The Effect of Sequential Transition of Self-Regulated Learning Processes on Performance: Insights from Ordered Network Analysis

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Abstract

Productively engaging in SRL is challenging for learners since it involves coordinating multiple motivational, affective, cognitive, and metacognitive processes. Researchers have investigated methods to adaptively scaffold learners' productive engagement using SRL processes automatically captured by SRL detectors. However, most previous studies relied solely on the frequency of SRL processes to drive adaptive scaffolds (e.g., feedback, hints), possibly missing the sequential characteristics inherent to self-regulation, a crucial dimension of productive SRL. To address this gap, this study analysed the impact of sequential transitions between multiple SRL processes on learners' performance on a reading-writing task with a hypermedia environment called Flora. A sample of 66 secondary-school learners completed the task and trace data were collected. Grounded in the COPES model of SRL, a rule-based SRL detector was employed to capture SRL processes from collected trace data. We employed a method combining logistic regression with ordered network analysis (ONA) to analyse the transitions between the detected SRL processes. This exploratory study revealed several influential transitions to learners' performance in different temporal learning blocks of self-regulation. The implications suggest the potential of using COPES SRL process transitions to drive adaptive scaffolds to facilitate engagement in productive SRL, benefiting performance outcomes in hypermedia environments.

CCS Concepts

• **Applied computing → Computer-assisted instruction**.

Keywords

Self-regulated learning, Learning analytics, Ordered network analysis, Learning strategies

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1 Introduction

Self-regulated learning (SRL) is a set of dynamic, goal-oriented processes that learners actively enact to achieve their learning goals [34]. Productively engaging in SRL has been recognised to benefit learners' academic performance [13]. However, productively engaging in SRL is challenging as it involves coordinating multiple interacting processes: motivation, affect, cognition, and metacognition [2, 28]. Learners often struggle to effectively employ SRL processes in response to task demands and challenges [25]. This highlights the importance of adaptively supporting learners' engagement in productive SRL. Yet, the complex and dynamic nature of SRL makes it difficult for educators to detect when learners are not performing SRL processes productively, complicating timely intervention and support [12].

To capture learners' SRL processes, one common approach is to record learners' trace data generated during learning tasks and then extract SRL processes from it [35]. Researchers have developed methods to achieve this automatically, such as by using rule-based algorithms to detect theoretically-based indicators, with emerging technologies (e.g., hypermedia-based systems, intelligent tutoring systems, etc.) [15, 18, 39]. Leveraging algorithms has enabled capturing SRL processes in real-time, thereby allowing timely intervention to adaptively scaffold learners to engage in productive SRL. For instance, detected SRL processes have enabled pedagogical agents to interact with learners during learning tasks via feedback and prompts to facilitate productive SRL [3]. Other recent work has utilised automated detectors of SRL to drive adaptive scaffolding, such as providing personalized messages based on individual SRL processes to enhance performance across various learning tasks [20, 21].

The majority of prior work has almost exclusively assessed the frequency of a specific (or a combination of) SRL processes to diagnose whether SRL is productive or not to drive adaptive scaffolding.

We argue that the frequency of SRL processes alone does not provide insight into the dynamic nature of self-regulation [34], missing the sequential aspect of SRL processes (i.e., sequential transitions between SRL processes) which may be useful in distinguishing between whether SRL is productive or unproductive [7, 30]. Although researchers have increasingly considered the sequential transitions of learning processes to better understand learners' behaviour and needs [30], little to no previous study has combined both the frequency and sequential characteristics of SRL processes to evaluate its relation to task performance. Thus, we extend prior literature by accounting for the frequency and dynamics of SRL processes, presenting implications for driving adaptive scaffolding to more effectively support learners' engagement in SRL.

This exploratory study investigates learners' frequency and the sequential transitions between multiple SRL processes during a learning task and the association of these data with learners' performance. This study was conducted in a 45-minute essay writing task with a hypermedia-based learning system designed for supporting and measuring SRL. We collected trace data from 66 secondary-school learners from two schools in Australia and data were distilled into SRL processes using a rule-based trace parser. Then, we organised the dataset into six temporal learning blocks according to a previous study [21]. These learning blocks were identified based on the analysis of successful learners' strategies in the learning task [22]. Next, we combined logistic regression and ordered network analysis (ONA) [33], a novel approach to model the frequency and sequential transitions between SRL processes detected from trace data, to reveal key transitions between high- and low-performers in the learning task. The analysis revealed several key transitions that positively or negatively contributed to learners' academic performance in each temporal learning block. The findings potentially can contribute to the development of monitoring tools or scaffolding tools to facilitate SRL.

