expected time allocation for each topic and the essay-writing task, as shown in Figure 2 – (b). Subsequently, the participants had the opportunity to specify the reading and writing tactics they aimed to adopt, as shown in Figure 2 – (c) and (d). Once finalized, the participants could submit and save their plan, and a summary of their choices was generated, as displayed in Figure 2 – (e). After saving, the participants could access, check, and revise their plans at any time by clicking on the planning tool icon located within the instrumentation tool area, and modifications could be made by selecting the edit button, as indicated in Figure 2 – (e). It is important to note that choosing an overall learning strategy was mandatory for saving the plan, whereas subsequent steps like determining time allocation and selecting specific tactics were optional. A detailed explanation of the options provided at each step is summarized in Table 1. The planner tool also allowed learners to create their own strategic plans if they felt that neither of the three options could summarize their planned strategies. Given the low sample size of this group (2 learners), they were excluded for the analysis of this study. Lastly, the choice of offering three learning strategies and options for specific reading and writing tactics were derived from two previous study that demonstrated that students self-reported (interviews) [25] and exhibited (trace data) [44] the use of these strategies on the same type of task.

*3.1.4 Task design.* The learning task was divided into three distinct sessions. The first, the pre-task session, required the participants to complete a pre-test to assess prior domain knowledge. In the second session, training was administered to acquaint the participants with the learning platform and the instrumentation tools they would utilize in the study, as elaborated in Section 3.1.2. The third session was the main task session, where the participants were instructed to employ all the provided tools and compose a 300-400 word essay, synthesizing reading material that focused on the application and future prospects of AI in education. With a time limit set at 120 minutes and intensive amount of reading material, this design aimed to encourage the participants not to read everything, but to skillfully self-regulate and engage in metacognitive monitoring and control, ensuring they would allocate their time to relevant reading and writing activities, aligned with the task instructions and marking rubric.

## 3.2 Data collection

*3.2.1 Pre-test score.* Learners' prior knowledge was assessed through a pre-test consisting of 15 multiple-choice questions. Each question carried one mark, with the total score indicating the learners' level of prior knowledge. The reliability of the pre-test was examined in previous lab studies [45].

*3.2.2 Trace data and trace parser.* The trace data collected from the CBLE comprised three main time-stamped components: 1) navigation logs, 2) mouse traces, including clicks, movements, and scrolls, and 3) keyboard strokes. Unlike self-reported survey data which is ineffective in capturing the dynamic flow of SRL processes [47], the advantage of using trace data to measure SRL processes is the ability to unobtrusively capture learner actions in real-time, allowing proximal identification of learning events [38, 41, 50]. In this study, a theoretically-informed trace parser was adopted, which converts raw trace data into meaningful SRL processes. The design of the trace parser is based on Bannert's framework of SRL in hypermedia learning context, which categories SRL processes into cognition, metacognition, and emotion [7, 9]. Extensive empirical studies were conducted with this framework to collect learning trace data and validate the measurement of SRL processes [24, 42–44]. The trace parser consists of an action library – which converts raw trace data to learning actions – and a process library – which labels learning actions into SRL processes (a summary of the trace parser is presented in Figure 3; a complete table of action and process libraries can be found in the

