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Examining change in students' self-regulated learning patterns after a formative assessment using process mining techniques

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ABSTRACT

The growing popularity of e-learning platforms, such as learning management systems, has foregrounded the role of self-regulated learning (SRL) in student success. In many e-learning environments, students typically complete learning assignments outside of school hours with little or no instructor support, which requires students to be highly self-regulated. The current study used trace data from a Moodle platform to examine both the temporal pattern of students' SRL behaviors and changes in high- and low-performing students' SRL behaviors following a formative in-course exam. This study employed repeated-measures ANOVA, multivariate ANOVA, Fuzzy miner, and pMineR on 122,167 event logs from 527 undergraduate students. Findings revealed that students engaged in a loosely sequenced recursive SRL cycle. Following the formative assessment, each group made different adjustments to their SRL processes. High-performing students exhibited more SRL behaviors and developed more structured and interconnected SRL patterns. Low-performing students displayed a smaller increase in SRL behaviors while maintaining their established SRL patterns. Findings from this study could provide a more in-depth theoretical understanding of the nature of SRL cycles. Furthermore, students' adjustment of SRL patterns in response to assessment may be informative for practitioners to assist students in enhancing their SRL through formative feedback.

1. Introduction

A fundamental goal of education is to equip students with the self-regulatory capabilities that enable them to educate themselves (Bandura, 1997). Therefore, self-regulated learning (SRL) has been an important topic from its inception, and extensive research has shown its significant effect on students' academic achievement and motivation (Clark, 2012; Dent & Koenka, 2016; Theobald, 2021). Previous research indicated two distinct perspectives regarding how SRL processes unfold. One perspective emphasizes a clear distinction among several phases in SRL, where each phase possesses distinct features and follows a linear order. In contrast, the other perspective views SRL as an open process with loosely sequenced recursive phases that are not clearly delimited (Panadero, 2017). Traditional methods, such as self-report questionnaires, think-aloud protocols, and interviews, often face challenges in exploring this dynamic sequencing of SRL processes due to their limited capacity for capturing real-time and fine-grained measurements of SRL (Biswas, Baker, & Paquette, 2017). However, the growing integration of learning management systems and artificial intelligence technologies in education (Turnbull, Chugh, & Luck, 2020; Zhang & Aslan, 2021) provides an opportunity to examine SRL processes in an objective and transparent manner. Specifically, e-learning platforms could generate system log files that record students' real-time actions throughout learning and assessments. In addition, machine learning techniques, such as pattern mining, can analyze large volumes of complex trace data and identify SRL patterns. Therefore, this study first aims to investigate two distinct perspectives by applying process mining techniques to behavioral trace data. After identifying SRL patterns, the current study investigates group differences in high- and low-performing students as well as any adjustments they may make to their SRL behaviors in response to a formative assessment.

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1.1. Conceptualization of self-regulated learning

Self-regulated learning concerns how learners become masters of their own learning processes (Zimmerman, 2013), which has become an important conceptual framework for understanding the cognitive, metacognitive, behavioral, motivational, and emotional aspects of learning (Panadero, 2017). In the concept of SRL, self-regulation refers to self-generated thoughts, feelings, and behaviors that are oriented towards attaining goals; learning is viewed as an activity that students do for themselves in a proactive way rather than as a covert event that happens to them in reaction to teaching (Zimmerman, 2001, 2013). Therefore, instead of just being a mental ability or academic performance skill, SRL refers to the self-directive process through which learners transform their mental abilities into task-related academic skills (Zimmerman, 2001). SRL has been investigated from various perspectives (Panadero, 2017; Schunk & Greene, 2017), including social (Hadwin & Oshige, 2011), social-cognitive (Pintrich & De Groot, 1990; Schmitz & Wiese, 2006; Usher & Schunk, 2017; Zimmerman, 2013), cognitive and metacognitive (Azevedo & Cromley, 2004; Winne, 2017), as well as motivation and emotion (Boekaerts, 1996; Efklides, 2011).

Although various theories conceptualize SRL differently, one of their commonalities is the cyclical nature of SRL, which indicates that SRL consists of multiple cyclical, sequenced, and contingent sets of interrelated phases and subprocesses (Bernacki, 2017; Panadero, 2017). There are two distinct views regarding the sequence of phases (Panadero, 2017). First, some models emphasize a clear distinction among several phases in SRL, with each phase having distinct features and being linearly ordered (Pintrich & De Groot, 1990; Schmitz & Wiese, 2006; Usher & Schunk, 2017; Zimmerman, 2013). For example, Zimmerman's cyclical phases model (Zimmerman, 2013) consists of three cyclical phases: forethought (i.e., a phase that occurs before efforts to learn, including task analysis, goal setting, and strategic planning, as well as a number of motivational beliefs influencing the activation of learning strategies), performance (i.e., a phase that occurs during behavioral implementations, including self-monitoring and self-control strategies to engage in the task), and self-reflection (i.e., a phase that occurs after learning effort, including self-evaluation and generating self-reactions). The second group of models views SRL as an open process, with loosely sequenced recursive phases that are not as delimited as in the first group (Azevedo & Cromley, 2004; Boekaerts, 1996; Efklides, 2011; Greene & Azevedo, 2007; Hadwin & Oshige, 2011; Winne, 2017). For instance, in the four-stage model proposed by Winne and Hadwin (1998), SRL is assumed to consist of four phases: defining the task, setting goals and planning how to reach them, enacting tactics, and adapting metacognition. Both the cyclical phases model (Zimmerman, 2013) and the four-stage model (Winne & Hadwin, 1998) consist of several phases. Their main difference is that the four-stage model postulates that SRL may not unfold linearly but rather recursively, meaning that information generated in one phase may jump phases, either forward or backward, or recurse to the same phase to create another cycle of information processing within that same phase (Winne, 2001).

Several empirical studies have examined the temporal pattern of SRL and group differences in SRL patterns (Bannert, Reimann, & Sonnenberg, 2014; Li et al., 2020; Saint, Fan, Gašević, & Pardo, 2022). For example, Bannert et al. (2014) examined students' SRL patterns by analyzing think-aloud data using a process mining technique, Fuzzy Miner. By comparing the frequency and pattern of SRL behaviors in successful and less successful students (i.e., students with a score more/less than one standard deviation from the mean), they found that successful students demonstrated more learning and regulation events, whereas the behaviors of less successful students resembled a superficial approach to learning. In addition, Li et al. (2020) investigated the temporal dynamics of SRL behaviors in STEM learning and focused on three groups of students: unsuccessful, success-oriented, and mastery-oriented. They found group differences in SRL evaluation behaviors, with the mastery-oriented and success-oriented groups performing more evaluation behaviors than the unsuccessful group, and the mastery-oriented group showing stronger interactions between SRL behaviors than the success-oriented group and the unsuccessful group. Despite these studies exploring the frequent temporal behavioral patterns of SRL in a particular context, few investigations have concentrated on examining the linear and recursive nature of the sequence of SRL processes. Only one study examined the sequence of SRL with a particular focus on recurrent behaviors. By comparing the behaviors of high- and low-performing students, Li, Zheng, and Lajoie (2022) found that low performers had a significantly higher ratio of single, isolated recurrent behaviors, whereas the recurrent behaviors of high performers were more likely to be part of a behavioral sequence.