2 Backround

2.1 Measuring self-regulated learning

A distinguishing characteristic of productive SRL is the trail of regulatory and cyclical patterns that it leaves behind. Winne [35] described SRL as a dynamic, task-level process comprised of five facets: Conditions, Operations, Products, Evaluations, and Standards (COPES). Specifically, *conditions* refer to the external (e.g., domain, tools available) and internal (e.g., achievement goal orientation, anxiety) factors that serve as resources to a learner. These conditions define the context which learners use to regulate their operations. Referring to the work of Winne [34], *operations* can be categorised into a set of processes named SMART, which stands for Searching, Monitoring, Assembling, Rehearsing, and Translation. These operations relate to how information is manipulated to facilitate understanding and knowledge construction. From executing operations, *products* are generated (e.g., knowledge gained). Using these products, learners can then *evaluate* their products according to the *standards* of the learning task. From this evaluation, learners can update or adapt their conditions, from which the learner may select the next operation to update or create new *product* toward achieving their goals. This procedure continues dynamically and non-cyclically until the learning goal is met. Thus, effectively identifying SRL requires measuring more micro-level learning processes longitudinally across a learning task to gain insight into the dynamics and non-cyclical patterns inherent to productive self-regulation [35]. The COPES model was used in our approach since it provides one of the more granular and micro-level frameworks of SRL processes that emerge over learning tasks.

State-of-the-art approaches utilise technologies (e.g., MOOCS [16], hypermedia [7, 18, 21, 22, 27, 39], intelligent tutoring systems [3, 8]) to collect longitudinal data on learners' SRL processes using multiple data channels. The most common methods involve 1) self-report questionnaires before, during, and after learning activities [3] or 2) think-aloud protocols that require learners to verbalise their thought processes while they interact with learning software [8, 22]. These methods largely focus on the cognitive and metacognitive aspects of SRL and have revealed the important relationships between academic performance and SRL processes. However, some studies found that utilising think-aloud and questionnaires can be error prone, as learners are not always aware of or able to accurately observe and report their cognitive and metacognitive processes [6, 36]. While think-aloud protocols are often advantageous for establishing 'ground truth' indicators of SRL (when conscious and accurate), copious resources are required to properly transcribe, segment, and code verbalisations to infer SRL processes, limiting researchers to exploit SRL data in real-time to support teachers and their students.

2.2 SRL detectors using trace data

More recently, capturing SRL using trace data that learners generate during their engagement with tasks, such as navigational logs and keystrokes, has become a common practice [14]. With the advancement of learning analytics techniques, researchers have developed a variety of SRL detectors, such as those developed by Hutt et al. [18] and Zhang et al. [39], enabling detection of a range of SRL processes, including COPES and SMART indicators from trace data. For example, Zhang et al. [39] used a combination of text responses and trace data generated from learners while using a mathematics learning platform. These data were used to operationalise different cognitive processes outlined by the COPES framework and SMART model [36], thereby developing several robust SMART detectors that could reliably detect indicators of Searching, Monitoring, Assembling, Rehearsing, and Translating Operations. Another study by [27] examined textual and trace data within an online learning environment where learners engaged in multiple writing tasks. Specifically, trace data was used to detect SRL processes according to the SRL framework of Bannert et al. [7], while textual features extracted from written essays were used to measure the products of SRL processes (e.g., copy and paraphrase vs. synthesise and evaluate). Based on these features, they created a classifier that achieved suitable performance. Moreover, the analysis of these features revealed one SRL product (coverage of reading topics) and three SRL processes (elaboration/organisation, re-reading, and planning) as important predictors of writing quality.

These studies have demonstrated the capability of using trace data to automate the detection of SRL processes in real-time. Researchers have further employed these detected SRL processes to support adaptive intervention [4, 24]. For example, Lim et al. [21]

utilised adaptive and personalised scaffolds administered at different learning blocks to support SRL. These scaffolds were driven by a rule-based algorithm that would prompt learners to engage in different SRL processes according to critical time points that were established based on empirical literature [22]. Specifically, the SRL processes that learners enacted in one time point would serve as a reference point for the algorithm to scaffold their SRL processes in the next time point. The researchers compared learners' SRL processes between the scaffolding condition and the no scaffolding condition, finding that scaffolding can effectively enhance learners' engagement in SRL as indicated by the higher frequency and transition rate of learners' SRL processes in the scaffolding group.

