Turning Real-Time Analytics into Adaptive Scaffolds for Self-Regulated Learning Using Generative Artificial Intelligence

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Abstract

In computer-based learning environments (CBLEs), adopting effective self-regulated learning (SRL) strategies requires sophisticated coordination of multiple SRL processes. While various studies have proposed adaptive SRL scaffolds (i.e. real-time advice on adopting effective SRL processes) and embedded them in CBLEs to facilitate learners' effective use of SRL strategies, two key research gaps remain. First, there is a lack of research on SRL scaffolds that are based on continuous assessment of both learners' SRL processes and learning conditions (e.g., awareness of learning resources) to provide adaptive support. Second, current analytics-based scaffolding mechanisms lack the scalability needed to effectively address multiple learning conditions. Integration of analytics of SRL with generative artificial intelligence (GenAI) can provide scalable scaffolding for real-time SRL processes and evolving conditions. Yet, empirical studies implementing and evaluating effects of this integration remain scarce. To address these limitations, we conducted a randomized control trial, assigning participants to three groups (control, process only, and process with condition groups) to investigate the effects of using GenAI to turn insights from real-time analytics about students' SRL processes and conditions into adaptive scaffolds. The results demonstrate that integrating real-time analytics with GenAI in adaptive SRL scaffolds – addressing both SRL processes and dynamic conditions – promotes more metacognitive learning patterns compared to the control and process-only groups. In addition, the learners showed varying levels of compliance with analytics-based GenAI scaffolds, and this was also reflected in how the learners coordinated their SRL processes, particularly in the performance phase of SRL. This study contributes to the literature by designing, implementing, and evaluating the impact of adaptive scaffolds on learners' SRL processes using real-time analytics with GenAI.

LAK 2025, March 03–07, 2025, Dublin, Ireland

ACM ISBN 979-8-4007-0701-8/25/03
https://doi.org/10.1145/3706468.3706559

Keywords

self-regulated learning, scaffolding compliance, GenAI, scaffolding, learning analytics

ACM Reference Format:
Tongguang Li, Debarshi Nath, Yixin Cheng, Yizhou Fan, Xinyu Li, Mladen Raković, Hassan Khosravi, Zachari Swiecki, Yi-Shan Tsai, and Dragan Gašević. 2025. Turning Real-Time Analytics into Adaptive Scaffolds for Self-Regulated Learning Using Generative Artificial Intelligence. In *LAK25: The 15th International Learning Analytics and Knowledge Conference (LAK 2025), March 03–07, 2025, Dublin, Ireland*. ACM, New York, NY, USA, 13 pages. https://doi.org/10.1145/3706468.3706559

1 Introduction

Self-regulated learning (SRL) is a pivotal concept in educational psychology, representing the comprehensive ability of learners to proactively and effectively employ various cognitive, metacognitive, and affective strategies tailored to different learning contexts [26, 42, 48]. SRL plays a significant role in online settings where students are expected to exercise great autonomy to, for example, independently search for information useful for their learning, set learning goals, and ensure timely task completion [16].

Despite the recognized importance of SRL, traditional methods of SRL support have exhibited limitations. Early SRL interventions, such as pre-defined scaffolds, provided fixed content that remained unchanged regardless of individual learner differences [3, 14, 44]. Such static interventions failed to address the unique needs of each learner, leading to ineffectiveness in enhancing SRL skills and learning performance [12]. The development of learning analytics (LA) has introduced new possibilities for enhancing SRL by enabling real-time collection and analysis of student online learning data. This data-driven approach holds the potential to inform and support learners' SRL processes by identifying 'spots' where the learners need improvement [5]. Hence, studies have begun leveraging LA to develop adaptive scaffolds, which offers tailored instruction informed by learning data, to provide more tailored SRL support to learners [19, 23]. However, current approaches still have notable limitations, including a lack of continuous assessment of the SRL process and an oversight of individual learning conditions (i.e., external and internal factors that affect the adoption of strategies, such as access to learning resources [41]) in providing automated SRL scaffolds. A critical reason underlying this limitation is the reliance on rule-based scaffolding systems, which commonly used pre-defined rules to monitor students' actions and automatically trigger scaffold messages when specific actions were not detected. When multiple learning conditions and their combined effects need to be considered, predefining messages for every possible combination becomes impractical due to the sheer volume and complexity involved in enumerating all potential rule combinations [2]. As such, current practices are limited in their ability to simultaneously incorporate real-time assessments of both SRL processes and learning conditions, making it difficult to adapt scaffolding in real-time to address each student's evolving needs.

Recent advancements in GenAI like GPT-4o offer promising approaches to address the limitations of existing rule-based approaches. GenAI can generate natural language responses based on prompts feed into a GenAI model [28]. By sending insights from real-time analytics about SRL processes and conditions to a GenAI system through well-designed prompts, we can create immediate and adaptive scaffolds that consider individual SRL processes and conditions in ways unattainable with rule-based systems [2, 33]. However, insufficient studies explored the effectiveness of the use of GenAI to turn real-time analytic insights into adaptive SRL scaffolding in CBLEs [20].

To investigate the potential of GenAI to turn insights of real-time analytics into adaptive scaffolds, we developed a system that integrates GPT-4o into a computer-based learning environment (CBLE) called FLoRA (Facilitating Learners' own Regulation Activities) previously designed to collect data about and support SRL. The CBLE collects trace data (i.e., clicks, mouse movements and keystrokes) and performs analytics in real-time; the insights from the analytics, using carefully crafted prompts, are fed into GPT-4o to generate adaptive SRL scaffolding. This adaptive support is intended to enhance learners' SRL by adjusting to their real-time SRL processes and conditions. We then conducted a randomized controlled trial in the context of a higher education course that aimed to (i) evaluate the effectiveness of adaptive scaffolds – crafted with GenAI based on real-time analytics – on learners' SRL processes; and (ii) examine how learners react to the prompted scaffolding in terms of the suggested processes (i.e., scaffold compliance) and their overall self-regulatory patterns.

2 Background

2.1 Integrating analytics and GenAI for advanced SRL scaffolding

In the current literature, many studies have attempted to implement SRL scaffolding that is adaptive to learners' real-time regulatory processes [19, 36]. This is achieved through analytics-based approaches which utilize trace data to measure and extract SRL processes in real-time [11]. For example, Lim et al. [19] designed rule-based scaffolding based on real-time assessment on learners' SRL process, and evaluated the effects of providing such scaffolds on learners' SRL processes. The results indicated that learners shown significant difference between experimental and control condition in terms of the frequency of high cognition and monitoring processes. However, a recent literature review revealed that the effects of adaptive SRL scaffolding in promoting effective metacognitive processes varies across studies, with an overall moderate improvements in SRL activities [12].