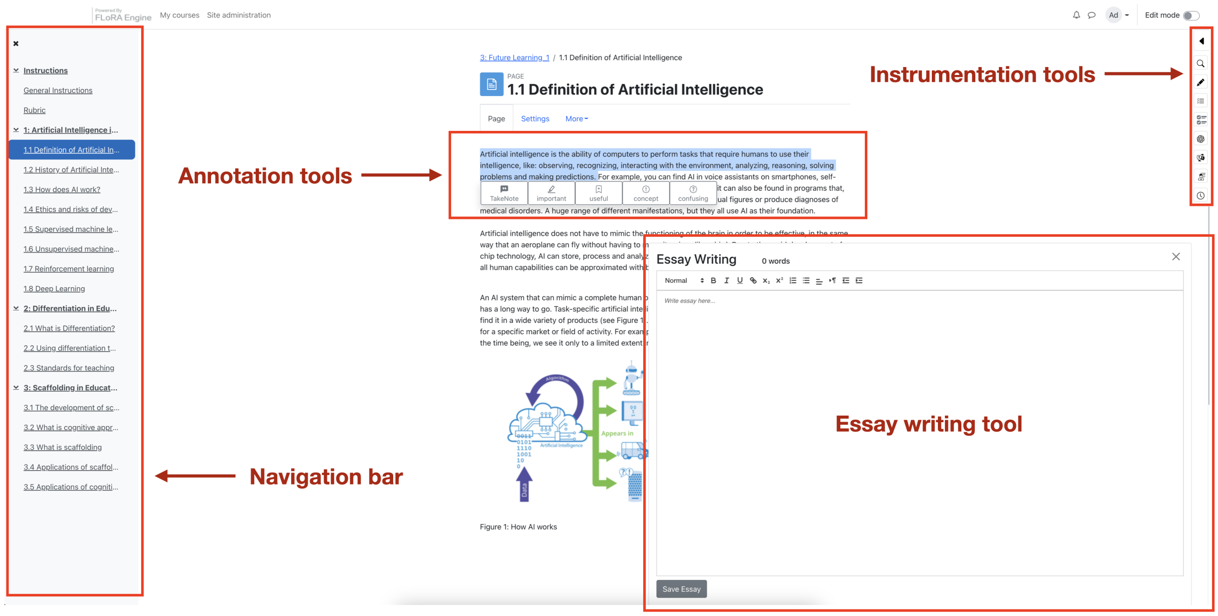


**Figure 1: Snapshot of the Moodle-based learning environment**

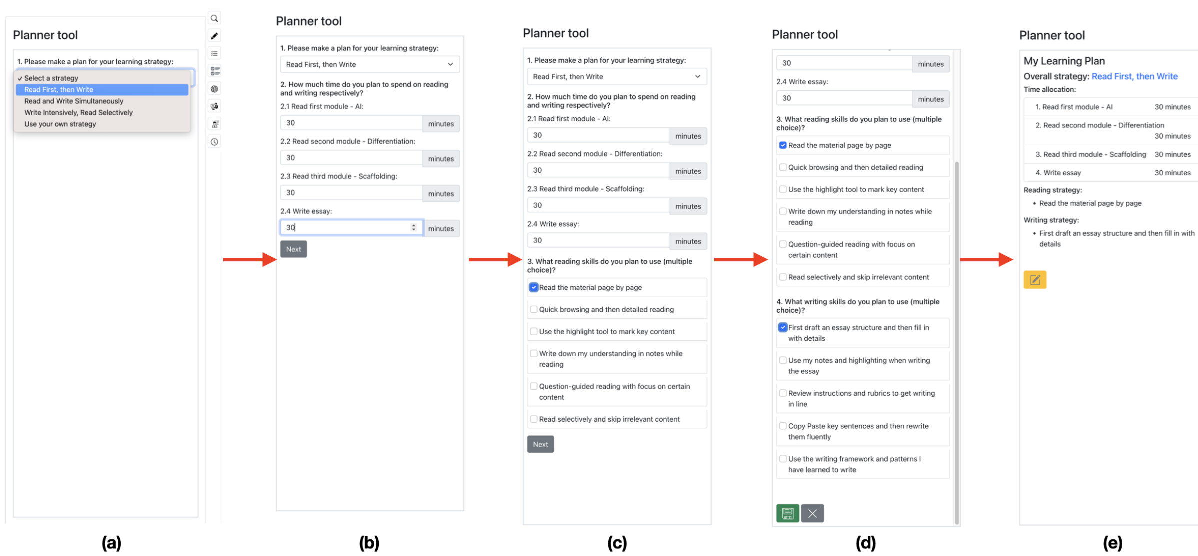


**Figure 2: Snapshot of the planning tool**

Appendix at this link. In total, there were 21 learning actions and seven SRL processes. As shown in Figure 3, for example, if a learner read the general instruction (action: GENERAL_INSTRUCTION) or rubric page (action: RUBRIC) and created or edit annotations (action: EDIT_ANNOTATION) during the reading, this specific learning action pattern (GENERAL_INSTRUCTION/RUBRIC <-> EDIT_ANNOTATION) were coded as MC.O.3, which represents the third (3) Orientation process (O) of metacognition (MC). The validity of employing this specific trace parser and trace data has been tested and proved using think-aloud data [14, 15].

## 3.3 Data analysis

To answer RQ1, this study first implemented a combination of cluster analysis and process mining to detect learners' actual adoption of learning strategies based on the existing approaches in learning analytics used for this task [14, 15, 30, 44]. First, for each individual participant, we computed the sequences of SRL processes, where a sequence comprised all the SRL processes detected for a participant during the task. Utilizing these sequences, we then generated a First Order Markov Model (FOMM) using the pMineR R package [18]. This model allowed us to derive the transition matrix representing

**Table 1: Outline of the planner tool content: strategy options, time allocation, and the options of planned reading and writing tactics**

| Learning strategy | Time allocation | Reading skills | Writing skills |
|---|---|---|---|
| Read First, then Write | 1. Read the first module - AI<br>2. Read the second module - Differentiation<br>3. Read the third module - Scaffolding<br>4. Write essay | 1. Read the material page by page<br>2. Quick browsing and then detailed reading<br>3. Use the highlight tool to mark key content<br>4. Write down my understanding in notes while reading<br>5. Question-guided reading with focus on certain content<br>6. Read selectively and skip irrelevant content | 1. First draft an essay structure and then fill in with details<br>2. Use my notes and highlighting when writing the essay<br>3. Review instructions and rubrics to get writing in line<br>4. Copy paste key sentences and then rewrite them fluently<br>5. Use the writing framework and patterns I have learned to write |
| Read and Write Simultaneously | 1. Read/write about the first module - AI<br>2. Read/write about the second module - Differentiation<br>3. Read/write about the third module - Scaffolding | | |
| Write Intensively, Read Selectively | 1. Conceive the structure of the essay<br>2. Write the first draft<br>3. Read additional information in relation to the essay<br>4. Review, refine and enhance the essay | | |