1.2. Measurement of self-regulated learning

In addition to the conceptualization of SRL, another important topic is the way in which the constructs that comprise SRL can be measured. The commonly used measurement approaches are self-report questionnaires, think-aloud protocols, and interviews (Schunk & Greene, 2017; Winne, 2010). These methods, however, have some limitations (Biswas et al., 2017; Winne, 2010). Specifically, self-report questionnaires are subjective and cannot easily capture SRL as it is happening, without disrupting some of the key processes. Think-aloud protocols are expensive to study for a large number of participants or longitudinally. Interviews are both retrospective and time-consuming. To improve measurement, researchers have sought to measure SRL as events or processes based on trace data (Maldonado-Mahauad, Pérez-Sanagustín, Kizilcec, Morales, & Munoz-Gama, 2018; Winne, 2010; Winne & Perry, 2000). Trace data (also known as log data) refers to time-stamped records stored in log files generated by users' interactions with a technology-enhanced learning environment (Du, Hew, & Liu, 2023; Hadwin, Nesbit, Jamieson-Noel, Code, & Winne, 2007; Hakimi, Eynon, & Murphy, 2021). The time-stamped records typically include users' real-time actions or behaviors (e.g., keystrokes or mouse clicks) as events and capture the timestamp (e.g., the start or end time), event context, affected user, and IP address of each action (Bernacki, 2017; Hakimi et al., 2021). Trace data could compensate for the limitations of questionnaires, think-aloud, and interview data because it unobtrusively logs behavioral information in real time as students interact with the platform, making it less susceptible to the memory and self-report biases presented in other methods. It is also economical, time-efficient, and fine-grained, enabling the rapid collection of a large volume of data from a large number of participants (Biswas et al., 2017). Furthermore, from the point of view of SRL, it could capture strategic adaptations that students make within and across study sessions (Hadwin et al., 2007). It is not typically possible to capture this type of information through self-report questionnaires. Due to these advantages, trace data has been increasingly used to examine SRL in recent years (Araka, Maina, Gitonga, & Oboko, 2020; ElSayed, Caeiro-Rodríguez, MikicFonte, & Llamas-Nistal, 2019). Moreover, a growing number of studies have supported the validity of measuring SRL with trace data by calibrating it to think-aloud data (Fan, van der Graaf, et al., 2022), self-report questionnaire data (Rovers, Clarebout, Savelberg, de Bruin, & van Merriënboer, 2019), and eye-tracking data (Fan, Lim, et al., 2022).

One of the challenges in trace-based measurement is mapping raw trace data to theoretically meaningful SRL phases (Du et al., 2023; Fan, van der Graaf, et al., 2022). The reason is that log files usually contain various types of low-level fine-grained events that may not necessarily correspond to high-level SRL processes. To address this granularity challenge, the trace-based microanalytic protocol (see Table 1) was proposed to deconstruct SRL into macro-level and micro-level processes and add meaning to trace data (Siadaty, Gasevic, & Hatala, 2016). The macro-level processes provide a general depiction of students engaging in SRL, and they consist of three phases: planning (i.e., a phase containing processes that preceded acting), engagement (i.e., a phase containing processes occurring during task effort), and evaluation &

Table 1
Trace-based microanalytic protocol (Siadaty et al., 2016).

Macro-level	Micro-level	Description
Planning	Task Analysis	To get familiar with the learning context and the definition and requirements of a (learning) task at hand
	Goal Setting	To explicitly set, define, or update learning goals
	Making Personal Plans	To create plans and select strategies for achieving a set learning goal
Engagement	Working on the Task	To consistently engage with a learning task, using tactics and strategies
	Applying Strategy Changes	To revise learning strategies or apply a change in tactics
Evaluation & Reflection	Evaluation	Evaluating one's learning process and comparing one's work with the goal
	Reflection	Reflecting on individual learning and sharing learning experiences

reflection (i.e., a phase containing processes occurring after a task ends). Each of the three macro-level processes comprises several micro-level processes which are a set of specific self-regulatory activities identified based on existing literature, enabling a way to conceptually define traces of learning (Saint, Whitelock-Wainwright, Gašević, & Pardo, 2020; Siadaty et al., 2016). In addition to this theoretical framework, a recent systematic review (Du et al., 2023) provided guidance on how to empirically derive SRL indicators from trace data. According to a review of six self-regulated theories (Panadero, 2017), Du et al. (2023) outlined three phases of SRL, namely preparatory (including processes and beliefs that occur before efforts to learn), performance (including processes that occur during behavioral implementation), and appraisal (including processes that occur after each learning effort). Du and colleagues also provided high-level and low-level behavioral indicators for each phase (see Table 2).

1.3. Self-regulated learning and formative assessment

According to the *Standards for Educational and Psychological Testing* (shortly, *Standards*), formative assessment (FA) refers to the assessment process used by teachers and students during instruction that provides feedback to adjust ongoing teaching and learning with the goal of improving students' achievement of intended instructional outcomes (AERA, APA, & NCME, 2014, p. 219). Different from summative assessment, which is conducted primarily for the purpose of making a judgment about the status of individual learners or determinations about the effectiveness of educational programs or systems, formative assessment is commonly used to inform instructional intervention and improve learning progress (Cizek, Andrade, & Bennett, 2019; Gikandi, Morrow, & Davis, 2011). For example, the midterm exam (also known as the benchmark or interim assessment) is a form of FA commonly used in teaching practices (Cizek et al., 2019; Wiliam, 2018, p. 50). Therefore, FA is inherently related to improving learning and achievement. Previous studies indicated that FA has a moderate effect on students' achievement in classroom learning settings (Andersson & Palm, 2017; Black & Wiliam, 1998). In addition, a systematic qualitative review revealed that FA can also foster learners' engagement and autonomy of learning in online and blended learning environments (Gikandi et al., 2011).

Given that SRL is fundamentally a type of learning, researchers have developed theoretical accounts of how FA may drive students' SRL (Andrade & Brookhart, 2016; Chen & Bonner, 2020; Nicol & Macfarlane-Dick, 2006; Panadero & Alonso Tapia, 2014). For example, Panadero and colleagues (Panadero & Alonso Tapia, 2014; Panadero, Broadbent, Boud, & Lodge, 2019) outlined how FA might impact each SRL phase based on Zimmerman's model. Specifically, in the forethought stage, assessment criteria and rubrics could help students better establish appropriate goals and plans when they analyze the tasks. In the performance phase, FA provides structured opportunities for students to practice self-assessment activities and facilitates students' help-seeking behaviors. In the self-reflection phase, results of the FA can be a source for students to discuss with their teachers, reflect on their mistakes, and make revisions in line with criteria and standards (Tay, 2015). Moreover, Andrade and Brookhart (2016) also explained the role of classroom assessment in supporting SRL by considering the similarities between the phases of SRL and classroom assessment, namely setting goals, monitoring or evaluating progress toward those goals, and reacting to feedback about gaps between goals and progress by making adjustments to teaching, learning, and/or work products. In general, FA may benefit students by assisting them in clarifying their learning goals, activating cognitive and motivational capacities, and providing feedback and strategies they can use to reach their goals (Cizek et al., 2019).

Compared to the number of studies on theoretical explanations, the empirical evidence regarding the effect of FA on SRL is relatively insufficient. Tay (2015) interviewed middle school students regarding their use of SRL strategies in essay writing in the two contexts of FA (i.e., traditional paper-and-pen and online forum). Findings showed that both contexts are beneficial for activating students' SRL, with the real-world online forum context being more engaging. Xiao and Yang (2019) also used interviews and classroom observation to examine how FA activities could potentially promote high school students to engage in SRL processes in the English language learning context. Their results supported Panadero and Alonso Tapia's (2014) theoretical assumption by indicating that FA activities could enhance students' self-regulation by

Table 2
Behavioral indicators of self-regulated learning (Du et al., 2023).

SRL processes	Behavioral indicators (High-level granularity)	Behavioral indicators (Low-level granularity)
Preparatory	Patterns of interactions with setting goals and making plans	Setting or modifying goals; planning learning strategies and time to reach goals
	Behaviors during initial attempts	Completing learning tasks at least 1 or 3 days earlier than due dates; skipping (<15 s), skimming through (15–35 s) or engaging in (>35 s) the tasks during initial attempt
	Overviewing course structure	Viewing course information page, syllabus with course details, resources, task lists or summaries
	Recall prior knowledge	Collecting evidence items from descriptions
Performance	Interacting with quizzes or assignments	Starting, viewing, or submitting quizzes, assignments, or forums; showing the answers or outcome of quizzes or assignments
	Interacting with learning materials and assessments	Accessing learning material pages (e.g., video lecture) then passing or attempting quizzes or discussions
	Monitoring the learning process	Showing the overview of the learning status
	Conducting tests or searching for more information	Outlining or managing hypotheses; adding tests; searching library
Appraisal	Interacting with self-reflection module	Evaluating the performance of time planning, performing strategy, or completing goals
	Revisiting completed tasks or prior contents	Number of visits to events or course resources, quizzes, submitted assignments or updated submissions
	Reviewing performance or match to final learning goals	Interactions with course details page or progress page after taking quizzes
	Validating the evidence items with test results and hypothesis	Link, check and rank evidence items and test result; make final diagnosis

Note. The figure is referred from "What can online traces tell us about students' self-regulated learning? A systematic review of online trace data analysis" by Du et al., 2023, Computer & Education, *201*, p. 7. Copyright 2023 by Elsevier Ltd.

engaging them in the process of goal setting, generating and responding to feedback, managing resources, and taking actions to move learning forward. In addition, Weldmeskel and Michael (2016) combined the quasi-experiment and focus-group interview to investigate whether the use of FA could improve undergraduate students' SRL. They found that compared to the control group, students whose courses used FA perceived that they had higher SRL and held a more positive and active attitude toward learning and assessment.