Given the variability in the effectiveness of SRL scaffolds in supporting the use of SRL processes, studies have begun to investigate conditions that may moderate the effectiveness of such scaffolds on SRL processes [12]. For example, Yeh et al. [45] investigated the impact of a self-explaining scaffold, which encouraged learners to articulate their understanding of the subject matter, on learning outcomes among learners with varying levels of prior knowledge. The study found that the effectiveness of the scaffold varied according to the learners' expertise in the subject. For another example, Milikić et al. [21] examined the effects of mirroring-based scaffolds (i.e., scaffolds designed to support social awareness) on self-regulation. Their findings revealed that the impact of scaffolds on self-regulation varied based on students' education level, goal orientation, need for cognition, and level of grit. In summary, these studies revealed that learning conditions are influential on the effects of SRL scaffolding.

According to the well-known COPES model of SRL [41, 42], learning conditions include external conditions – elements from the learning environment such as access to learning resources – and internal condition – attributes that learners bring to the task, such as their level of prior knowledge [42]. External and internal conditions create the context in which learners cognitively and metacognitively operate to produce learning products [42]. For example, in a timed reading and writing task (an external condition), a student with extensive experience in such tasks and a clear understanding of the task requirements (internal conditions) is more likely to allocate more time to writing while employing selective reading strategies (cognitive and metacognitive operations) to successfully complete the essay (learning product). However, while numerous studies have demonstrated that learning conditions can moderate the impact of SRL scaffolding on SRL processes [46], current research typically employs pre-task surveys to collect these conditions and designs scaffolds based on their "condition repertoire" (i.e., varied combinations of conditions) [2]. This reliance stems from the lack of effective methods to capture and integrate multiple aspects of learning conditions in real-time [2]. Moreover, this approach is limited by two main factors: it treats conditions as "static characteristics" [33], thereby neglecting their dynamic nature [42], and each survey only addresses a single aspect of a condition, making it impractical to incorporate multiple conditions without overburdening students with numerous surveys prior to task commencement. To address these limitations, there is a need for methods that can simultaneously capture dynamic changes in multiple learning conditions in real-time to inform SRL scaffolding design.

The emergence of GenAI offers the potential to integrate GenAI models with existing analytics-based protocols. Analytics can effectively monitor real-time SRL processes and learning conditions. The insights of these analytics can be used to prompt GenAI to produce adaptive scaffolds in natural language at scale [28]. However, there is a shortage of studies that have either considered this approach or assessed the effectiveness of such scaffolding in supporting self-regulation. Therefore, this study 1) designed and implemented a scaffolding tool that integrates an analytics-based mechanism for capturing learners' real-time SRL processes and dynamic learning conditions with GenAI for generating adaptive scaffolding informed by analytics, and 2) examined the effectiveness of such scaffolding in supporting self-regulation. Consequently, our first research question (**RQ1**) is: To what extent does the combination of real-time analytics and GenAI enhance the effectiveness of adaptive SRL scaffolding in supporting learners' self-regulation?

2.2 Compliance on SRL scaffolding

Compliance to SRL scaffolding refers to the extent to which learners execute the suggested SRL processes from scaffolds [5]. Due to learners' varying cognitive and metacognitive reactions, scaffolds often yield inconsistent results – some learners act on the suggestions, while others do not adopt the recommended actions even after repeated interventions [25]. It is believed that insufficient compliance hindered students from gaining advantages from the scaffolding [19].

Extensive studies have examined student compliance with different types of SRL scaffolding. For example, Moser et al. [22] implemented metacognitive scaffolds by interrupting students' learning for 2 to 3 minutes and prompting them to use suggested metacognitive strategies. They found that learners who actively engaged with the scaffolds, such as by taking notes and regularly reviewing the suggestions, performed significantly better on post-tests. Similarly, [32] employed five analytics-based scaffolds in a CBLE, presenting suggestions through pop-up windows, and analyzed compliance based on student interactions with the scaffolding tool. They found that when students were more complied to the scaffold (i.e., more inclined to interact with the scaffolding tool), they tended to follow the suggestions especially for scaffolds provided earlier in the task.

Despite emerging studies investigating the compliance of SRL scaffolding, significant gaps remain in the current literature. First, compliance is predominantly examined in terms of the effort or frequency with which learners use and interact with scaffolding tools [32], rather than analyzing how learners directly respond to and integrate the suggested SRL processes into their learning activities. Second, there is a notable lack of research on learners' compliance with adaptive scaffolds that integrate analytics-based protocols with GenAI. Leveraging analytics techniques to capture learners' real-time SRL processes and learning conditions, and subsequently providing this data to a GenAI model – which excels at integrating and comprehensively understanding prompted inputs [28] – could enable the generation of more adaptive scaffolding based on a thorough understanding of students' real-time behaviors and capabilities.

Yet, no studies have analyzed students' reactions and compliance when receiving adaptive scaffolding that combines analytics-based protocols with GenAI. This study aims to fill this gap by investigating how learners adhere to and integrate the specific SRL processes suggested by the scaffolds into their learning. Accordingly, we propose our second research question (**RQ2**) as: To what extent do students comply to suggestions offered by GenAI-empowered scaffolds?

3 Methodology

3.1 Participants

This study involved students from a research-oriented university in China. Participants were graduate-level students who enrolled into an academic English writing course spanning 16 weeks. In total, 211 students initially participated in this study. However, the final sample size was reduced for several reasons: two students opted out from the study, three were excluded due to missing essay data, 25 were excluded for short participation, three did not complete the prior knowledge test, five did not complete the ISDIMU learning strategy questionnaire (see Section 3.2 where the prior knowledge test and ISDIMU questionnaire are explained), and two were removed due to technical issues. We excluded participants with short participation using Tukey's method (whose participation was lower than the 25th percentile value minus 1.5 times the interquartile range), a valid statistical approach for identifying and excluding outliers [38]. This exclusion ensures that students received sufficient scaffolding and continued their learning tasks, thereby allowing for a more accurate assessment of the scaffolding impact on SRL. Ultimately, data from 171 students (46% male, 54% female, M = 23.12, SD = 1.260) were successfully collected and analyzed – 62 in the control group (i.e., no scaffolds), 59 in the scaffolds based on processes only group (Po group), and 50 in the scaffolds based on processes with condition group (PwC group). Briefly speaking, participants in the Po group received scaffolds adaptive to their real-time SRL processes, while those in the PwC group received scaffolds adaptive to both their real-time SRL processes and learning conditions. How each group was designed is further elaborated in section 3.4. Participants' educational backgrounds were widely distributed across various fields, including psychology, educational technology, and computer science.

3.2 Task design

A Moodle-based online learning environment was used in this study, and the learning task adopted was an academic English writing task which was part of the academic writing course offered in the Spring semester of 2024. The outcome of this task did not contribute to their final grade for the course; rather, students were encouraged to use this task as an opportunity to practice their academic English writing skills. The task was available for one week, during which students were expected to find time to complete it on their own, using their own laptops.