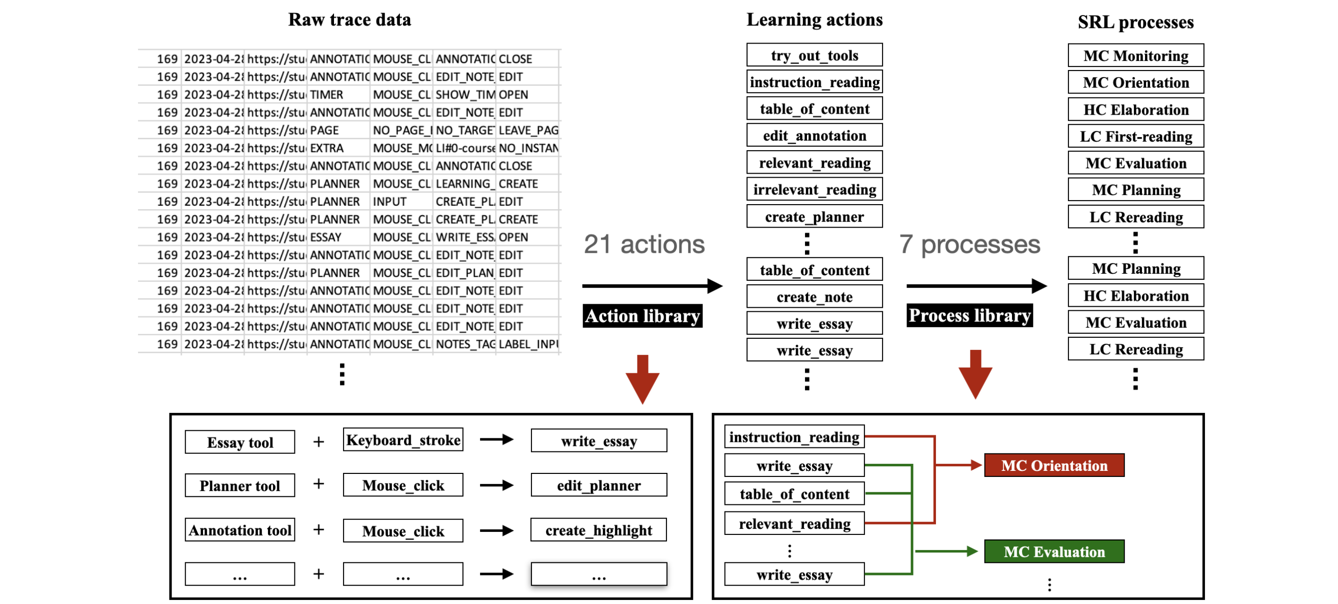


**Figure 3: The trace pacer to label raw trace data into SRL processes**

the likelihood of transitions between various SRL processes. Subsequently, we employed the transition matrix from the FOMM to formulate the expectation-maximization clustering method, enabling us to effectively detect and categorize distinct learning strategies. As informed by the previous study which adopted the same cluster technique and analytical methods, we expected to identify three clustered strategies [44]. Afterwards, to determine and interpret the clustered groups, several data analytic approaches were used, including 1) descriptive statistical analysis, 2) exploratory sequence analysis (including frequency and temporal distribution of SRL processes), 3) temporal distribution of learning actions, and 4) FOMM process mining. Then, to examine the consistency between the planned learning strategies and the actual adopted strategies, the McNemar-Bowker test was conducted. McNemar-Bowker test was used to determine whether there are differences on a dichotomous dependent variable between paired groups [1]. In our study, this test was particularly useful as it allowed the comparison of the proportions of categorical responses (three types of planned learning strategies and the actual learning strategies to be determined by the cluster analysis), allowing for a precise exploration of whether the participants tended to significantly adopt the strategies they initially planned. Essentially, it enabled a focused investigation into the alignment, or the lack thereof, between the planned learning strategies and the actually adopted strategies. Given that multiple McNemar-Bowker tests were performed, Bonferroni correction was applied to control for the family-wise error rate.

To address RQ2 and RQ3, multinomial logistic regression analysis was utilized to investigate the associations between learners' prior knowledge, their planned learning strategies, and their actual adoption of strategies, with a control for the level of prior knowledge. This analytical approach was well-suited to our research as it facilitated the exploration of how the participants with varying levels of prior knowledge planned and adopted different strategies.

While trace data from 202 students were collected, the statistical test in answering RQ2 and RQ3 is based on 200 students, as 2 did not complete the pre-test. For RQ2, the focus was specifically on examining the relationship between prior knowledge and planned learning strategies, while for RQ3 on the connection between the actual adoption of strategies and plan-making, while controling for prior knowledge. Specifically, the models for RQ2 and RQ3 were articulated as follows:

RQ2:

$$\text{Planned Learning Strategies} \sim \text{Score of Pre-test}$$

where

- *Planned Learning Strategies* was the reported strategies that learners planned to adopt by using the planner tool.
- *Score of Pre-Knowledge Test* was a continuous predictor variable, representing the students' prior knowledge measured by the pre-test score (the maximum score was 15).

The RF strategy was used as the reference category.

RQ3:

$$\text{Adopted Learning Strategies} \sim \text{Plan Making} + \text{Score of Pre-test}$$

Here:

- *Adopted Learning Strategies* was obtained by combining clustering and process mining methods outlined in RQ1.
- *Plan_Making* was a binary predictor variable, representing whether students submitted or not their strategic plan by using the planner tool.

The RF strategy under the condition of no plan reported served as the reference category.

# 4 RESULTS

## 4.1 RQ1: Alignment between planned and adopted learning strategies

Three cluster groups representing the three learning strategies were identified as consistent with our expectation based on previous research [44]. Figure 4 summarizes the results of data analytic techniques used to characterize SRL processes and learning actions performed by the participants in each learning strategy group. Based on the analysis, we found that the three clustered groups differ in terms of the 1) temporal distribution and frequency of SRL processes (Figure 4 - (A) and (B)); 2) temporal distribution of learning actions (Figure 4 - (C)); and 3) SRL process transitions based on the FOMM model (Figure 4 - (D)). Accordingly, three learning strategies are summarized as follow:

***Group-1: read and write simultaneously (RW) strategy.*** The learners in this group predominantly displayed a linear learning process. They appeared to allocate balanced efforts towards both reading and writing activities (Figure 4 - (A) and (C)). Also, learners were observed to exhibit the highest frequency of re-reading in comparison to the other two groups (Figure 4 - (B)). Meanwhile, there was an inclination to continuously orient their reading and writing processes by recurrently checking the task requirements (Figure 4 - (A) and (B)), which showed a high frequency of MC Orientation throughout the task), proving that they were reading and writing simultaneously with task-guided orientation. As such, the learners in this group predominantly went back and forth between reading and writing processes, reflecting an integration of the two processes.

***Group-2: write intensively, read selectively (WI) strategy.*** The learners in this group allocated a relatively substantial amount of time and effort to writing and commenced intensive writing earlier compared to those in the other two groups, (Figure 4 - (A) and (C)). Their efforts expended on first- and re-reading were comparatively minimal, as depicted in Figure 4 - (A), (B), and (C). Also, the FOMM comparisons also indicated that this group demonstrated higher frequency of self-transition (the arcs from and end to the same process) of Elaboration/Organization compares to the other groups (Figure 4 - (D), Group 1 vs. 2 and Group 2 vs. 3 comparisons).

***Group-3: read first then write (RF) strategy.*** The learners in this group started their learning with intensive the first-reading process and then gradually started to draft the essay (Figure 4 - A and D). This can also be evidenced from the FOMM comparisons, where they demonstrated relatively high frequency of self-transition of First Reading as compared to the other groups (Figure 4 - (D), Group 1 vs. 3 and Group 2 vs. 3 comparisons).