In addition to investigating the impact of FA on students' static SRL behaviors, it is also important to examine the impact of FA on the temporal change in students' SRL behaviors (Baker et al., 2020). From a social cognitive perspective, the cyclical process in which SRL skills and strategies develop is a function of personal, behavioral, and environmental factors adjusting, modifying, and changing as they interact with one another in each cycle (Bandura, 1997; Barnard-Brak, Paton, & Lan, 2010; Schunk, 1989). Therefore, in the learning context, FA as an environmental factor may interact with other factors in each cycle, resulting in changes in student's SRL skills and strategies (Barnard-Brak et al., 2010). However, only a few studies investigated the role of FA on changes in SRL behaviors. Granberg, Palm, and Palmberg (2021) examined how students' SRL behaviors change between the beginning and end of the period in which FA is implemented in the class. Based on their classroom observation and interviews, they found that middle school students' SRL behaviors, such as task-solving and help-seeking, significantly increased at the end of the class. Another relevant study examined the influence of metacognitive evaluation following an FA on the change in SRL behaviors (Raković et al., 2022). They collected the frequency of event logs from a learning management system as an indicator of the frequency of SRL behaviors among undergraduate students. The results of a structural equation modeling showed that students with more metacognitive evaluation were likely to have more explicit and forward-looking study plans, leading to a greater increase in SRL behaviors and higher achievement scores.

1.4. The present study

Researchers have made remarkable advancements in conceptualizing and measuring SRL. However, there are still inconsistent views regarding how SRL phases are sequenced - whether phases are enacted as a linear cycle or have other sequential patterns, such as a loosely sequenced recursive cycle. Although previous studies have explored temporal patterns in SRL (Bannert et al., 2014; Li et al., 2020; Saint et al., 2022), few empirical investigations have concentrated on this inconsistency. In addition to this inconsistency, empirical evidence about how FA impacts SRL or might trigger changes in student SRL behaviors has yet to be explored (Granberg et al., 2021; Panadero, Andrade, & Brookhart, 2018; Tay, 2015). Moreover, previous studies mainly used qualitative approaches, such as interviews and classroom observation, to investigate the influence of FA on students' SRL behaviors. However, as mentioned earlier, these approaches come with certain limitations, such as their retrospective nature, associated cost, and laboriousness (Biswas et al., 2017; Winne, 2010). Finally, inspired by previous findings regarding group differences in high- and low-performing students (Bannert et al., 2014; Li et al., 2020; Saint et al., 2022), this study also intends to investigate group differences in SRL patterns, especially for high-performing versus low-performing students, as well as students whose ranking increased versus decreased in the second assessment. Taking these together, this study aims to examine the following research questions and test the associated hypotheses.

1) Are SRL patterns cycled linearly or recursively? Based on previous findings (Li et al., 2022), we assume a loosely sequenced recursive cycle.
2) How might SRL behaviors and patterns change following an FA? According to prior research (Granberg et al., 2021; Tay, 2015; Weldmeskel & Michael, 2016; Xiao & Yang, 2019), we hypothesize that students engage in more SRL behaviors after an FA. However, we are unable to make a specific assumption for the change in SRL patterns due to limited prior research.
3) How does the change in SRL patterns differ between groups (i.e., high-performing vs. low-performing, ranking increased vs. ranking decreased) before and after an FA? Drawing on previous research (Bannert et al., 2014; Li et al., 2020; Saint et al., 2022), we hypothesize that low-performing students may have more single, isolated recurrent behaviors, whereas high-performing students may have more structured SRL patterns. However, we have no assumptions about the difference in the SRL pattern for students whose ranking increased or decreased due to a lack of supporting evidence in the previous literature.

2. Method

2.1. Data source

This study used data from a course designed for undergraduates enrolled in the Elementary and Secondary Education program at a university in western Canada. The course is offered for ten weeks every fall and winter semester. The course structure has been kept consistent in recent years. It has eleven lectures, three group assignments, two midterm exams (i.e., formative assessment), and a final exam (i.e., summative assessment). These three exams were administered following the completion of lectures 1–4 (midterm 1), 5–8 (midterm 2), and 9–11 (final). Students were provided with their grades, the correct answers for each question, and explanations for the correct answers after the grading process for both midterms. These assessments collectively contributed to students' final grades, with each assignment accounting for 10%, each mid-term exam for 20%, and the final exam for 30%. In addition, instructors taught the course in person, while course materials (e.g., slides, course readings, learning activities, and exams) were shared via Moodle.

Students' and instructors' interactions with the system, especially their clickstreams, were stored in the system log files, which contained information such as user identifiers, the start time of each event, the event name, the event context, and the event description. The user identifiers of the log file were anonymized before they were given to the research team for analysis, and all research activities were conducted according to the ethical and scientific requirements of the university research ethics board. A total of 527 students and 267,981 event logs were collected in the 2018 winter term. After removing event logs from individuals who did not have final grades in the grade file, such as instructors, teaching assistants, and students who withdrew from the course, a total of 227,527 event logs were included in the analysis.

2.2. Data pre-processing

In the log file, there were 35 types of events (see Table 3 for detailed descriptions and frequency of each event type). The first step of the pre-processing was to remove the event "course viewed" since it was the very first action that students had to take upon entering the course, meaning that this event had a larger granularity than all remaining events. Second, we removed the event "User graded" which was the system's automated grading of students' quiz (the term "quiz" refers to all exams in general) attempts rather than actions performed by students. Third, eight events with fewer than ten occurrences were removed, including course searched, comment deleted, post updated, discussion subscription deleted, discussion deleted, post deleted, user report viewed, and subscription created. Fourth, we addressed data granularity by mapping the remaining 25 events to four SRL phases (i.e., planning, learning, engagement, and evaluation & reflection; see Table 3 for details). This mapping procedure was grounded on the trace-based microanalytic protocol that was originally proposed for use in workplace settings (Siadaty et al., 2016). There is one addition made for the

Table 3
Descriptions of each event and corresponding SRL components.

Event name (smaller granularity)	Event context	Event Description	Count	SRL process (larger granularity)
1. Course module viewed	File	viewed the course modules, such as files, quizzes, URLs, forums, and pages	47,704	Learning
2. Quiz attempt viewed	Quiz	viewed the questions in the quiz	22,893	Engagement
3. The status of the submission has been viewed	Submission	viewed the submission status page for the assignment	7227	Evaluation & Reflection
4. Grade user report viewed	System	viewed the user report in the gradebook	5577	Evaluation & Reflection
5. Quiz attempt started	Quiz	started the attempt for the quiz	5211	Engagement
6. Quiz attempt summary viewed	Quiz	viewed the summary page of the quiz	5131	Evaluation & Reflection
7. Quiz attempt submitted	Quiz	submitted the attempt for the quiz	4924	Engagement
8. Quiz attempt reviewed	Quiz	reviewed the attempt for the quiz	1819	Evaluation & Reflection
9. Submission form viewed	Submission	viewed the submission form for the assignment	1726	Evaluation & Reflection
10. An online text has been uploaded	Submission	uploaded an online text submission for the assignments	1341	Engagement
11. User list viewed	System	viewed the list of users in the course	1234	Planning
12. A submission has been submitted	Submission	submitted the assignment	1131	Engagement
13. Submission created	Submission	created an online text submission for the assignment	1032	Engagement
14. Discussion viewed	Forum	viewed the discussion in the forum	773	Learning
15. Course module instance list viewed	System	viewed the instance list for the module assignment, quiz, forum	753	Planning
16. Submission confirmation form viewed	Submission	viewed the submission confirmation form for the assignment	717	Evaluation & Reflection
17. Course user report viewed	System	viewed the user report for the course	439	Evaluation & Reflection
18. Submission updated.	Submission	updated an online text submission in the assignment	309	Evaluation & Reflection
19. Grade overview report viewed	System	viewed the overview report in the gradebook	168	Evaluation & Reflection
20. User profile viewed	System	viewed the profile of the user	153	Planning
21. Some content has been posted	Forum	posted content in the forum post	97	Engagement
22. Discussion created	Forum	created the discussion in the forum	48	Engagement
23. Post created	Forum	created the post in the discussion	44	Engagement
24. Discussion subscription created	Forum	subscribed to the discussion in the forum	27	Engagement
25. Comment created	Submission	added the comment to the submission for the assignment	20	Engagement
26. Course viewed	System	clicked into the course	101,119	Removed
27. User graded	System	user is automatically graded after submitting the quiz attempt	4206	Removed
28. Course searched	Forum	searched the course from a forum post	10	Removed
29. Comment deleted	Submission	deleted the comment to the submission for the assignment	8	Removed
30. Discussion subscription deleted	Forum	unsubscribed from the discussion in the forum	5	Removed
31. Post updated	Forum	updated the post in the discussion	5	Removed
32. Discussion deleted	Forum	deleted the discussion in the forum	2	Removed
33. Post deleted	Forum	deleted the post in the discussion	2	Removed
34. User report viewed	Forum	viewed the user report	2	Removed
35. Subscription created	Forum	subscribed to a specific user in the forum	1	Removed