The overall study comprised three parts (as shown in Figure 2). Part 1, the pre-task activities, encompassed the administration of two questionnaires and a prior knowledge test. The first questionnaire collected basic demographic data, including participants' gender, age, and educational background. The second, the ISDIMU questionnaire, was aimed at assessing learners' knowledge of various learning strategies [4]. In the questionnaire, each item asked participants to indicate how appropriately they would apply a specific learning strategy within a given learning context. For instance, one question was written as "repeatedly and successively reading their own notes on the topic for memorizing key content while working individually", then selecting "the most suitable" option indicates the participant's likelihood of employing this strategy in the hypothesized context. The third, prior knowledge test, consisted of 15 multiple-choice questions covering topics related to artificial intelligence (AI), differentiation and scaffolding. These topics were closely related to the learning topic of the writing task, thereby gauging the participants' level of prior knowledge on the topic. In Part 2, the training session, participants were introduced to the learning environment and various tools designed to support their SRL processes throughout their main task. The training was delivered through a 10-minute introductory video. Part 3, the main task, where participants were asked to complete a two-hour reflective writing task focused on the topic of AI, the application of AI in differentiation and scaffolding based on the reading resources provided in the learning environment. Figure 1 illustrates the overall design of the interface utilized in Part 3. The right side of the interface provides several instrumentation tools, including a planner tool for outlining a strategic approach to the task, a timer tool for monitoring the remaining time, an annotation search tool for accessing previously made notes and highlights, a dictionary tool for translating individual words from Chinese to English, and an essay writing tool for drafting essays. These tools play a crucial role in capturing and measuring SRL processes, particularly to the extent of higher cognition and metacognition [39]. Moreover, GPT scaffolding tool was also in place for participants who were allocated to the two experimental conditions (see Section 3.4). The navigation bar on the left provided access to various pages containing the general instruction, rubric, and reading pages. On each page, reading text was presented, and participants were allowed to highlight and/or annotate the text.

3.3 Data collection

3.3.1 Pre-test and pre-task survey. Figure 2 shows overall data collection process. In Part 1, upon completing the prior knowledge test and the ISDIMU questionnaire, scores were automatically calculated and recorded to inform the GPT scaffolding prompts (as elaborated in Section 3.4).

3.3.2 Trace data and trace parser. During Part 3, learning trace data were collected while participants worked on the writing task. The trace data comprised three main time-stamped elements: 1) navigation logs, 2) mouse activity, including clicks, movements, and scrolls, and 3) keyboard inputs. Compared to self-reported surveys, trace data have the advantage of identifying learner actions in real-time unobtrusively, thereby capturing the dynamic flow of SRL processes more effectively [30, 43, 47]. While students were working on the writing task, their trace data were automatically coded into learning actions and SRL processes based on our LA techniques embedded in the platform (refer to Figure 2). First, the raw traces were coded into learning action events according to the action library that mapped raw trace data onto learning actions. For instance, continuous key-stroking in the essay window would be labeled as actions of ESSAY writing. Following that, the identified actions would be further processed through the process library, which converted sequenced or continuous learning actions into SRL processes. For instance, if a learner was firstly on the general instruction (action: INSTRUCTION) or rubric page (action: RUBRIC), and then navigated and proceeded (action: NAVIGATION) to another reading page (READING), this sequenced action pattern (i.e., INSTRUCTION/RUBRIC -> NAVIGATION -> READING) was labeled as MC.O.1, representing the first (1) orientation process (O) of metacognition (MC). Refer to the Appendix at this link for the complete action and process libraries. In total, there are seven SRL processes, and the list of each process can be found in Table 1. This trace data parsing approach has been extensively adopted in previous empirical studies [17, 19, 24, 32] and has been validated by using think-aloud data [9]. Lastly, the auto-coded learning actions and SRL processes were used to inform the scaffolding design (elaborated in Section 3.4).

3.4 Scaffold design

3.4.1 Timing and content of scaffolds. Three scaffolds were implemented during the writing task for the Po and PwC groups. Figure 3 illustrates the overall design of these scaffolds and the scaffolding panel. Each scaffold corresponds to one expected SRL process. The first scaffold, triggered at the 5th minute, prompted students to guide their reading based on the task instructions and/or the marking rubric (MC.O.1 — Metacognition - Orientation). The second scaffold, triggered at the 56th minute, encouraged students to initiate effective writing by reviewing the content they had previously read (HC.EO.1 —- High Cognition – Elaboration/Organization).