After identifying the actual strategies used by learners, we cross-tabulated the distribution of both planned and actual strategies in Table **??**. The table revealed that the actual strategies adopted by the 90 learners who reported their planned strategies were diverse and dispersed. The results of the McNemar–Bowker test of symmetry (Table 3) indicated a significant global inconsistency ($\chi^2(3) = 22$, $p < 0.0001$) across the strategies, with an odds ratio of 3.85 and a Cohen's g of 0.294, showcasing a medium effect size and suggesting a general deviation between the planned and adopted strategies. Specifically, the post-hoc pairwise comparisons revealed a significant deviation between the planning and adoption of the RF and RW strategies, with a p-value of 0.0002, adjusted to 0.0006 (FDR), and an odds ratio of 4.83, illustrating a higher likelihood of strategy alteration, accompanied by Cohen's g of 0.329, indicating a medium effect size. This highlights a substantial alteration in the learners' learning strategies, demonstrating a shift from the initially planned RF strategy to the actual adoption of the RW strategy. However, the discrepancies between RF and WI and between RW and WI strategies were not significant, with adjusted p-values of 0.1200 and 0.1490, respectively, and both showcased the odds ratio of 3 and Cohen's g of 0.25, pointing to a small effect size and highlighting that the alterations in these strategy pairings were not as substantial. Hence, while some level of inconsistency between the planned and adopted strategies was evident, it was particularly pronounced between the RF and RW strategies.

## 4.2 RQ2: Prior knowledge and planned strategies association

The results of the multinomial logistic regression (Table 4) showed that for the learners who planned to adopt the RW strategy, there was a significant negative association with pre-test scores (Coef. = -0.25944, SE = 0.1149, p = 0.0334). This suggests that a one-unit increase in the pre-test score was associated with a decrease in the log-odds of choosing the RW strategy relative to the RF strategy.

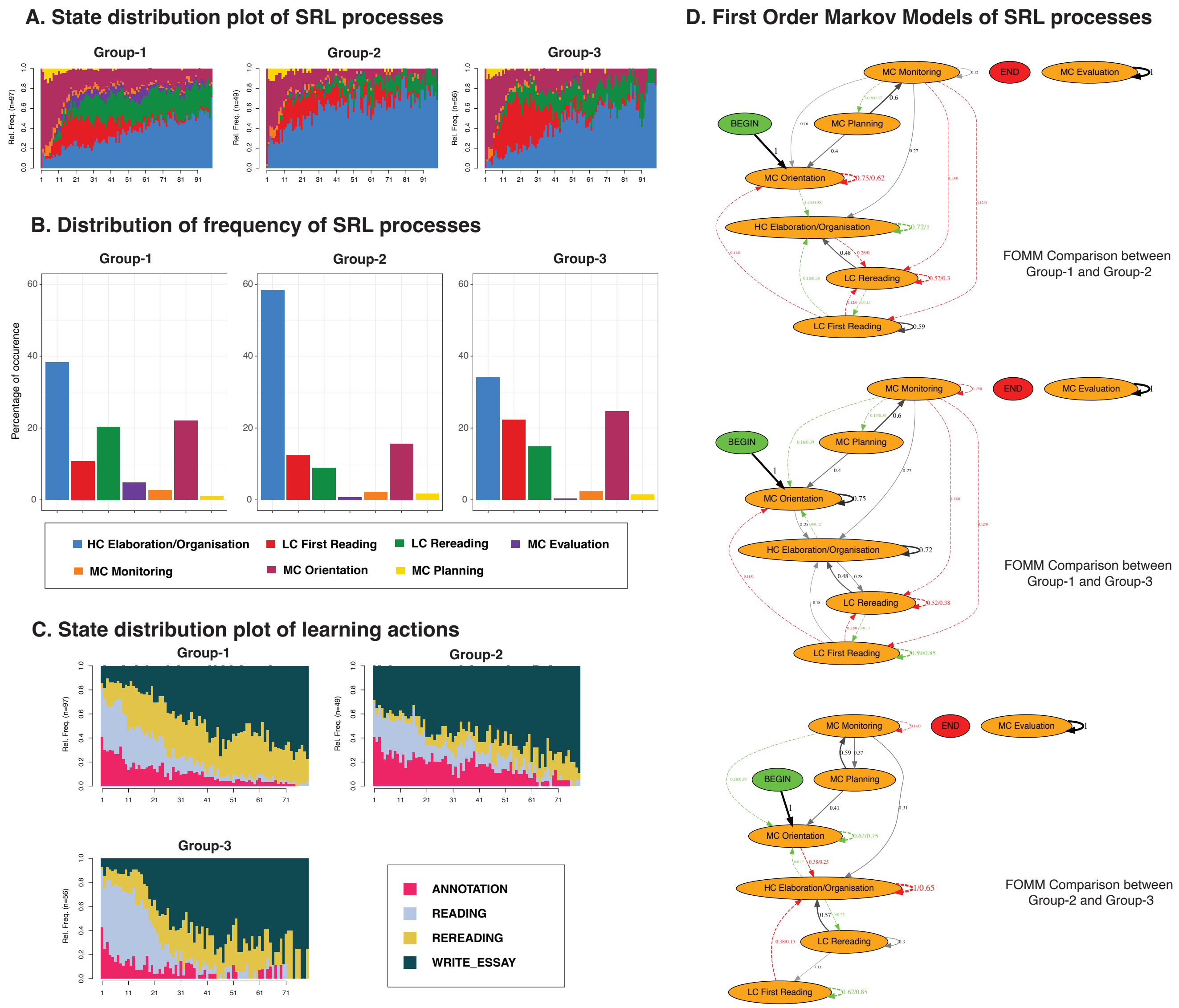


**Figure 4: Summarization of the clustering analysis and the detected learning strategy groups A. State distribution plot of SRL processes showing the relative frequency proportion of each SRL process among three clustered groups for the first 100 time-points, where x-axis represents time, and y-axis represents percentage scale. B. Bar chart showing the frequency distribution of each SRL process for the three clustered groups, where y-axle represents the count. C. State distribution plot of learning actions showing the relative proportion of each learning action (status) for the first 80 time-points, where x-axis represents time, and y-axis represents percentage scale. D. First-Order Markov Model comparisons among the three clustered groups (higher resolution images can be found at this link). The arcs connecting different states are color-coded to indicate variations in transition probabilities between these groups: Red Arcs represent cases where the transition probability of the first group is greater than that of the second group; Green Arcs indicate instances where the transition probability of the first group is lower than the second group's; and Black/Gray Arcs are used when the difference in transition probabilities between the two groups is subtle (specifically within a 10 % margin).**

Therefore, it can be concluded that prior knowledge was significantly associated with the choice of planned strategy, with higher prior knowledge learners tended to omit adoption of the RW strategy as compared to the RF strategy. Conversely, for the WI strategy, the association with pre-test scores was not statistically significant (Coef. = -0.00255, SE = 0.1731, p = 0.9536), implying that pre-test scores were not significantly associated with the choice of the WI strategy over the RF strategy.