present study. This addition represents learning activities, which had not been included in the original protocol since learning is not a primary focus in workplace settings. In this study, we separated the learning process (denoted as "working on the task" in the trace-based microanalytic protocol) from the original engagement process, constructing it as an independent SRL process. This distinction was made because both learning the course materials and engaging in exams or assignments are important in educational contexts. Therefore, drawing on previous research in the learning context (Cerezo, Bogarín, Esteban, & Romero, 2020), we separated learning as the fourth SRL phase. This addition was also made to address methodological concerns. In this course, the Moodle platform was mainly used for delivering learning materials and administering assignments or exams. If these two categories were combined, the number of raw events in each category would be highly imbalanced, which may introduce biases (Weijters, van Der Aalst, & De Medeiros, 2006). Hence, events in the current study were classified into four main SRL processes: planning, learning, engagement, and evaluation & reflection. Planning encompassed activities that contributed to familiarizing oneself with the learning context, the task's definition and requirements, and the creation of plans for reaching a learning goal. Learning included viewing the course learning materials and forum posts. Engagement specifically included activities related to performance evaluations, such as starting, viewing, and submitting assignments or exams. Evaluation & reflection included activities for checking and evaluating one's progress, comparing one's work to the objective, as well as reflecting on their learning. As a result, there were a total of 122,167 event logs, which included 2,140 planning events, 60,146 learning events, 36,768 engagement events, and 23,113 evaluation & reflection events.

2.3. Data analysis

After assigning SRL processes to the logged events, this study analyzed the entire dataset using educational process mining techniques to examine the first research question (i.e., the overall SRL pattern). Educational process mining is a subfield of educational data mining that focuses specifically on the learning process, rather than learning outcomes, which involves the discovery, analysis, and enhancement of temporal processes and flows underlying the event logs generated by e-learning environments (Bogarín, Cerezo, & Romero, 2018; Cerezo et al., 2020). In the process mining literature, a variety of discovery algorithms are available for identifying interaction patterns, which are differentiated by their use of various metrics, such as time, frequency, and probability (Maldonado-Mahauad et al., 2018; Saint, Fan, Singh, Gasevic, & Pardo, 2021). Of the available process-mining algorithms, heuristics miner, inductive miner, fuzzy miner, and pMineR are commonly used when investigating SRL processes (Saint et al., 2021). A systematic comparison of four algorithms (Saint et al., 2021) found heuristic miner could identify multi-directional relationships between processes based on the dependency metric, but the metric values are difficult to interpret. They also found inductive miner was more suitable for structured process data but is challenging when applied to cyclical SRL processes. Therefore, this study followed the recommendation of Saint et al. (2021) and applied the fuzzy miner and pMineR algorithms to gain insight into SRL processes. Fuzzy miner (Günther & Van Der Aalst, 2007) is based on frequency metrics and offers the advantage of providing simpler and more interpretable patterns. However, it is not able to provide a strict articulation of sequential process permutations. This limitation can be mitigated by using pMineR (Gatta et al., 2017), which uses first-order Markov modelling to provide the probability of transitioning to the next event depending only on the current event. Furthermore, the pMineR algorithm offers information for comparing the transition probability for two models, enabling us to compare the SRL process before and after formative assessment, as well as across groups.

To further examine the second and third research questions, this study separated the entire log file into several files (see Fig. 1). First, to examine the change in students' SRL behaviors before and after the midterm exam, the log file was divided into two files: before midterm exam 1 and after midterm exam 1. The latter file contains logs generated between midterm exam 1 and exam 2, and it contains data from the same number of days as the first file. Second, to investigate the difference in high- and low-performing students' SRL behaviors before and after exam1, the two temporal log files were further divided into four files based on student performance. We classified students as high-performing or low-performing according to their Z scores on midterm exam 1. Students in the top 30% were considered high-performing, while those in the bottom 30% were considered low-performing. Finally, to examine group differences in SRL patterns between students whose ranking increased or decreased in the second assessment, the four log files were further split into eight according to the changes in Z scores. The changes in Z scores were calculated by subtracting Z scores in exam 1 from Z scores in exam 2 ($Z_{change} = Z_{exam2} - Z_{exam1}$). Positive values represent increased ranking, whereas negative values represent decreased ranking. To obtain clearer group differences in SRL patterns, this study only included 20% of students in the top and bottom of Z_{change} scores, resulting in around 30 students in each category (i.e., high-performing increased ranking students before exam 1, high-performing decreased ranking students before exam 1, low-performing increased ranking students before exam 1, low-performing decreased ranking students before exam 1, high-performing increased ranking students after exam 1, high-performing decreased ranking students after exam 1, low-performing increased ranking students after exam 1, low-performing decreased ranking students after exam 1). Hence, this analysis only included data from 242 students in total. After splitting the file, the frequency of four SRL behaviors for each student was computed using a pivot table for each log file. Then, a two-way repeated-measures ANOVA was conducted to compare the difference in frequency of SRL behaviors before and after the midterm exam. In addition, a three-way repeated-measures ANOVA and two multivariate ANOVAs were conducted to investigate group differences (high-performing vs. low-performing, increased-ranking vs. decreased-ranking) in students' SRL behaviors before and after the exam. For each file, we also applied fuzzy miner (Günther & Van Der Aalst, 2007) and pMineR (Gatta et al., 2017) to obtain SRL patterns.

All data preprocessing procedures and pMiner analyses were conducted in R 4.2.3. Statistical analyses, including repeated-measures and multivariate ANOVAs, were conducted in SPSS 26. Fuzzy mining was conducted in a process mining software, Fluxicon Disco 3.5.7 (Günther & Rozinat, 2012). Fluxicon Disco includes two sliders for adjusting the level of detail displayed in the process map. The activities slider influences the number of activities shown in the process map, ranging