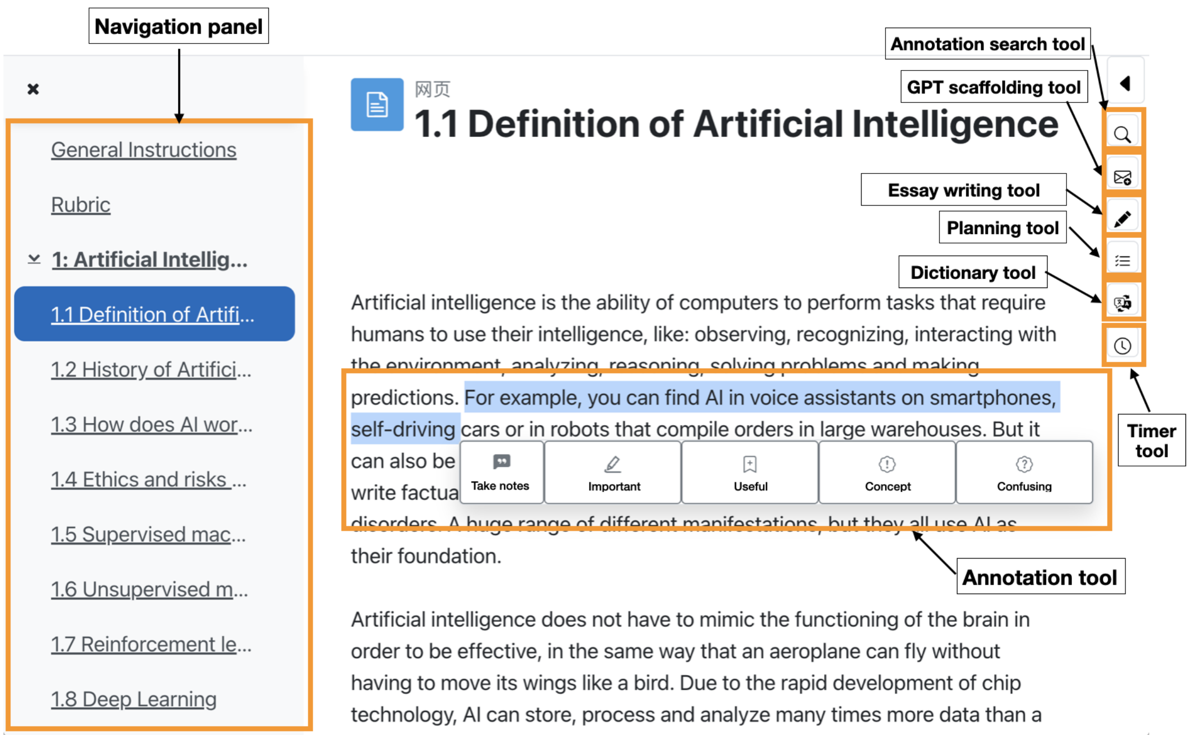


Figure 1: Main writing task interface overview

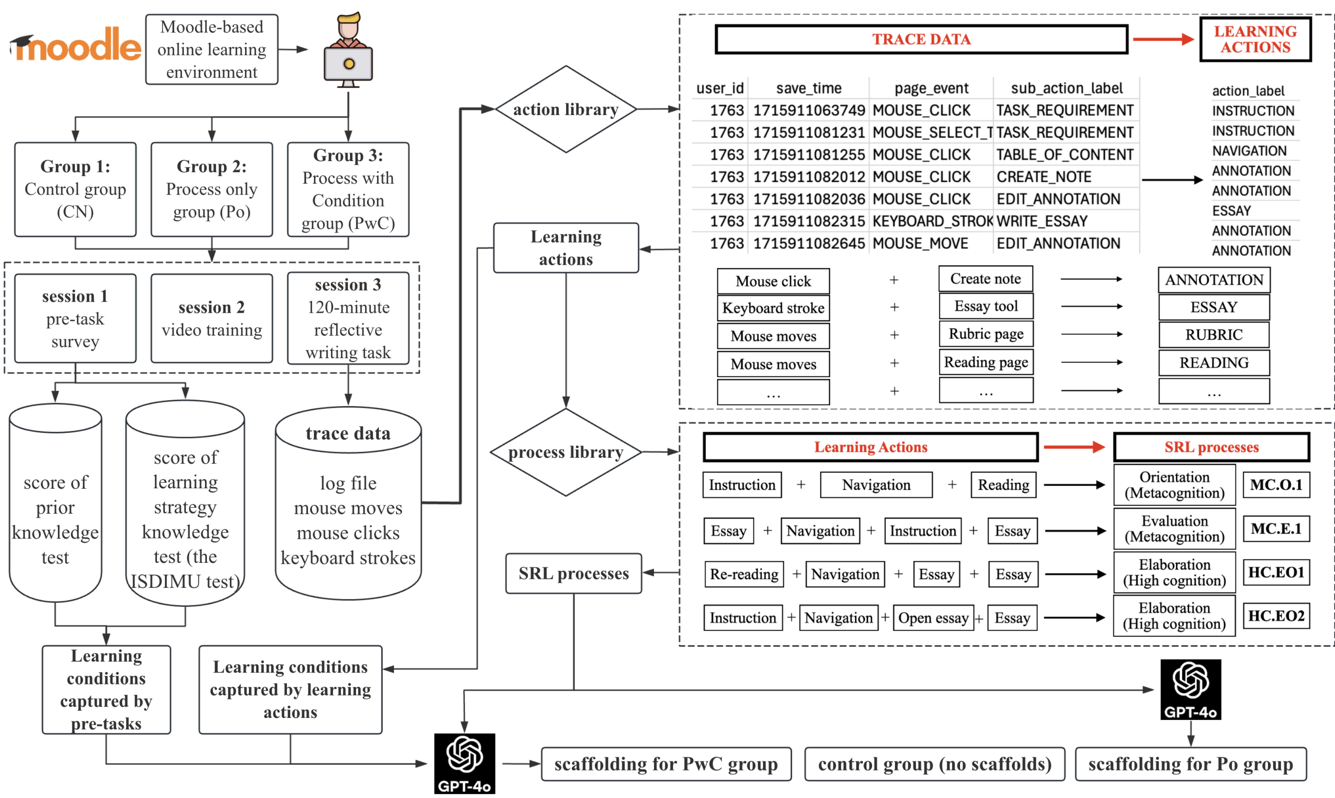


Figure 2: The data collection, data parser, and scaffolding generation

Main Category	Sub-category	Definitions
Metacognition	Orientation	Focusing on gaining an overview of the task. For example, reading instructions and browsing different pages to understand the topics.
	Planning	Organizing activities and strategies for reading and writing, such as using the planner tool to allocate time for reading and writing.
	Evaluation	Assessing the accuracy of learning content or essay draft, such as checking instructions or rubrics when composing the essay.
	Monitoring	Tracking progress in reading and writing, for example, using a timer or planner tool to monitor learning progress.
Low Cognition	First-reading	Reading new content for the first time.
	Re-reading	Revisiting content previously read.
High Cognition	Elaboration/Organization	Connecting related concepts during reading or writing, such as using annotation tools or composing essays.

Table 1: SRL Process Categories

The final scaffold, triggered at the 93rd minute, suggested that learners evaluate their written essays by revisiting the marking rubric, task instructions, and their own notes from the earlier reading process (MC.E.2 – Metacognition – Evaluation). When a scaffold was triggered, a "new suggestion" icon started flashing continuously. Upon clicking it, participants receive a message designed to support their SRL processes, which appears in the designated area (as shown in Figure 3).

The timing of the scaffold prompts was informed by our previous lab study, field study, and interview study [18, 24, 40]. For example, the 5th-minute prompt for guided reading was initially selected based on findings from the lab study [40], and further confirmed by the follow-up field study [24]. These studies used temporal analysis of SRL processes and found that high performers (i.e., those achieving higher final essay scores) demonstrated an earlier “orientation” process compared to their counterparts. Additionally, the three scaffolds align with the SRL conceptual framework, which emphasizes SRL’s cyclical nature: forethought, enactment, and reflection [48].

3.4.2 Scaffold triggering mechanism. We designed three groups to address the proposed research questions (RQs): Control, Po, and PwC. We had the Po (condition-agnostic) and PwC (condition-aware) groups to investigate the extent to which addressing dynamic changes in learning conditions in addition to process only supported effective SRL. The control group was included to evaluate the viability of our proposed scaffolding approach – analytics-based GenAI scaffolding. This section provides a detailed description of how the two scaffolding groups were designed.

For the Po group, scaffolds were triggered based on real-time analytics of SRL processes. Scaffolds were triggered when analytics determined that students had not engaged in the expected SRL processes within the designated detection period for each scaffold (Figure 3). If the expected SRL processes were detected, scaffolds were not provided. For example, if the real-time assessment showed that a participant had not engaged in HC.EO.1 between the 5th and 56th minute, Scaffold 2 would be triggered at the 56th minute with information prompting the student to engage in HC.EO.1.

For the PwC group, scaffolds were triggered based on real-time analytics of their 1) SRL processes and 2) learning conditions. For SRL processes, the scaffold triggering mechanism is the same as to the Po group. Meanwhile, learners’ learning conditions were also assessed in real-time and incorporated into the prompts. Table 2 specifies how each learning condition was captured. Fist of all, we used theory-driven approach to determine constructs of learning conditions that should be included. Based on the COPES model of SRL [41, 42], conditions include, but are not limited to, interest, goal orientation, learning strategies, time constraints, available resources, knowledge of strategies, task knowledge, and subject matter expertise. These conditions formulated the contextual background for learners’ following cognitive and metacognitive operations [42]. Accordingly, our study design attempted to capture and collect these conditional information for each participants. As shown in Table 2, two types of learning conditions were used in this study: dynamic conditions and static conditions. Dynamic conditions included strategic plan-making, awareness of time constraints, awareness of available instrumentation tools, awareness of reading materials, awareness of task requirements, and awareness of the available marking rubric. These were captured through our analytics-based real-time assessment on learning actions. They are termed “dynamic” because they could vary for each scaffold. For example, a student’s awareness of time constraints was determined by detecting the TIMER action, which occurred when a student clicked on the timer tool. If a student did not perform the TIMER action before the first scaffold was triggered but did so before the second scaffold, the student’s awareness of the time constraint was “dynamically” changed. Meanwhile, there were two static conditions – level of prior knowledge and level of knowledge in learning strategies (ISDIMU). These conditions are static as they were informed by the auto-generated scores from the two pre-task session activities, and these conditions remain the same throughout the task. Based on the scores from these assessments, students were categorized into three levels – low, medium, and high – for each condition using a three-tiered classification approach.