**Table 2: Comparison between learners' planned learning strategies and actual adopted learning strategies**

| | | Adopted strategies | | | Total |
|---|---|---|---|---|---|
| | | RF | RW | WI | |
| Planned strategies | Read first then write (RF) | 13 | 29 | 12 | 54 |
| | Read and write simultaneously (RW) | 6 | 11 | 9 | 26 |
| | Write intensively, read selectively (WI) | 4 | 3 | 3 | 10 |
| | Total | 23 | 43 | 24 | 90 |

**Table 3: Summary of the McNemar–Bowker symmetry test and post-hoc test results**

| Comparison | Chi-squared (df) | p-value | p-value Adjusted (FDR) | Odds Ratio | Cohen's g |
|---|---|---|---|---|---|
| Global Test | 22 (3) | 0.00006* | – | 3.85 | 0.294 |
| RF vs RW | – | 0.0002* | 0.0006* | 4.83 | 0.329 |
| RF vs WI | – | 0.0801 | 0.1200 | 3 | 0.25 |
| RW vs WI | – | 0.149 | 0.1490 | 3 | 0.25 |

Note: The significance level is set at 0.05. The reference category for the outcome variable is the RF strategy under the condition of no plan reported.

**Table 4: Multinom Regression Results**

| Prior knowledge | Planned strategies | Coef. | SE | p value |
|---|---|---|---|---|
| (Intercept) | RW | 0.511 | 0.862 | 0.166 |
| | WI | -2.378 | 1.424 | 0.295 |
| Pre-test score | RW | -0.25944 | 0.1149 | 0.0334* |
| | WI | -0.00255 | 0.1731 | 0.9536 |

Note: * denotes significance at the 0.05 level. The reference category for the outcome variable is the RF strategy.

## 4.3 RQ3: Planning-making and strategy adoption, controlling for prior knowledge

Table 5 shows that 112 learners did not submit their plans, and 90 learners submitted their plans. The multinomial logistic regression (Table 6) showed that reporting vs not reporting a plan and variations in prior knowledge scores were not significantly associated with the probability of opting for either RW or WI strategies over the RF strategy.

# 5 DISCUSSION AND IMPLICATIONS

## 5.1 RQ1: Alignment between planned and adopted learning strategies

The three strategies students actually used echoed the results of previous studies employing the same clustering techniques within similar learning contexts [44], thereby reinforcing the reliability of the observed learning strategies. To examine the extent to which learners adopted consistent strategies as they planned, a paired McNemar-Bowker's Chi-squared test revealed that the learners who planned the use of the RF strategy exhibited a significant tendency to actually adopt the RW strategy. This finding contributes to the literature on strategic planning in SRL. Prior studies predominantly emphasized the relationships between strategic planning and learning performance [28], attainment of course goals [23], and the adoption of strategic learning processes, including frequent utilization of learning tactics [10]. While such studies offered valuable insights into the predictive nature of strategic planning on subsequent learning processes and outcomes, the present study took a different perspective by exploring the extent of compliance to planned strategies. This divergence between learners' planned and adopted learning strategies highlighted the dynamic nature of SRL. This inconsistency can be attributed to the influences on regulatory processes, which are shaped not only by pre-existing learning conditions (e.g., learning resources) but also by the dynamic contextual changes as learners proceed with the task [8]. In other words, learning conditions are kept updating and therefore, as explained in the COPES model of SRL [49], updated conditions can shape learners' perception on the task, and in turn may result in updated operations [30, 48]. For example, learners may initially plan to read first (RF strategy), given the task instructions, but the volume of reading and time constraints can lead to a strategy adjustment to write while reading (RW strategy).

## 5.2 RQ2: Prior knowledge and planned strategies association

Our results showed that the learners with a higher level of prior knowledge would be less likely to plan to adopt the RW strategy as compared to the RF strategy. One explanation of this finding is that learners with high prior knowledge were more confident on the learning topic and therefore tended to adopt a more linear learning process (i.e., RF strategy). This can also be supported by the current literature showing that learners with high prior knowledge tended to use few learning tactics and less complicated combination of tactics [32]. From a theoretical perspective, according to the four-stage COPES model of SRL [49], the learners' prior knowledge, as one of the internal conditions, determines their perception of the learning task (the product in stage 1). This, in turn, can further impact learners' plans in coordinating learning tactics for subsequent learning processes (the product in stage 2) [46, 49]. Therefore, our current finding provides additional empirical evidence, aligning with Winne and Hadwin's model of SRL, showing that learning conditions are related to how learners plan to approach the learning task. Lastly, this finding could inform the design of supportive measures on SRL (i.e., SRL scaffolding). As prior knowledge was found to be associated with strategic planning, designing supportive measures are suggested to be adapted to learners' proficiency level on the learning topic [34]. This can be achieved by, for example, when the learners' level of prior knowledge is low, adaptive prompt can

**Table 5: Number of Students in Each Cluster Based on Plan Reported**

| | No Plan Reported (NO) | Plan Reported (YES) | Total |
|---|---|---|---|
| **Read First then Write (RF)** | 33 | 23 | 56 |
| **Read and Write Simultaneously (RW)** | 54 | 43 | 97 |
| **Write Intensively, Read Selectively (WI)** | 25 | 24 | 49 |
| **Total** | 112 | 90 | 202 |

**Table 6: Multinom Regression Results**

| Input variables | Output variable (adopted strategies) | Coef. | SE | OR (95% CI) | p value |
|---|---|---|---|---|---|
| No plan reported | RW | 0.422 | 0.737 | 1.526 (0.360, 6.47) | 0.567 |
| | WI | -0.179 | 0.856 | 0.836 (0.156, 4.47) | 0.431 |
| Plan reported | RW | 0.0751 | 0.344 | 1.08 (0.550, 2.11) | 0.827 |
| | WI | 0.2565 | 0.398 | 1.29 (0.593, 2.82) | 0.606 |
| Pre-test score | RW | 0.0165 | 0.0877 | 1.017 (0.856, 1.21) | 0.850 |
| | WI | -0.0045 | 0.1019 | 0.996 (0.815, 1.22) | 0.816 |

Note: The significance level is set at 0.05. The reference category for the outcome variable is the RF strategy under the condition of no plan reported.

be provided to suggest and guide learners to choose more optimal strategies for the task.