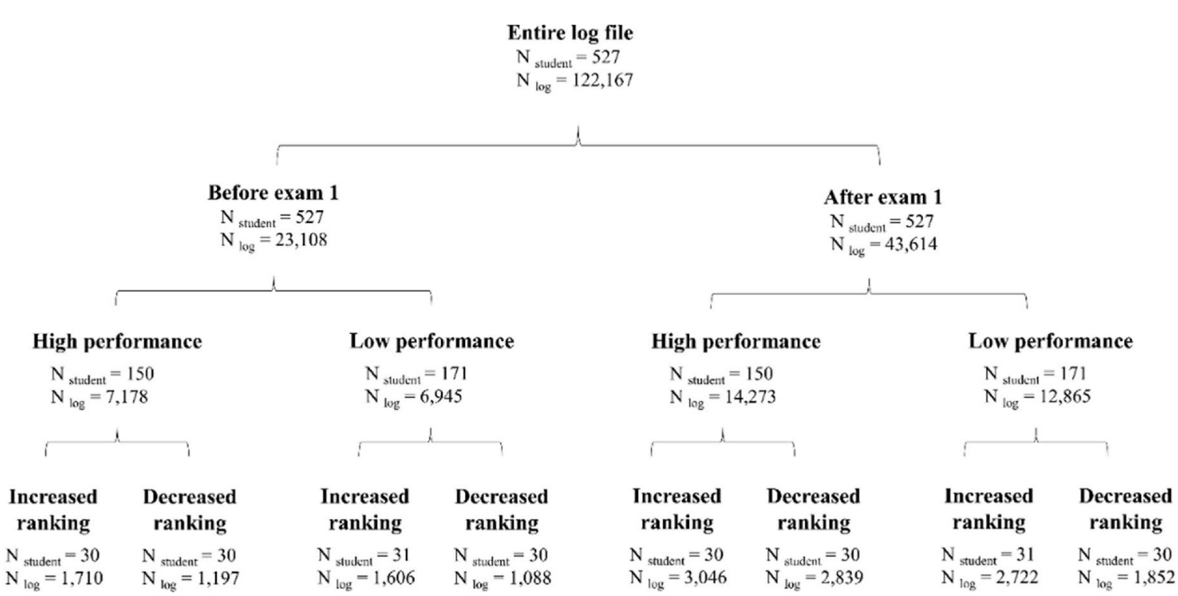


Fig. 1. The separation of log file.

from 0% (i.e., only the most frequent activities) up to 100% (i.e., including all activities). The paths slider determines how many transition paths are shown in the process map, ranging from 0% (i.e., only the most dominant paths) to 100% (i.e., showing all connections between activities). This study set the activities and path sliders to 100% and 10% to obtain frequent paths for meaningful interpretation (Astromskis, Janes, & Mairegger, 2015; Doleck, Jarrell, Poitras, Chaouachi, & Lajoie, 2016). Materials and data for this study are not available because participants did not consent to their data being shared. The code used for analysis is available at https://osf.io/t3eky/.

3. Results

3.1. Students' overall SRL patterns

The process maps generated by fuzzy miner and pMineR are shown in Fig. 2. The fuzzy miner map primarily displayed event frequency and transition frequency, including all student activities and transition paths with a frequency rate of 90% or higher to avoid plotting infrequent transitions (Astromskis et al., 2015; Doleck et al., 2016). The plot shows that most students started with the learning process, and most of them repeatedly engaged in learning activities. After learning materials, they also conducted evaluation & reflection, engagement, or planning behaviors. In most cases, however, the planning process was independent of their evaluation & reflection and engagement processes. Additionally, transitions between processes were bidirectional, as opposed to occurring in a linear, unidirectional sequence. The pMineR map that displays paths with a transition rate of at least 90% also yielded comparable results. In all four SRL processes, the self-recursive activities account for the greatest proportion. The learning process was mostly initiated first, and students transitioned to evaluation & reflection or engagement processes.

3.2. Change in students' SRL behaviors before and after the exam

Since the results from the two-way repeated measures ANOVA analysis showed that the assumption of sphericity had been violated and the epsilon was less than 0.75, the Huynh-Feldt corrected degrees of freedom are reported. The effect of time ($F_{(1,\ 525)} = 268.555$, $\eta_p^2 = 0.338$), SRL behaviors ($F_{(2.209,\ 1579)} = 849.479$, $\eta_p^2 = 0.618$), and the interaction effect of time and SRL behaviors ($F_{(2.137,\ 1575)} = 153.994$, $\eta_p^2 = 0.227$) were all significant, indicating that the frequency of students' SRL behaviors changed after the exam. Moreover, the results of the pairwise comparison showed that the frequency of students' planning behaviors decreased significantly after the exam, with the mean difference (MD thereafter) $= -0.952$, $p < 0.001$. However, the frequency of learning (MD $= 10.599$), engagement (MD $= 20.937$), and evaluation & reflection behaviors (MD $= 8.297$) increased significantly ($ps < 0.001$). As shown in Fig. 3, fuzzy mining maps revealed that students' SRL patterns were similar before and after the exam, but their action frequencies differed. The comparison plot generated by pMineR showes that students had more isolated repetitive behaviors before the exam (green lines) and more transition behaviors after the exam (red lines).

3.3. Group differences in students' SRL behaviors

The results of the three-way repeated measure analysis revealed that all main effects and interaction effects were significant, except for the interaction effect of Time, SRL, and Group (see Table 4). We further conducted a pairwise comparison for the interaction of three factors in case of counter effects. High- and low-performing students mainly showed significant differences in their learning activities before the midterm exam. After the midterm exam, more of their behaviors fell into the learning, engagement, and evaluation & reflection categories (see Table 5). Finally, process maps (see Fig. 4) indicated that SRL patterns of high- and low-performing students were similar before the exam, with identical patterns in fuzzy miner maps and no green or red lines in the pMineR map. After the exam, however, their patterns began to diverge, with high-performing students exhibiting a more structured and interconnected pattern and engaging in more transitions from planning to evaluation & reflection behaviors (red lines). Similar to previous findings, both high- and low-performing students engaged in more transitions after the exam compared to more isolated repetitive activities before the exam.

A multivariate ANOVA showed that the frequency of students' learning activities had significant differences between the four groups both before and after the exam (see Table 6). Pairwise comparisons with Bonferroni correction showed a marginally ($p = 0.063$) significant difference (see Fig. 5a). Group differences in learning behaviors were observed between group 1 (low-performing students who decreased their ranking in exam 2) and group 4 (high-performing students who increased their ranking in exam 2). However, since the sample size in each group was greater than or equal to 30, this study regarded this marginal significance as non-significant. After the midterm exam, both frequencies of students' learning and evaluation & reflection activities had group differences (see Table 6). Group 1 had significantly fewer learning and evaluation & reflection behaviors than group 4, as well as significantly fewer learning behaviors than group 3 (high-performing students who decreased their ranking in exam 2) (see Fig. 5b and c). Furthermore, the mined patterns showed that all four groups of students had similar learning patterns before the exam, with two dominant sequential patterns in their SRL activities (i.e., learning → evaluation &

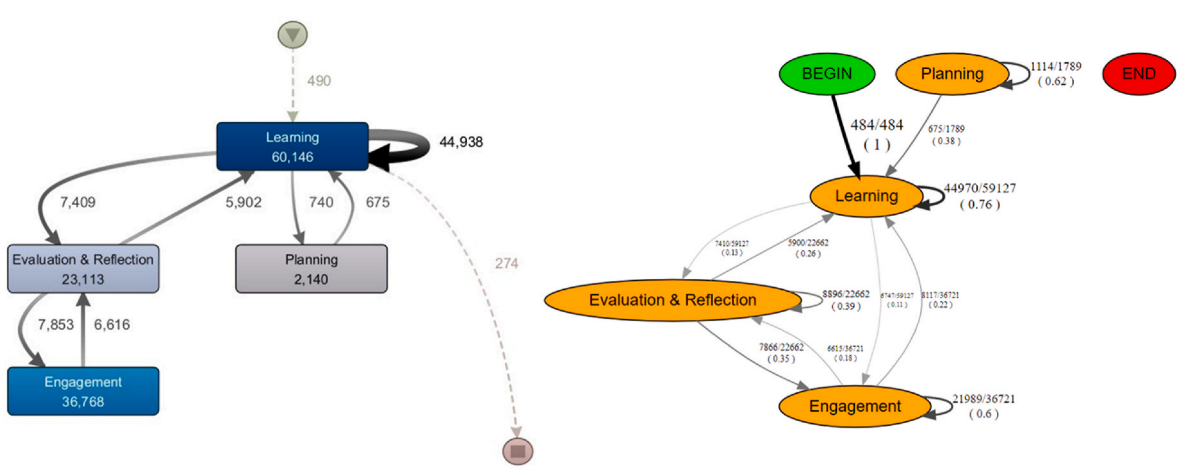


Fig. 2. Process maps from Fuzzy Miner and pMineR.