Based on our analytics-based real-time assessment of SRL processes (for the Po group) or both SRL processes and learning conditions (for the PwC group), a pre-structured prompt message was sent to GPT-4o. This message was tailored according to the real-time assessment results and consists of several parts: (1) prompts

Condition Type	Learning Condition	How the Conditions were Captured
Dynamic conditions	Strategic plan-making	action detection: SAVE_PLANNER
	Awareness of the time constraint	action detection: TIMER
	Awareness of the available instrumentation tools	action detection: TRY_OUT_TOOLS
	Awareness of the available reading material	action detection: PAGE_NAVIGATION
	Awareness of the task requirement	action detection: TASK_REQUIREMENT
	Awareness of the available marking rubric	action detection: RUBRIC
Static conditions	Level of knowledge of learning strategies	ISDIMU questionnaire score
	Level of prior knowledge	Pre-test score

Table 2: Learner's learning condition design

describing the basic information regarding the task, (2) task instruction and rubric, (3) results from the real-time assessment of SRL processes, (4) results from the real-time assessment of learning conditions (**for the PwC group only**), and (5) guidance on providing effective feedback. Following the effective feedback framework [31], this structured prompt design ensures that GPT-4o receives comprehensive information about the learning context, the specific areas requiring support, and the appropriate phrasing for feedback, thereby enabling more adaptive scaffolding based on each learner's unique situation. A complete example of the prompt can be found in the Appendix at this link.

3.5 Data analysis

3.5.1 RQ1: Ordered Network Analysis (ONA). For RQ1, we compared the overall SRL patterns across different groups (CN, Po, and PwC) and examined how the SRL processes were related within each group's pattern. To achieve this, we employed ordered network analysis (ONA). ONA, which builds on epistemic network analysis (ENA), quantifies and visualizes the frequency of transitions between coded events [37]. In ONA, these transitions are represented as points within a low-dimensional embedding space and as network diagrams, where nodes correspond to the codes and edges to the relative frequencies of transitions between them. We then created subtracted ONA models to compare the SRL patterns between CN vs. Po, CN vs. PwC, and Po vs. PwC. We chose ONA for analyzing SRL processes because SRL is inherently dynamic and evolves over time, and ONA effectively models the temporal associations of these processes, providing robust insights into the frequency and sequentiality [8, 24]. As such, this approach allowed us to visually and statistically compare how learners who received scaffolds (Po and PwC) and those who did receive any scaffolds (CN) demonstrated their SRL patterns.

The networks were set up as follows: each participant was represented by a distinct network, characterized by user and course IDs. Seven codes – Monitoring, Orientation, Elaboration/Organization, First-reading, Planning, Re-reading, and Evaluation – were employed to represent the seven SRL processes derived from the trace data. Each conversation consisted of trace events grouped by user IDs and course IDs. A window size of 45 lines was applied across all models, determined by sampling 23 events and selecting the median window length.

The ONA algorithm yields a network embedding space for each unit of analysis. We constructed ONA models using the means rotation (MR) method, which identifies the network embedding space where the first dimension maximizes variance between groups. All models were centered on comparing the mean differences among participants in each group. To highlight more frequent co-occurrences and transitions between the two groups, we applied network subtractions by subtracting the weights and transitions of the mean networks. Lastly, we conducted a Wilcoxon rank-sum test of ONA results that compared with above pair-wise groups. Effect size of the groups of interest was calculated by using Pearson's r.

3.5.2 RQ2: Dynamic Time Warping (DTW). For RQ2, we aimed to analyze and compare how learners reacted to and complied with the scaffolds over time, and how they differed in terms of their overall SRL patterns. To achieve this, we firstly employed Dynamic Time Warping (DTW) combined with k-means clustering to analyze and visualize the variations in learners' reactions. DTW is particularly efficient and robust in identifying time-series similarities, even when the series are unequal in length [34], and has been found effective in identifying student behaviors in e-learning systems [35] and clustering navigational interactions in multi-source reading tasks [13]. We excluded the CN group from this analysis, as they did not receive any scaffolds. For the two scaffolding groups, we filtered learners' trace data based on whether they had received the scaffolds – recall that a learner would not receive a scaffold if they had already exhibited the expected SRL processes during the detection time period. Clustering analyses were conducted at the scaffold level, resulting in three separate analyses corresponding to the three scaffolds. The time period for each analysis began when a learner clicked on the scaffold icon to open the window and continued until the task was completed. For example, if a learner received the first scaffold in the 5th minute and opened the window in the 6th minute, trace data from the 6th minute onward were included in the clustering analysis for the first scaffold. This approach allowed us to observe learners' immediate reactions and how they complied with the scaffolds after interacting with them.

For each scaffold, we first conducted separate silhouette analyses to determine the optimal number of clusters [29]. Ultimately, two clusters were chosen for each scaffold because the silhouette scores did not improve significantly with a higher number of clusters across all three scaffolds. Additionally, we experimented with higher