## 5.3 RQ3: Planning-making and strategy adoption, controlling for prior knowledge

Overall, we did not find a significant association between plan-making and strategy adoption as well as between prior knowledge and strategy adoption. Embedding the planner tool can be seen as an intervention to stimulate learners to make effective strategic plans, and previous studies have found a positive impact of offering the tools on learning engagement and performance [12, 36, 37]. However, the current study showed that inserting the planner tool did not significantly differentiate the types of strategies adopted. One explanation can be that different learning engagement does not necessarily imply different strategy adoption, as selecting learning strategies can be affected by many factors such as learning motivation [16] and implementation of SRL scaffolding [24, 26]. Therefore, future research is needed to investigate the extent to which changes in learning condition predict the adoption of strategies, and to provide more empirical evidences to inform the design of planner tools which can stimulate effective strategy choice.

We did not identify a significant association between prior knowledge and learners' actual adoption of strategies. This finding resonates with previous studies which also found no significant association [44]. Combined with the findings in RQ2, it is interesting to note that prior knowledge was found to be significantly associated with the planned strategy, while not with the actual adoption of strategies. One explanation is that not only are sophisticated self-regulated learners capable of planning and adopting optimal learning strategies for a given task, but they are also capable of adjusting their learning strategies as they dig deeper into the learning task. As emphasized by [32], self-regulated learners engaged in more frequent metacognitive monitoring processes and concurrently evaluate if there are any discrepancies between their goals, plans, and domain knowledge, and they would adapt their plans and learning strategies when a discrepancy existed. Therefore, given the recursive nature of SRL, one explanation that prior knowledge has significant effects on planned strategy while not on actual strategy adoption is that learners kept adapting their use of strategies based on their ongoing metacognitive monitoring process as well as their ongoing evaluation on the learning products while they were engaged with the task [48, 49].

## 5.4 Implications

This study offers several novel findings that are informative to future research and practice. First, as we observed that learners tended to adopt different strategies compared to their planned ones, the design of a planner tool should be improved to capture this dynamic nature of strategy adoption. This can be achieved by, for example, implementing SRL scaffolding during the task to prompt learners to check their submitted plan and provide self-regulatory level suggestions. For example, when a learner changed their planned strategy during a task, adaptive prompts can be embedded in the planner tool to suggest learners to evaluate the current learning condition and offer suggestions on optimal strategies. To this end, the planner tool acts not only as an intervention to support the monitoring process but also enriches trace data to reflect learners' engagement in monitoring. Second, as learners adopt different strategies than those they planned, researchers should not solely rely on the planned strategies that are reported at the early learning stage to reflect on their overall actual strategy adoption [47]. Lastly, since implementing an easy-to-use planner tool is invaluable for capturing learners' strategic planning and monitoring processes, future studies should keep exploring ways to make planner tools more usable. Thus, the enriched trace data about learners' dynamic planning process could inform the design of adaptive SRL scaffolding to support learners' strategic planning and SRL processes.

## 5.5 Limitations and future work

First, among learners who submitted their plans, five out of 104 learners changed their plans during the task (i.e., resubmitted a different plan). One explanation for this small number may be due to the fact that the task was time-limited and learners were pressured to finish the task so that, even though they may have a different plan in mind, they were reluctant to manually re-submit their changed plan [45]. While self-reporting changes in planned strategies can be valuable to investigate, we did not utilize this information for the current analysis due to the small sample size of students who submitted changed plans. Therefore, future studies should improve the design of the planner tool and learning platform so that they can capture subtle changes of their strategic plan, and based on which more insights can be offered by examining their adaptation in making strategy plans. Second, our planner tool was also capable of allowing the learners to create customized plans if they did not agree with the three pre-defined strategies listed in the tool. In our study, two learners submitted their customized plan, but they were excluded from the analysis given the small sample size of this group. Future studies should further investigate their SRL processes with their customized plans. For instance, it would be interesting to understand if the learners demonstrate higher consistency between SRL process and their strategic plan when they designed the plan by themselves.