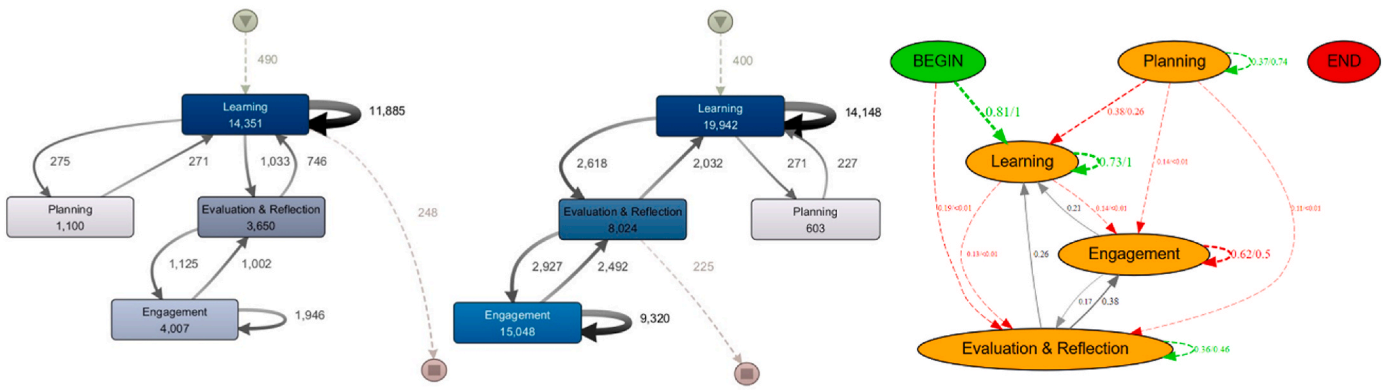


Fig. 3. Students' SRL behavioral pattern before and after the exam.

Table 4
Tests of within and between subject effects in three-way repeated measures of ANOVA.

Source	Type III Sum of Squares	*df*	Mean Square	*F*	Sig.	Partial Eta Squared
Within-subject effects						
Time	67030.274	1	67030.274	176.662	<0.001	0.356
SRL	330870.846	2.197	150635.193	520.535	<0.001	0.620
Time * SRL	41584.453	2.187	19017.438	101.462	<0.001	0.241
Time * Group	1605.975	1	1605.975	4.233	0.040	0.013
SRL * Group	4434.301	2.197	2018.799	6.976	0.001	0.021
Time * SRL * Group	891.449	2.187	407.678	2.175	0.109	0.007
Between-subject effect						
Intercept	83659.296	1	83659.296	974.233	<0.001	0.753
Group	920.918	1	920.918	10.724	0.001	0.033

Note. The assumption of sphericity had been violated, and the epsilon was less than 0.75. Therefore, the current study reported Huynh-Feldt corrected degree of freedom.

Table 5
Pairwise comparison in three-way repeated measures of ANOVA.

Time	SRL	Mean (low performance)	Mean (high performance)	Mean Difference (High - Low)	Std. Error	Sig.
Before exam	Planning	2.029	1.873	−0.156	0.486	0.749
	Learning	24.409	30.107	5.697	2.104	0.007
	Engagement	7.257	8.300	1.043	1.100	0.344
	Evaluation & Reflection	6.918	7.573	0.655	0.622	0.293
After exam	Planning	1.175	1.193	0.018	0.422	0.966
	Learning	34.187	42.547	8.360	2.544	0.001
	Engagement	25.766	33.593	7.827	3.439	0.024
	Evaluation & Reflection	14.105	17.820	3.715	1.301	0.005

reflection → engagement, and learning → planning). After the midterm exam, as shown in Fig. 6, low-performing students maintained the same SRL pattern as before the exam, whereas high-performing students changed their SRL pattern. Particularly, high-performing students with increased ranking, developed more structured and interconnected SRL patterns (i.e., learning → planning → engagement → evaluation & reflection). Finally, this study is conservative regarding the higher transition probabilities of the planning behaviors depicted in Figs. 4 and 6, as they may be due to small process frequency rather than actual probable transitions (Saint et al., 2021).

4. Discussion

This study examined the temporal sequence of SRL processes and found that SRL is more likely a recursive and non-linear process. Students displayed the flexibility to repeat phases and unfold in a non-linear pattern by jumping either forward or backward. In addition, the current study revealed that after a formative assessment, students actively adjusted the way they engaged in SRL behaviors, exhibiting a boost in SRL behaviors and more transition between processes. This adjustment also applies to group differences, with high-performing students having more learning, engagement, and evaluation & reflection behaviors than low-performing students. Moreover, high-performing students who increased their ranking in the second assessment developed more structured and interconnected SRL patterns. On the other hand, low-performing students, although they increased the frequency of SRL behaviors, maintained their established SRL patterns.

4.1. *The temporal pattern of SRL*

Findings from the current study showed that the temporal pattern of SRL processes displayed a recursive and non-linear structure. In general, self-recursion was the most frequent transition for each SRL process. Moreover, there were more transitions between learning, evaluation & reflection, and engagement. The transitions between these three processes were bidirectional, with a greater probability of occurring in the sequence "learning → evaluation & reflection → engagement". These findings align more with the four-stage model (Winne & Hadwin, 1998) which proposes that SRL is an open process, with loosely sequenced stages that unfold in a non-linear pattern. The potential mechanism underlying this recursive non-linear structure may be that monitoring and control serve as the hubs of regulation within each phase, allowing

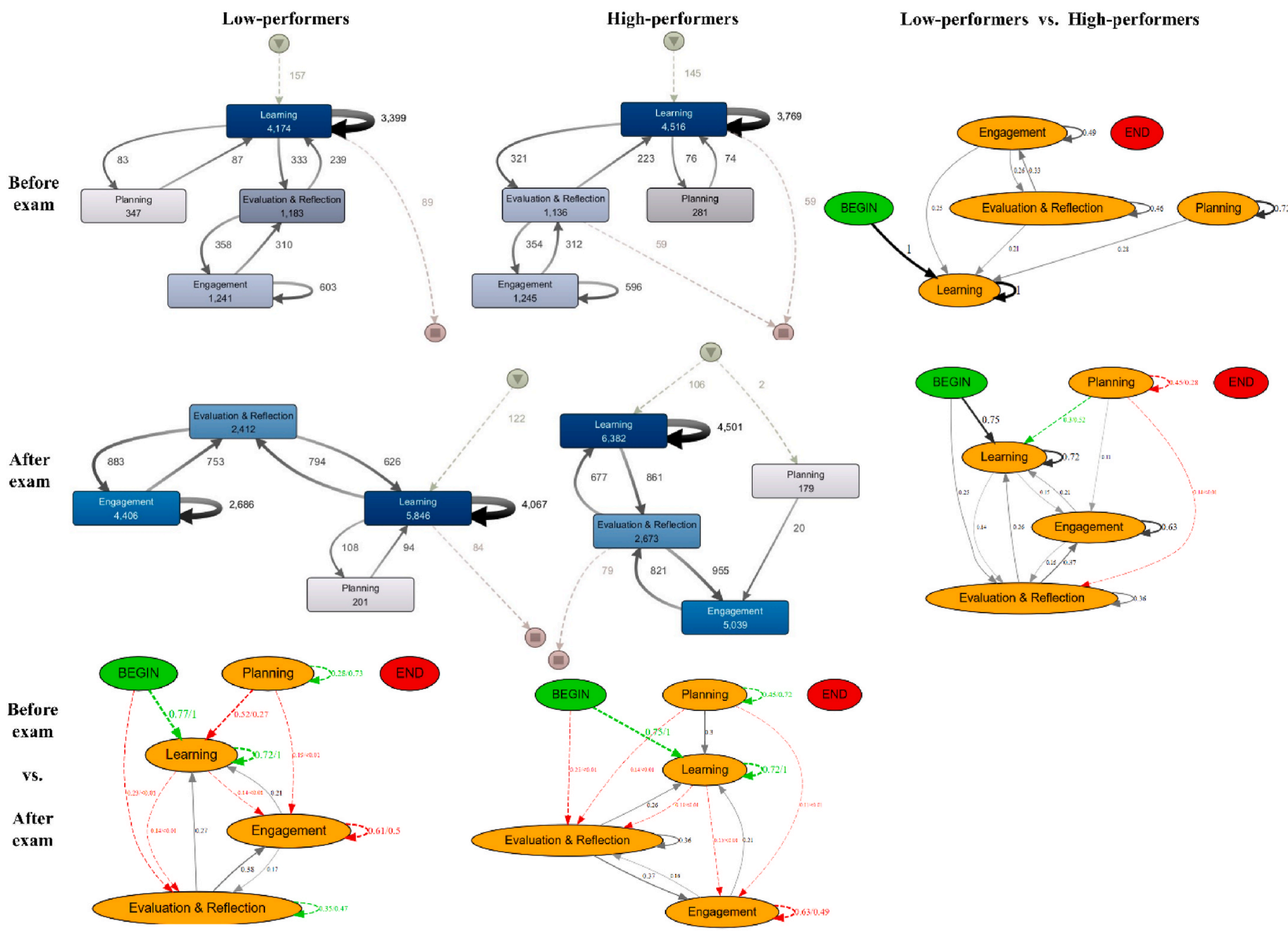
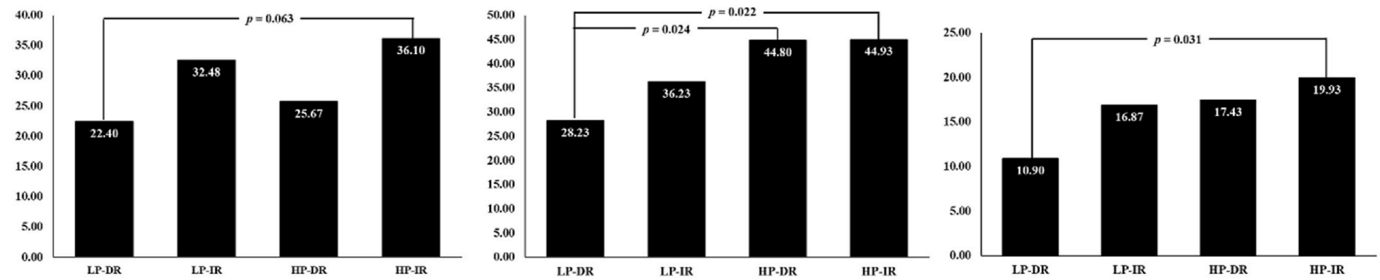