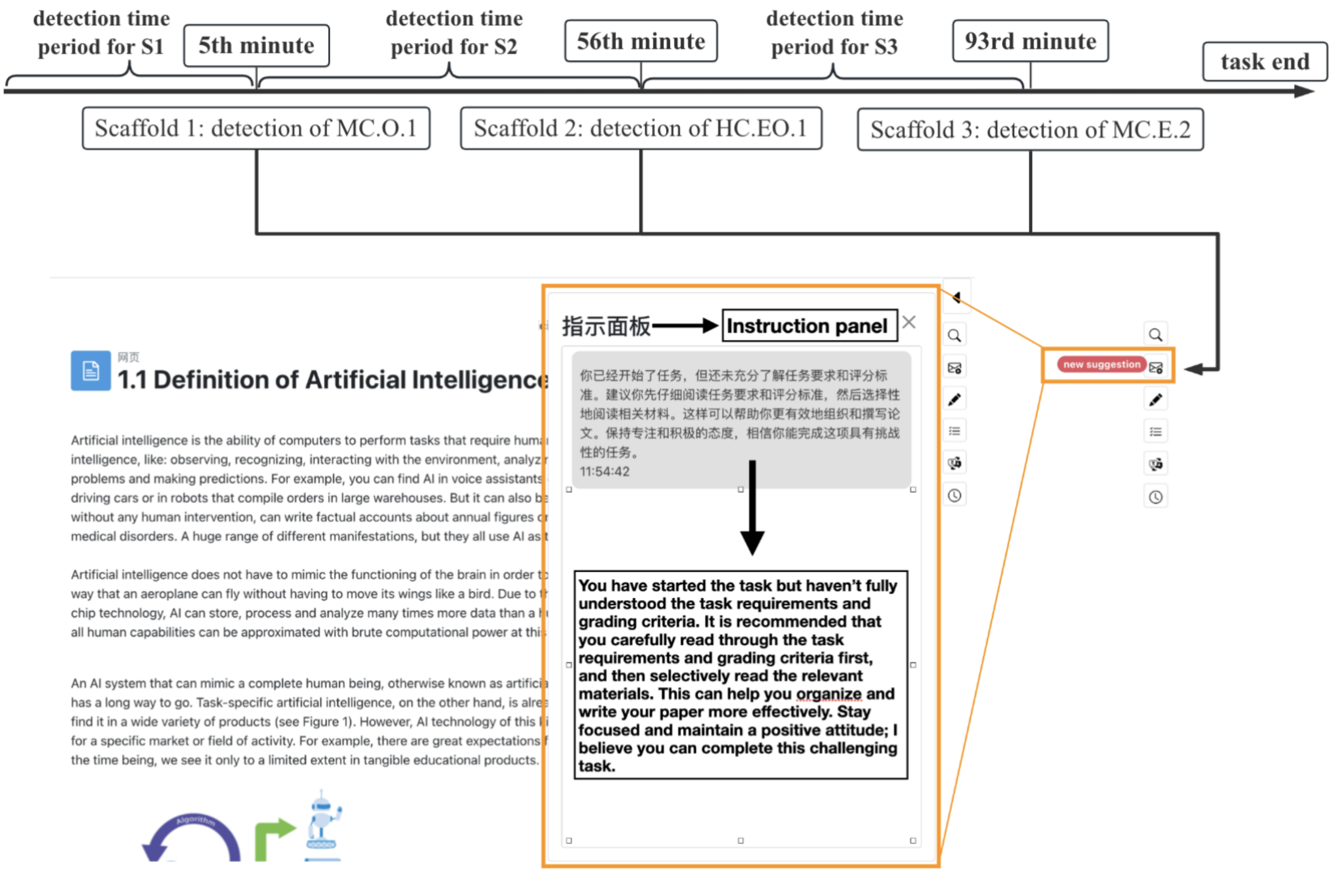


Figure 3: The scaffolding panel

numbers of clusters, but two clusters were sufficient to explain the behaviors of our learners. Based on the DTW clustering results, we generated ONA models for each identified cluster. Individual ONA models were constructed for each cluster and scaffold. We then compared ONA networks at the scaffold level, resulting in three subtracted ONA plots – one for each scaffold. The model configurations were identical to those used for RQ1. To perform pairwise comparisons of ONA networks for each scaffold, we used Wilcoxon rank-sum tests and calculated Pearson's r to determine the effect sizes.

4 Results

4.1 RQ1: effects of GenAI scaffolding on SRL

Figure 4 shows the pair-wise comparisons among three groups (for each individual group, refer to the Appendix at this link). Figure 4 – (a) shows the network subtraction for the CN and Po groups. Blue edges signify more frequent transitions among CN learners, whereas green edges denote those among Po learners. Additionally, larger colored nodes signify that the corresponding group (blue or red) engaged in more self-transition processes, meaning they continuously repeated those specific SRL processes. The first dimension (MR1[1]) explained 36% of the total variance in the data. This dimension mainly differentiates learners who frequently connected to MONITORING on the left from those who more often connected to RE-READING on the right. The network subtraction shows that CN learners made more frequent transitions from RE-READING to FIRST-READING, RE-READING to ELABORATION/ORGANIZATION, and self-transition of RE-READING. These transitions indicate that CN learners mainly adopted a linear learning strategy – drafting their essay with continuous reading and re-reading. In contrast, Po learners demonstrated slightly more frequent transitions from MONITORING to FIRST-READING, self-transitions of FIRST-READING, and self-transitions of ELABORATION/ORGANIZATION. These transitions indicate that they were more engaged continuous reading and writing, and meanwhile monitor their learning process by, for example, checking the remaining time. However, the Wilcoxon test on the first dimension of the ONA space indicated an insignificant difference with large effect size between the two groups ($W = 2105$, $n = 121$, $p = .1531$, $r = 0.707$).

[1]MR1 means "Means Rotation", a dimension reduction technique that maximizes between-group variance and in this study, we do not take the second dimension into account as rotation makes sure the mean of the groups is zero along the second dimension. For detail, see [6]

Figure 4 – (b) represents the network subtraction for the CN and PwC groups, with more frequent SRL processes represented in blue for CN and red for PwC groups. The first dimension explained 19% of total variance. This dimension mainly differentiates learners who frequently connected to Elaboration/Organization on the left from those who more often connected to First-reading and Re-reading on the right. The network subtraction revealed that CN learners performed more frequent transitions from First-reading to Re-reading, and self-transitions of First-reading and Re-reading. These transitions conclude that, compared to PwC learners, CN learners spent more effort on continuous reading processes. In contrast, PwC learners showed more frequent transition from Orientation to Elaboration/Organization, self-transition of Orientation, and self-transition of Elaboration/Organization. These patterns revealed that PwC learners engaged in more effective SRL on essay drafting – regularly consulting instructions and the marking rubric to guide their writing. The Wilcoxon test on the first dimension revealed a significant difference with large effect size between the two group (W = 1944, n = 112 , p = .0213, r = 0.707).

Figure 4 – (c) illustrates the network comparison between the two scaffolding groups – Po and PwC, with more frequent transitions represented in green for Po and red for PwC groups. The first dimension explained 35% of total variance. The dimension mainly distinguished the two groups with Po demonstrated strong self-transition of First-reading on the left and PwC demonstrated more frequent transitions from Elaboration/Organization to Orientation and from Orientation to Re-reading on the right. These dimensional and transitional differences indicate that, overall, the Po learners spent more effort on continuous reading while the PwC learners tended to frequently check instruction (Orientation) to guide their writing (Elaboration/Organization) and reading processes (Re-reading). As such, compared to Po group, learners in PwC group engaged more metacognitive reading and writing processes. The Wilcoxon test on the first dimension revealed significant difference with large effect size (W = 1149, n = 109, p = .0478, r = 0.863).