The approach and findings in this previous work emphasised the need to go beyond the frequency characteristics of SRL to evaluate the quality of SRL processes and provoke scaffolding. The nuanced regulatory patterns that are inherent to self-regulation require evaluating the temporality of SRL processes (e.g., transitions, sequences, or dynamics), thereby providing deeper insight into the complexity and cyclical nature of self-regulation. In the last few years, more work has begun examining the temporality of SRL [24]. Yet, how the sequential aspect of the SRL processes can be used to provoke scaffolding for learners remains underexplored.

2.3 Research questions

This study aims to further the research into the sequential aspect of the SRL processes by investigating to what extent the sequential transitions between SRL processes can be indicative of learner performance. Specifically, we investigated two research questions in this study: **RQ1**: What transitions between SRL processes are indicative of learners' performance in different learning blocks? **RQ2**: What SRL processes, which learners frequently transition to or from, are indicative of their performance in different learning blocks?

3 Method

3.1 Research context

This study was conducted in 2023 in the context of an essay writing task. Participants were provided with reading materials on artificial intelligence (AI) and its potential impact on future medicine. They were instructed to write a 200-300 word English essay within 45 minutes to address three components: 1) the concept of AI, including its definition, explanation, and examples. 2) the current use of AI-based technology in daily life and medicine, and 3) the future integration of AI-based technologies in daily life and medicine. Participants were offered the opportunity to draw a 50 Australian dollar gift card as compensation. A total of 71 secondary-school learners participated, of which 66 learners submitted an essay. These learners were from two secondary-schools in Australia and accessed the platform using desktop computers provided in their classrooms. The average age of these learners was 13.45 years (SD = 0.84), ranging from 12 to 15 years, with 38 males, 26 females, 1 non-binary, and 1 preferring not to disclose their gender. All participants consented to the data collection approved by Monash University.

Submitted essays were marked and used to define task performance. Each essay was scored according to the originality of the response to each component listed above. Specifically, 0 marks for no response, 1 mark for copy-and-paste the reading materials, 2 marks for paraphrasing those materials, and 3 marks for providing novel information that did not appear in the reading material. Additionally, these essays were also marked based on satisfying the word count requirement. Zero marks were given for essays with fewer than 50 words or more than 400, 1 mark for essays having 50-100 or 400-450 words, 2 marks for essays having 100-150 or 350-400 words, and 3 marks for essays having 150-350 words. In total, the full mark of an essay is 18. The 66 submitted essays were marked by two researchers. To determine the level of agreement in marking, 25% of essays were randomly selected and independently marked by both researchers. After one turn of resolving conflict, a Cohen's kappa above .8 was achieved for each marking criterion, indicating a strong level of agreement [23]. The remaining essays were then assigned to the two researchers for marking.

3.2 Flora learning platform

Participants completed the essay-writing task using an online learning platform called Flora. As illustrated in Figure 1, Flora provides reading materials and task requirements are listed in a table of contents on the left. Participants can click the topic hyperlinks to navigate to the corresponding page. On each page, reading materials are displayed in the centre of the page with the tools on the right. These tools are used to facilitate SRL and completion of the writing task, including: 1) an annotation, highlighting, and note-taking tool for taking notes on the selected text in the reading materials; 2) a list of notes, where students can access the notes; 3) a searching tool, where students can search across their notes; 4) a writing tool for drafting the essays; 5) a planner tool, where participants can organise their tasks and time allocation on tasks; and 6) a timer displaying the remaining time for the task. Participants could click on the button to show the window for the corresponding tool and then use it. All interaction traces made by participants were time-stamped and recorded by the platform. An example of the key attributes of the collected trace data is illustrated in the *raw trace data* part in Figure 2.

3.3 Data processing

3.3.1 Trace parser. An overview of the procedure of parsing the raw trace data into process labels is illustrated in Figure 2. The trace parser consists of two components — an action library and a process library. The action library was used to parse raw trace data to learning actions according to the instant event and source of the event. For example, the "WRITE" event occurring in the essay writing tool would be parsed into "WRITE_ESSAY" action.