Fig. 4. High- and low-performing students' SRL behavioral patterns before and after the exam.

Table 6
Tests of between-subject effects in multivariate ANOVA.

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Before the exam model							
Intercept	Planning	598.037	1	598.037	31.038	<0.001	0.210
	Learning	102884.826	1	102884.826	247.399	<0.001	0.679
	Engagement	6699.920	1	6699.920	72.118	<0.001	0.381
	Evaluation & Reflection	6652.087	1	6652.087	246.746	<0.001	0.678
Group	Planning	26.636	3	8.879	0.461	0.710	0.012
	Learning	3524.319	3	1174.773	2.825	0.042	0.068
	Engagement	324.499	3	108.166	1.164	0.326	0.029
	Evaluation & Reflection	157.277	3	52.426	1.945	0.126	0.047
After the exam model							
Intercept	Planning	231.680	1	231.680	9.122	0.003	0.072
	Learning	179764.605	1	179764.605	376.430	<0.001	0.763
	Engagement	110409.248	1	110409.248	117.996	<0.001	0.502
	Evaluation & Reflection	32080.550	1	32080.550	212.209	<0.001	0.645
Group	Planning	54.908	3	18.303	0.721	0.542	0.018
	Learning	5754.696	3	1918.232	4.017	0.009	0.093
	Engagement	3040.497	3	1013.499	1.083	0.359	0.027
	Evaluation & Reflection	1319.459	3	439.820	2.909	0.038	0.069

the information processed and produced in one phase to freely flow into any other phase, without rigid adherence to a linear sequence (Greene & Azevedo, 2007). A few empirical studies also provide evidence supporting this non-linear pattern. For example, the research on learners' navigation patterns in a Massive Open Online Course (MOOC) showed that learners frequently used non-linear learning paths and performed backjumps to previous video lectures. In addition, older learners tended to plan their own learning paths, ignoring the linear course structure (Guo & Reinecke, 2014). Moreover, our study found that the planning process had more connections with the learning process but fewer connections with evaluation & reflection and engagement processes. This pattern may be due to the distance between planning and learning being shorter than the distance between planning and each of the evaluation & reflection and engagement processes, making the



Note. The number of three plots are Figure 5a, 5b, and 5c from left to right. In addition, LP-DR, LP-IR, HP-DR, and HP-IR represent low-performance decreased-ranking, low-performance increased-ranking, high-performance decreased-ranking, and high-performance increased-ranking groups respectively. Labels inside each bar indicate the mean scores of each group.

Fig. 5. Pairwise comparison plots in multivariate ANOVAs

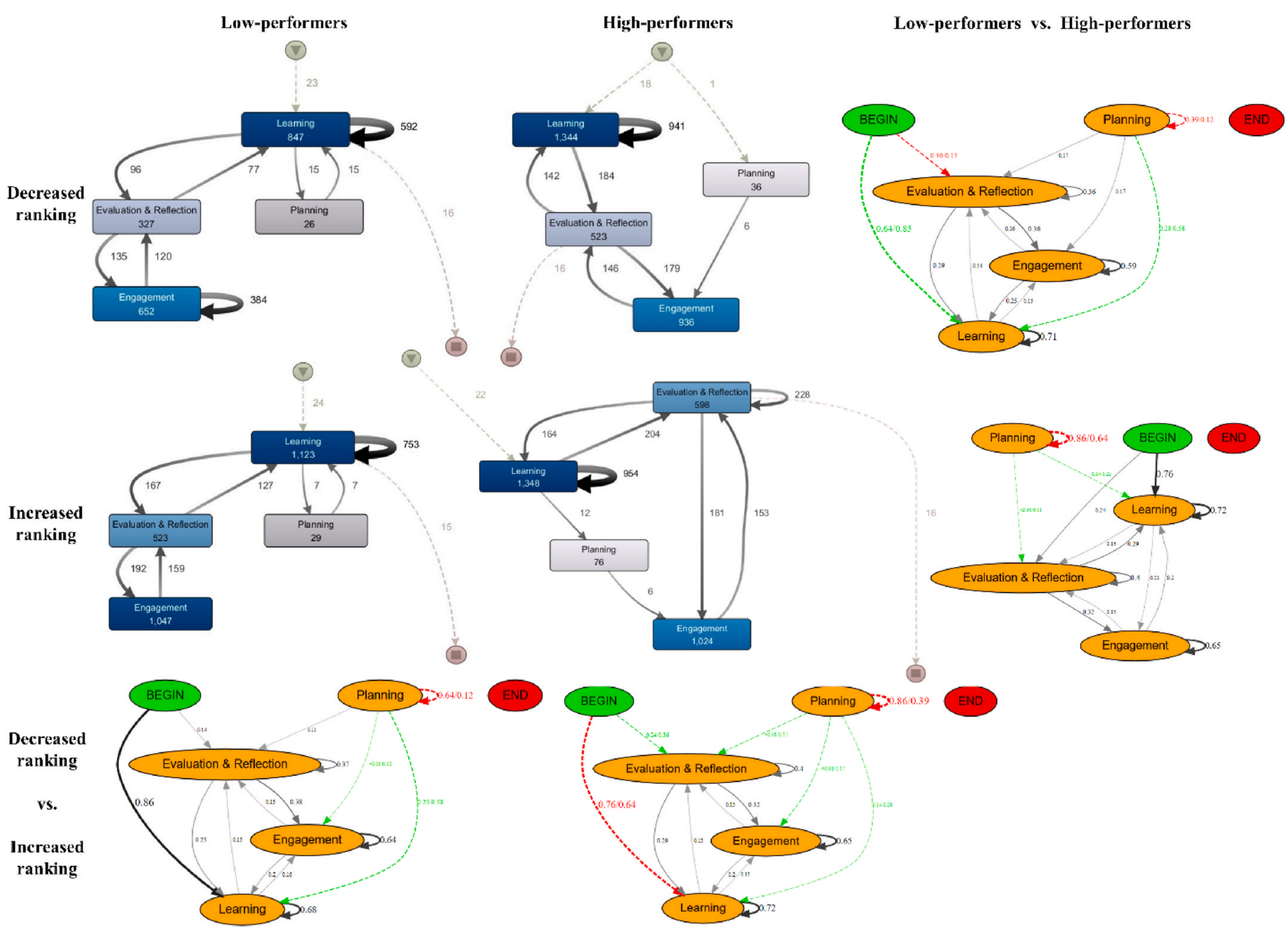


Fig. 6. SRL patterns of four groups of students after the exam.

transition easier. Future research could examine the existence of the jumping phenomenon and its potential causes and underlying mechanisms.