4.2 RQ2: reactions upon receiving scaffolds

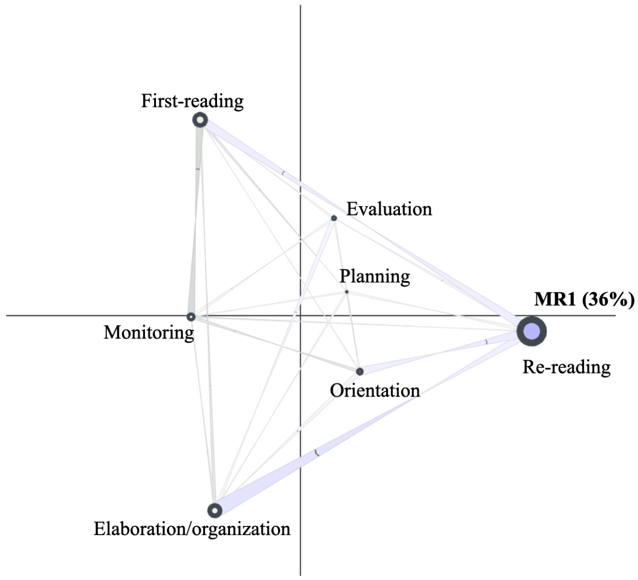
By using DTW and k-means clustering, the analysis consistently revealed two distinct learner groups across all three scaffolds: compliers and non-compliers (the DTW clustering visualizations can be found in the Appendix at this link). Compliers exhibited engagement patterns characterized by either short-term intensive interactions immediately after receiving the scaffold or sustained long-term engagement throughout the task. In contrast, non-compliers demonstrated significantly fewer interactions, with minimal engagement or only sporadic activity upon receiving the scaffolds. Overall, the combination of DTW and K-means clustering differentiated learners based on their compliance with the scaffolds. Compliers either engaged intensively with the prompted processes immediately after receiving the scaffold or sustained their engagement over the long term, while non-compliers largely disregarded the suggestions from scaffolds.

Based on the DTW clustering results, we further created ONA models for the comparison between clusters for each scaffold. Figure 5 summarized the ONA visualizations. In each network visualization, blue edges represent transitions for the compliers, while red edges represent those in the non-compliers for the corresponding scaffold.

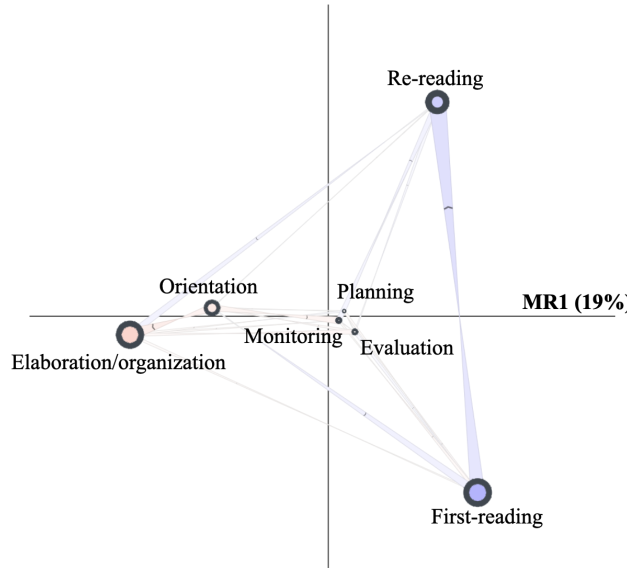
Figure 5-(a) presents the ONA network comparison upon receiving the first scaffold. The first dimension explained 41% of total variance. This dimension mainly differentiates learners who frequently connected to Orientation on the left from those who more often connected to First-reading on the right. Overall, the differences between the two groups were minimal at this stage, as indicated by the small edge sizes in the networks. Non-compliers predominantly exhibited self-transitions in First-reading and transitions from First-reading to Elaboration/Organization, suggesting a focus on sequential reading and essay drafting. In contrast, compliers showed more significant transitions from Orientation to Elaboration/Organization, self-transitions in Re-reading, and transitions from Re-reading to Elaboration/Organization. These patterns indicate that compliers engaged more in oriented writing by utilizing task instructions or rubrics and frequently referring back to previously read materials to guide their writing. The Wilcoxon test revealed no significant difference with large effect size between the groups at this stage (W = 519, n = 74, p = 0.0878, r = 0.707).

Figure 5-(b) presents the ONA network comparison upon receiving the second scaffold. The first dimension explained 16% of total variance. This dimension mainly differentiates learners who frequently connected to Orientation on the left from those who more often connected to Planning and Re-reading on the right. Compliers exhibited prominent bidirectional transitions between Elaboration/Organization and Re-reading, with a stronger transition from Re-reading to Elaboration/Organization. This suggests that, upon receiving the second scaffold, they engaged in effective writing while continuously refining their work based on previously read information. Conversely, non-compliers primarily demonstrated transitions from First-reading to Elaboration/Organization and from Orientation and Monitoring to Elaboration/Organization. These patterns indicate that non-compliers also initiated writing but tended to sequentially check the rubric or task instructions and proceed by reading new material before writing. The Wilcoxon test showed a significant difference between the groups with large effect size (W = 596, n = 54, p < 0.000, r = 0.548), confirming that learners exhibited significantly different SRL patterns upon receiving the second scaffold. Overall, compliers adhered to the scaffold's suggestion to revisit previous notes or previously read information to guide their writing, whereas non-compliers followed a more linear writing process – checking instructions, continuously reading, and then writing.

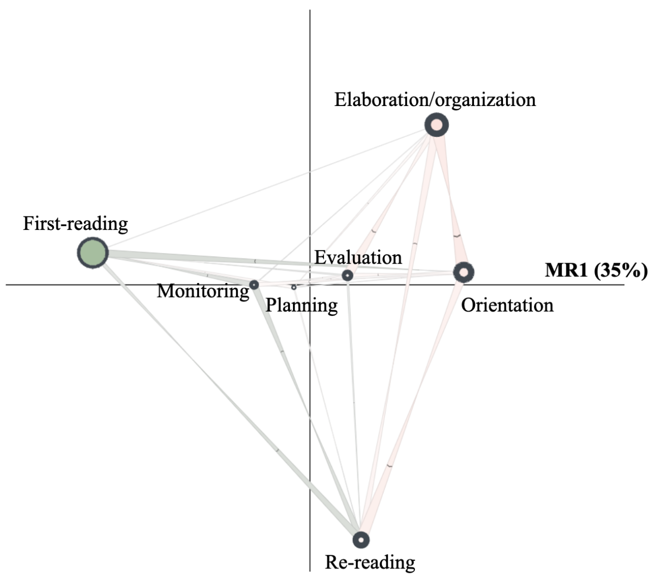
Figure 5-(c) compares the SRL patterns upon receiving the third scaffold. The first dimension explained 17% of total variance. This dimension mainly differentiates learners who frequently connected to Re-reading on the left from those who more often connected to Evaluation on the right. Compliers demonstrated frequent bidirectional transitions between Elaboration/Organization and Evaluation, with a higher prevalence of transitions from Elaboration/Organization to Evaluation. These processes were linked to other metacognitive activities, including transitions from Orientation to Elaboration/Organization and Evaluation, from



(a) subtraction between CN (blue) and Po groups (green)



(b) subtraction between CN (blue) and PwC groups (red)



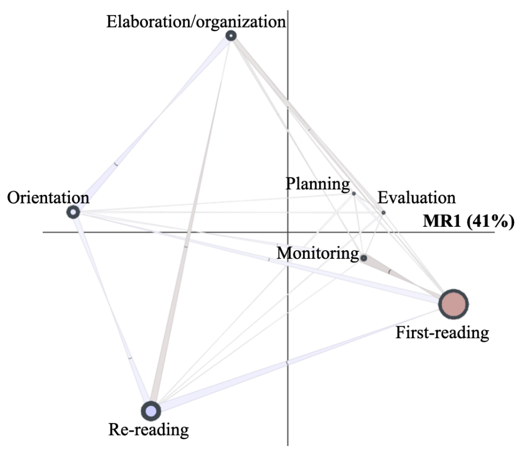
(c) subtraction between Po (green) and PwC groups (red)