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## REFERENCES

[1] Omolola A Adedokun and Wilella D Burgess. 2012. Analysis of paired dichotomous data: A gentle introduction to the McNemar test in SPSS. *Journal of MultiDisciplinary Evaluation* 8, 17 (2012), 125–131.
[2] Icek Ajzen. 1991. The theory of planned behaviour. Organizational behaviour and human decision processes, 50 (2), 179-211.
[3] Tuija Alasalmi. 2021. Students Expectations on Learning Analytics: Learning Platform Features Supporting Self-regulated Learning.. In *CSEDU (2)*. 131–140.
[4] Roger Azevedo, François Bouchet, Melissa Duffy, Jason Harley, Michelle Taub, Gregory Trevors, Elizabeth Cloude, Daryn Dever, Megan Wiedbusch, Franz Wortha, et al. 2022. Lessons learned and future directions of metatutor: Leveraging multichannel data to scaffold self-regulated learning with an intelligent tutoring system. *Frontiers in Psychology* 13 (2022), 813632.
[5] Roger Azevedo, Amy Johnson, Amber Chauncey, and Candice Burkett. 2010. Self-regulated learning with MetaTutor: Advancing the science of learning with MetaCognitive tools. In *New science of learning*. Springer, 225–247.
[6] Roger Azevedo, Daniel C Moos, Jeffrey A Greene, Fielding I Winters, and Jennifer G Cromley. 2008. Why is externally-facilitated regulated learning more effective than self-regulated learning with hypermedia? *Educational Technology Research and Development* 56 (2008), 45–72.
[7] Maria Bannert. 2007. *Metakognition beim lernen mit hypermedien.* Waxmann Verlag.
[8] Maria Bannert and Peter Reimann. 2012. Supporting self-regulated hypermedia learning through prompts. *Instructional Science* 40 (2012), 193–211.
[9] Maria Bannert, Peter Reimann, and Christoph Sonnenberg. 2014. Process mining techniques for analysing patterns and strategies in students' self-regulated learning. *Metacognition and learning* 9 (2014), 161–185.
[10] Gregory L Callan and Timothy J Cleary. 2019. Examining cyclical phase relations and predictive influences of self-regulated learning processes on mathematics task performance. *Metacognition and Learning* 14 (2019), 43–63.
[11] Ismail Celik, Egle Gedrimiene, Anni Silvola, and Hanni Muukkonen. 2023. Response of learning analytics to the online education challenges during pandemic: Opportunities and key examples in higher education. *Policy Futures in Education* 21, 4 (2023), 387–404.
[12] Dan Davis, Guanliang Chen, Tim Van der Zee, Claudia Hauff, and Geert-Jan Houben. 2016. Retrieval practice and study planning in MOOCs: Exploring classroom-based self-regulated learning strategies at scale. In *Proc. the 11th European Conf. on Technology Enhanced Learning*. 57–71.
[13] Jiahui Du, Khe Foon Hew, and Lejia Liu. 2023. What can online traces tell us about students' self-regulated learning? A systematic review of online trace data analysis. *Computers & Education* (2023), 104828.
[14] Yizhou Fan, Lyn Lim, Joep Van der Graaf, Jonathan Kilgour, Mladen Raković, Johanna Moore, Inge Molenaar, Maria Bannert, and Dragan Gašević. 2022. Improving the measurement of self-regulated learning using multi-channel data. *Metacognition and Learning* 17, 3 (2022), 1025–1055.
[15] Yizhou Fan, Joep van der Graaf, Lyn Lim, Mladen Raković, Shaveen Singh, Jonathan Kilgour, Johanna Moore, Inge Molenaar, Maria Bannert, and Dragan Gašević. 2022. Towards investigating the validity of measurement of self-regulated learning based on trace data. *Metacognition and Learning* 17, 3 (2022), 949–987.
[16] Dragan Gasevic, Jelena Jovanovic, Abelardo Pardo, and Shane Dawson. 2017. Detecting learning strategies with analytics: Links with self-reported measures and academic performance. *Journal of Learning Analytics* 4, 2 (2017), 113–128.
[17] Dragan Gašević, Vitomir Kovanović, Srećko Joksimović, and George Siemens. 2014. Where is research on massive open online courses headed? A data analysis of the MOOC Research Initiative. *International Review of Research in Open and Distributed Learning* 15, 5 (2014), 134–176.
[18] Roberto Gatta, Mauro Vallati, Jacopo Lenkowicz, Eric Rojas, Andrea Damiani, Lucia Sacchi, Berardino De Bari, Arianna Dagliati, Carlos Fernandez-Llatas, Matteo Montesi, et al. 2017. Generating and comparing knowledge graphs of medical processes using pMineR. In *Proceedings of the Knowledge Capture Conference*. 1–4.
[19] Jeffrey Alan Greene and Roger Azevedo. 2009. A macro-level analysis of SRL processes and their relations to the acquisition of a sophisticated mental model of a complex system. *Contemporary educational psychology* 34, 1 (2009), 18–29.
[20] Lin Guo. 2022. Using metacognitive prompts to enhance self-regulated learning and learning outcomes: A meta-analysis of experimental studies in computer-based learning environments. *Journal of Computer Assisted Learning* 38, 3 (2022), 811–832.
[21] Sami Heikkinen, Mohammed Saqr, Jonna Malmberg, and Matti Tedre. 2023. Supporting self-regulated learning with learning analytics interventions–a systematic literature review. *Education and Information Technologies* 28, 3 (2023), 3059–3088.
[22] Nina Hood, Allison Littlejohn, and Colin Milligan. 2015. Context counts: How learners' contexts influence learning in a MOOC. *Computers & Education* 91 (2015), 83–91.
[23] René F Kizilcec, Mar Pérez-Sanagustín, and Jorge J Maldonado. 2017. Self-regulated learning strategies predict learner behavior and goal attainment in Massive Open Online Courses. *Computers & education* 104 (2017), 18–33.
[24] Tongguang Li, Yizhou Fan, Yuanru Tan, Yeyu Wang, Shaveen Singh, Xinyu Li, Mladen Raković, Joep Van Der Graaf, Lyn Lim, Binrui Yang, et al. 2023. Analytics of self-regulated learning scaffolding: effects on learning processes. *Frontiers in Psychology* 14 (2023).
[25] Tongguang Li, Jionghao Lin, Sehrish Iqbal, Zachari Swiecki, Yi-Shan Tsai, Yizhou Fan, and Dragan Gašević. 2023. Do Learners Appreciate Adaptivity? An Epistemic Network Analysis of How Learners Perceive Adaptive Scaffolding. In *ICQE*. Springer, 3–17.
[26] Lyn Lim, Maria Bannert, Joep van der Graaf, Shaveen Singh, Yizhou Fan, Surya Surendrannair, Mladen Rakovic, Inge Molenaar, Johanna Moore, and Dragan Gašević. 2023. Effects of real-time analytics-based personalized scaffolds on students' self-regulated learning. *Computers in Human Behavior* 139 (2023), 107547.
[27] Edwin A Locke and Gary P Latham. 2002. Building a practically useful theory of goal setting and task motivation: A 35-year odyssey. *American psychologist* 57, 9 (2002), 705.
[28] Jorge Maldonado-Mahauad, Mar Pérez-Sanagustín, Pedro Manuel Moreno-Marcos, Carlos Alario-Hoyos, Pedro J Muñoz-Merino, and Carlos Delgado-Kloos. 2018. Predicting learners' success in a self-paced MOOC through sequence patterns of self-regulated learning. In *Proceedings of the 13th European Conference on Technology Enhanced Learning*. Springer, 355–369.
[29] Wannisa Matcha, Dragan Gašević, Abelardo Pardo, et al. 2019. A systematic review of empirical studies on learning analytics dashboards: A self-regulated learning perspective. *IEEE Transactions on Learning Technologies* 13, 2 (2019), 226–245.
[30] Wannisa Matcha, Dragan Gašević, Nora'Ayu Ahmad Uzir, Jelena Jovanović, and Abelardo Pardo. 2019. Analytics of learning strategies: Associations with academic performance and feedback. In *Proceedings of the 9th international conference on learning analytics & knowledge*. 461–470.
[31] Danielle S McNamara. 2001. Reading both high-coherence and low-coherence texts: Effects of text sequence and prior knowledge. *Canadian Journal of Experimental Psychology/Revue canadienne de psychologie expérimentale* 55, 1 (2001), 51.
[32] Daniel C Moos and Roger Azevedo. 2008. Self-regulated learning with hypermedia: The role of prior domain knowledge. *Contemporary Educational Psychology* 33, 2 (2008), 270–298.
[33] Daniel C Moos and Roger Azevedo. 2009. Self-efficacy and prior domain knowledge: to what extent does monitoring mediate their relationship with hypermedia learning? *Metacognition and Learning* 4 (2009), 197–216.
[34] Anabil Munshi, Gautam Biswas, Ryan Baker, Jaclyn Ocumpaugh, Stephen Hutt, and Luc Paquette. 2023. Analysing adaptive scaffolds that help students develop self-regulated learning behaviours. *Journal of Computer Assisted Learning* 39, 2 (2023), 351–368.