4.2. Role of formative assessment

The present study also found that students actively adjusted their SRL behaviors in response to a formative assessment. Specifically, all students increased their frequency of SRL behaviors, particularly those related to learning, engagement, and evaluation & reflection. They also performed more transitions among several SRL processes. These results provide empirical support for the role of formative assessment on SRL and its adaptation. The mechanism underlying this effect may be feedback obtained through formative assessment, which can originate from instructors, peers, or the students themselves. This feedback could provide information to students for self-assessing whether particular strategies are effective in meeting their learning goals and making adjustments to their knowledge, motivation, behavior, and even context (Andrade & Brookhart, 2016). In addition, evaluative judgment may be another possible explanation. Several studies have highlighted the importance of evaluative judgment (e.g., metacognitive evaluation) on the adaption of SRL (Panadero et al., 2019; Raković et al., 2022). For instance, Raković et al. (2022) examined how struggling students' evaluative judgments made after a first unit exam predicted changes in learning behaviors as well as how those changes predicted performance on a subsequent exam. They revealed that metacognitive evaluation of learning at the end of the learning cycle can induce students' plans to adapt and then enhance the enactment of effective SRL behaviors to improve performances. While these findings provide valuable insights into how formative assessment increases SRL behaviors, it is worth noting that no study has specifically focused on how formative assessment influences behavioral transitions or SRL patterns. Since behavioral transition is a more complex process, future studies could investigate its potential influencing factors and mechanisms in greater depth.

4.3. Group differences in SRL behaviors

The current study revealed group differences in the frequency and pattern of SRL behaviors. To be specific, before the exam, high-performing students exhibited significantly more learning behaviors compared to low-performing students, but their SRL patterns were found to be similar. After the exam, however, high-performing students demonstrated significantly more learning, engagement, and evaluation & reflection behaviors than low-performing students. More importantly, high-performing students actively adjusted the way they engaged in SRL behaviors and developed more structured and interconnected SRL patterns, while low-performing students maintained their established SRL patterns. This pattern adaptation was especially evident for high-performing students who increased their rankings in the second exam. These findings are consistent with previous research indicating that high-performing students demonstrated more learning and regulation events (Bannert et al., 2014), followed the videos and submitted quizzes in a more structured way (Mukala, Buijs, Leemans, & van der Aalst, 2015, p. 18–32), and their recurrent behaviors were more likely to be part of a behavioral sequence (Li et al., 2022). In contrast, low-performing students exhibited less learning and regulation behaviors (Bannert et al., 2014), their behaviors resembled a surface approach to learning (Bannert et al., 2014), and they had a significantly higher ratio of single and isolated recurrent behaviors (Li et al., 2022). In addition to these findings, this study revealed that the behavioral gap between high- and low-performing students was not as large before receiving any feedback or stimulus; however, implementing a formative assessment exacerbated this disparity in SRL patterns.

A possible explanation is that high-performing students have better metacognitive abilities, such as metacognitive monitoring and control. Binbasaran Tuysuzoglu and Greene (2015) investigated the contingent relationship between metacognitive monitoring and control and how students' adaptation after making negative judgments of learning predicted their achievement. They found that students who metacognitively judged their learning strategy to be insufficient and subsequently chose to adopt a new strategy achieved higher scores on a post-test. Another possibility is that high-performing students have a mastery-oriented view toward assessments. An interview of high-performing students regarding their perspectives on the formative and summative assessments showed that high-performing students considered all assessments to be formative to some degree (Brookhart, 2001). They considered studying for a test or doing a project as a contribution to their learning, looked for ways to transfer their current learning to future study, and intentionally worked on self-monitoring (Andrade & Brookhart, 2016). This kind of mastery-oriented thinking enables students to perform more evaluation behaviors and stronger interaction between SRL behaviors (Li et al., 2020).

One implication of the findings from the current study is to enhance students' SRL. This study found that both an increase in the frequency of SRL behaviors and the development of a structured SRL pattern are associated with improved academic performance. Therefore, instructors could intervene in students' SRL from either a specific or holistic perspective (Panadero, 2017). For example, if a teacher observes that one of the students engages in less evaluation & reflection behaviors, they can assist the students by providing more detailed feedback and comparing the student's current achievement to their own goal expectations. If the teacher recognizes that students have an average number of SRL behaviors and that increasing the number of SRL behaviors cannot further improve student performance, they can help students engage in more transitions between SRL behaviors so that students can develop a more structured SRL cycle. Moreover, these findings can serve as resources for teachers to better comprehend the SRL processes of their students. As mentioned by Chen and Bonner (2020), the low prevalence of explicit instruction in SRL may partly be due to teachers' incomplete understanding of student SRL, and how to support it. Lawson et al. (2019) revealed that pre-service teachers' knowledge of learning strategies was generic and that they were unable to articulate why the strategies they mentioned would support learning. Therefore, this study may have the potential to help pre-service teachers understand how SRL operates and the differences between high- and low-performing students' SRL patterns.

4.4. Strengths, limitations, and future directions

The current study investigated the temporal pattern of SRL, and these findings may contribute to a better theoretical conceptualization of the loosely sequenced recursive structure of SRL. In addition, this study provided empirical evidence of the benefits of formative assessment for the change in SRL, considering not only the score on the first assessment but also the ranking change on the second. From a practical perspective, findings from the present study can be used to intervene in both high- and low-performing students' SRL, thereby improving their academic performances. Nevertheless, this study also has several limitations. First, the generalizability of findings is the most significant limitation of most learning analytic studies based on trace data and process mining techniques (Bernacki, 2017). In our study, findings regarding the differences in SRL patterns between high- and low-performing students are consistent with previous findings, supporting the generalizability of the results. However, findings regarding the linear vs. recursive structure of the SRL process and the effect of formative assessment require additional validation. Future studies could focus on exploring this relationship under different contexts. Second, our study manually linked event logs to SRL micro-processes based on the trace-based microanalytic protocol (Siadaty et al., 2016) and previous research (Cerezo et al., 2020; Du et al., 2023). Although this has been the best endeavor feasible under the current circumstances, future research could develop a better approach for linking the event logs with the micro- and macro-SRL processes. Third, this study is conservative regarding the higher transition probabilities of the planning behaviors depicted in Figs. 4 and 6, as they may be due to small process frequency rather than actual probable transitions (Saint et al., 2021). In addition, since both fuzzy miner and pMiner are fundamentally based on the frequency of SRL behaviors, findings from this study may not provide insights into the quality of SRL (Kistner et al., 2010). Given that the quality of planning and other processes is important for enhancing achievement, future research could focus more on the quality aspect of SRL. Finally, the current study examined the change in students' ranking based on calculating the Z score. However, the Z score is indicative of relative rankings rather than actual changes in students' abilities. Future studies could examine the change in students' abilities using latent variable modeling such as item response theory.

5. Conclusion

Findings from this study support that SRL is a loosely sequenced recursive cyclical process. In response to a formative assessment, students actively adjusted their SRL patterns by increasing the frequencies of their SRL behaviors or transitions between processes. There were also group differences in this adjustment: high-performing students exhibited more SRL behaviors and developed more structured and interconnected SRL patterns, while low-performing students displayed a smaller increase in the frequency of SRL behaviors but very little change in their SRL patterns. These findings may contribute to a better understanding of SRL patterns and their adaptation, as well as the role of formative assessment in promoting SRL.

Submission declaration and verification

We declare that this manuscript is original, has not been published before, and is not currently being considered for publication elsewhere. We have no conflicts of interest to disclose.

Authors' contributions

Surina He: Conceptualization, Methodology, Formal analysis, Writing - Original Draft, Writing - Review & Editing, Carrie Demmans Epp: Conceptualization, Supervision, Writing - Review & Editing, Fu Chen: Data curation, Writing - Review & Editing, Ying Cui: Supervision, Resources, Writing - Review & Editing.

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CRediT authorship contribution statement

Surina He: Conceptualization, Formal analysis, Methodology, Project administration, Visualization, Writing - original draft, Writing - review & editing. **Carrie Demmans Epp:** Conceptualization, Supervision, Writing - review & editing. **Fu Chen:** Data curation, Writing - review & editing. **Ying Cui:** Resources, Supervision, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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