Figure 4: ONA visualizations for pair-wise comparisons

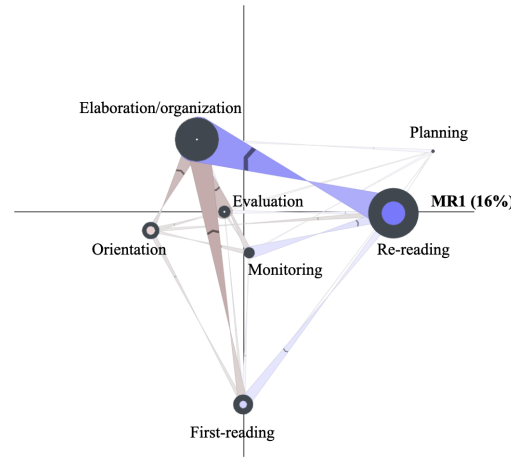
Evaluation to Monitoring, and from Monitoring to Elaboration/Organization. In contrast, non-compliers exhibited notable transitions from Elaboration/Organization to Re-reading and First-reading, and from Re-reading to Monitoring. This suggests that, as the task time was nearing its end, non-compliers devoted more effort to continuous reading and writing while simultaneously monitoring the remaining time, possibly due to time pressure. The Wilcoxon test indicates a significant difference with large effect size between the groups ($W = 291$, $n = 40$, $p < 0.000$). However, the effect size r could not be calculated due to the small sample size. Therefore, the magnitude of the observed differences between the groups remains uncertain for the third scaffold.

5 Discussion and Implications

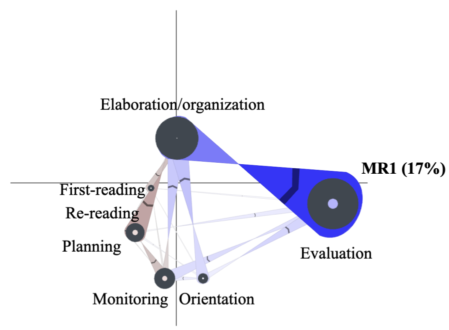
Our study proposed a scaffolding tool that integrates real-time analytics of SRL with GenAI to automatically generate scaffolds for learners' SRL processes. Our pairwise comparisons (RQ1) indicated that learners who received adaptive scaffolding tailored to both their unique learning conditions and SRL processes (PwC) demonstrated significantly more effective SRL patterns. PwC learners consistently consulted task instructions and the rubric, facilitating effective reading and writing processes compared to those in the CN and Po groups. Conversely, scaffolding adapted solely to learners' SRL processes (Po) did not produce significant differences in SRL patterns



(a) subtracted ONA model between two clustered groups for scaffold 1



(b) subtracted ONA model between two clustered groups for scaffold 2



(c) subtracted ONA model between two clustered groups for scaffold 3

Figure 5: ONA Subtracted Models for Each Scaffold: (a) Scaffold 1, (b) Scaffold 2, and (c) Scaffold 3. In all models, blue edges indicate SRL process transitions for compliers, while red edges represent transitions for non-compliers.

relative to the CN group. These findings confirm existing literature, which has shown that scaffolding designed with consideration of learners' conditions is more effective in supporting self-regulation [21, 45]. We also found (RQ2) that learners responded differently to the scaffolds: some consistently engaged with the prompted SRL processes, while others did not. These differences were reflected in distinct overall SRL patterns, particularly when scaffolds encouraged learners to initiate effective writing. Specifically, when the scaffold suggested checking previously read information and annotations to guide their writing, compliers demonstrated clear patterns of following these instructions, proving the effectiveness of our analytics-based GenAI scaffolding in supporting effective use of SRL strategies. These findings also resonate with current literature [22], which found that learners who "made the most out of the prompt" and those who used the scaffolding tool regularly performed significantly higher on the post-test.

In conclusion, these findings contribute to the literature in two significant ways. First, they confirm that analytics-based GenAI scaffolding can feasibly capture dynamic changes in learning conditions alongside the real-time analysis of SRL processes, thereby informing scaffold design for supporting SRL. Second, and more importantly, our scaffolding approach is found to effectively support SRL by capturing and assessing multiple learning conditions at scale. This contrasts with previous studies, which typically assessed SRL processes and learning conditions through pre-task activities or quizzes and were limited in scope, addressing only a narrow range of processes or conditions [2, 23].

Recent studies have begun exploring how GenAI can support SRL [1, 27]. For example, Ali et al. [1] developed a GenAI chatbot that assists students in SRL by promoting inquiry-based learning and self-assessment. However, these studies have primarily focused on prompt engineering – designing prompts to support SRL, while neglecting a fundamental element of effective learning analytics cycle: the learner [7, 10]. On the other hand, the current literature has designed and implemented varies of analytical approaches to leverage multimodal data to understand learners, such as by creating learner profiles or capturing students' use of SRL strategies [15, 20]. Nevertheless, when leveraging these analytical approaches to provide SRL interventions, the current literature falls short in designing automated scaffolding that is comprehensively tailored to learners' real-time SRL processes and learning conditions. Therefore, our study contributes to the field of learning analytics by offering a comprehensive solution that combines analytics-based approaches with GenAI. This integration provides more tailored and adaptive SRL support, moving beyond static, rule-based interventions to deliver dynamic and adaptive scaffolding. Consequently, our approach, which ensures scaffolding is responsive to the evolving needs of learners, advances the concept of "closing the loop" in the age of AI.

6 Limitations and future work

Several limitations should be acknowledged in this study. First, the prompt design used in our adaptive scaffolding is highly contextual, which limits the generalizability of our findings to similar learning environments. Future research could replicate this study design across different subject domains and age groups to evaluate the applicability and effectiveness of the adaptive scaffolding in diverse contexts. Second, we observed a subset of students who did not comply with the scaffolds provided. Further investigation is needed to understand the reasons behind learners' non-compliance and to develop strategies to address this issue. For example, implementing interviews or post-task surveys could yield valuable insights into learners' motivations and perceptions regarding compliance, allowing us to refine the scaffolding approach from the learners' own perspectives. Lastly, we could not assess differences in SRL patterns between compliers and non-compliers for the third scaffold due to a small sample size. The scaffold was triggered near task completion, causing many students to finish early and not receive it. Future studies should increase the sample size to obtain valid statistical results and contribute to our findings.

Apart from these limitations, our study introduces a novel approach that leverages GenAI to provide adaptive support for learners' self-regulation through continuous assessment of their learning conditions and real-time SRL processes. By bridging learning analytics with advanced GenAI technologies, this research contributes to scalable adaptive learning support, advances educational technology by providing empirical insights into the application of GenAI, and lays the groundwork for future AI-driven personalization studies.

Acknowledgments

This research was funded partially by the Australian Government through the Australian Research Council (project number DP240100069 and DP220101209) and the Jacobs Foundation (CELLA 2 CERES).

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