[35] Ernesto Panadero. 2017. A review of self-regulated learning: Six models and four directions for research. *Frontiers in psychology* (2017), 422.
[36] Ronald Antonio Pérez-Álvarez, Jorge Maldonado-Mahauad, Kshitij Sharma, Diego Sapunar-Opazo, and Mar Pérez-Sanagustín. 2020. Characterizing learners' engagement in MOOCs: An observational case study using the NoteMyProgress tool for supporting self-regulation. *IEEE Transactions on Learning Technologies* 13, 4 (2020), 676–688.
[37] Mar Pérez-Sanagustín, Diego Sapunar-Opazo, Ronald Pérez-Álvarez, Isabel Hilliger, Anis Bey, Jorge Maldonado-Mahauad, and Jorge Baier. 2021. A MOOC-based flipped experience: Scaffolding SRL strategies improves learners' time management and engagement. *Computer Applications in Engineering Education* 29, 4 (2021), 750–768.
[38] Sanne FE Rovers, Geraldine Clarebout, Hans HCM Savelberg, Anique BH de Bruin, and Jeroen JG van Merriënboer. 2019. Granularity matters: comparing different ways of measuring self-regulated learning. *Metacognition and Learning* 14 (2019), 1–19.
[39] James R Segedy, John S Kinnebrew, and Gautam Biswas. 2013. The effect of contextualized conversational feedback in a complex open-ended learning environment. *Educational Technology Research and Development* 61 (2013), 71–89.
[40] Melody Siadaty, Dragan Gašević, and Marek Hatala. 2016. Associations between technological scaffolding and micro-level processes of self-regulated learning: A workplace study. *Computers in Human Behavior* 55 (2016), 1007–1019.
[41] Melody Siadaty, Dragan Gašević, and Marek Hatala. 2016. Measuring the impact of technological scaffolding interventions on micro-level processes of self-regulated workplace learning. *Computers in Human Behavior* 59 (2016), 469–482.
[42] Christoph Sonnenberg and Maria Bannert. 2015. Discovering the effects of metacognitive prompts on the sequential structure of SRL-processes using process mining techniques. *Journal of Learning Analytics* 2, 1 (2015), 72–100.
[43] Christoph Sonnenberg and Maria Bannert. 2019. Using process mining to examine the sustainability of instructional support: How stable are the effects of metacognitive prompting on self-regulatory behavior? *Computers in Human Behavior* 96 (2019), 259–272.
[44] Namrata Srivastava, Yizhou Fan, Mladen Rakovic, Shaveen Singh, Jelena Jovanovic, Joep Van Der Graaf, Lyn Lim, Surya Surendrannair, Jonathan Kilgour, Inge Molenaar, et al. 2022. Effects of internal and external conditions on strategies of self-regulated learning: A learning analytics study. In *LAK22: 12th international learning analytics and knowledge conference*. 392–403.
[45] Joep van der Graaf, Lyn Lim, Yizhou Fan, Jonathan Kilgour, Johanna Moore, Dragan Gašević, Maria Bannert, and Inge Molenaar. 2022. The dynamics between self-regulated learning and learning outcomes: An exploratory approach and implications. *Metacognition and Learning* 17, 3 (2022), 745–771.
[46] Philip H Winne. 2013. Self-regulated learning viewed from models of information processing. *Self-regulated learning and academic achievement* (2013), 145–178.
[47] Philip H Winne. 2017. Learning analytics for self-regulated learning. *Handbook of learning analytics* 754 (2017), 241–249.
[48] Philip H Winne. 2022. Modeling self-regulated learning as learners doing learning science: How trace data and learning analytics help develop skills for self-regulated learning. *Metacognition and Learning* 17, 3 (2022), 773–791.
[49] Philip H. Winne and Allyson Hadwin. 1998. Studying as self-regulated learning. https://api.semanticscholar.org/CorpusID:143411461
[50] Philip H Winne and Nancy E Perry. 2000. Measuring self-regulated learning. In *Handbook of self-regulation*. Elsevier, 531–566.
[51] Tzu-Chi Yang, Meng Chang Chen, and Sherry Y Chen. 2018. The influences of self-regulated learning support and prior knowledge on improving learning performance. *Computers & Education* 126 (2018), 37–52.
[52] Michael Yeomans and Justin Reich. 2017. Planning prompts increase and forecast course completion in massive open online courses. In *Proceedings of the seventh international learning analytics & knowledge conference*. 464–473.