Next, the process library parsed learning actions into SRL processes based on the patterns in learning actions. In detail, the process library was developed based on the COPES model [34, 35]. Several SRL processes were categorised under the five SRL facets in the COPES model. For each SRL process, specific patterns of learning actions were designed to extract SRL processes using a rule-based algorithm. For example, as illustrated in the *Parsing actions (example)* part of Figure 2, checking the timer was labelled as the first case of monitoring time constraint (C.MTC.1). Moreover, the sequence of actions can also influence the labelling. An example of this is the timing of actions, where accessing task requirements

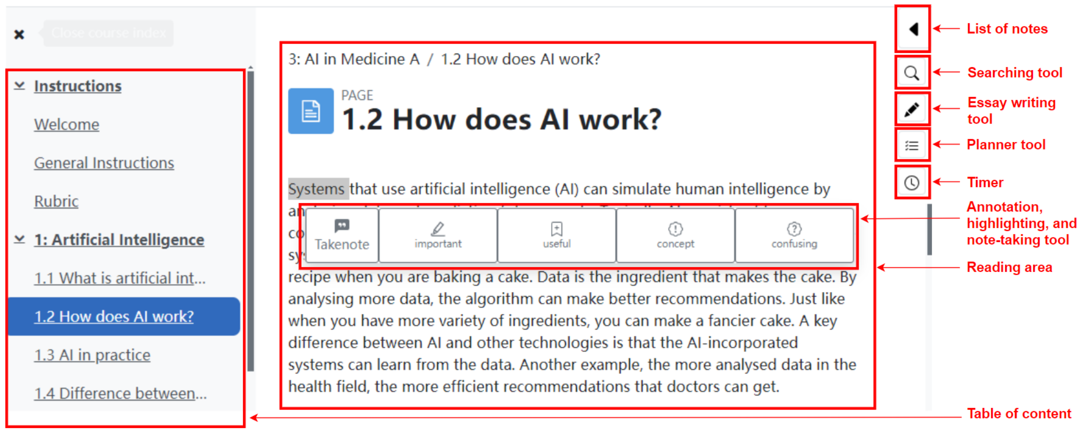

Figure 1: A snapshot of the learning environment of this study.

for the first time is labelled as the second case of surveying task requirements (C.STR.2), while the second time of doing so is labelled as monitoring task requirements (C.MTR.2).

Besides labelling according to the pattern of actions, some SRL processes related to essay writing operations were labelled based on the similarity between the reading materials and learners' essay responses, including the second cases of rehearsing (O.R.2), assembling (O.A.2), and translating (O.T.2). Specifically, the trace parser computed these SRL processes by: 1) breaking the reading materials into sentences; 2) inputting these sentences to sentence transformer to create embeddings [29]; 3) for each time a learner finished writing a sentence, the sentence was input into the sentence transformer; and 4) a cosine similarity was calculated between the learner's sentence and each sentence in the reading materials. If all sentences in reading materials had a cosine similarity score below 0.8, it implied that the learner was paraphrasing or expressing their own understanding, as a cosine similarity above 0.8 typically indicates high similarity in text [1]. This case was labelled as O.T.2. In case of only one sentence in the reading materials having a similarity above 0.8, it indicated that the learner was rehearsing the reading materials, resulting in an O.R.2 label. In contrast, if at least two sentences in reading materials had a similarity above 0.8, it suggested the learner was assembling the information in the material, leading to a label of O.A.2.

More details of the SRL processes that occurred in the dataset used in our analysis can be found in Table 1. Notably, the facets of Product and Evaluation in the COPES model were not included in this table. The Evaluation was excluded because no instances of it were identified in this dataset. Regarding the Product, it is not included in the framework because the product of the learning task was only the essay. Thus, the focus is on the cognitive and metacognitive processes that created the Product. In total, there were 31 learning actions and 30 SRL processes in the framework. Yet, only 15 processes were identified from the dataset used in this study. A complete table of this framework can be found in this online repository [1]. The validity of this framework has been evaluated in a separate paper that is currently under peer-review. This evaluation of validity was conducted by assessing match rates between SRL processes extracted from think-aloud data and those detected from trace data, following the method proposed by Fan et al. [17].

3.3.2 Data processing for analysing transition. To analyse the transition in the SRL process, we merged rows that have the same process labels and removed those where learners did not initiate an SRL process. Then, we empirically selected six learning blocks, as conducted by prior studies [21, 22], to explore different COPES processes that learners used across different temporal learning blocks. Specifically, these learning blocks were organized based on the time spent on the learning task. The six blocks were defined as follows: 0-2 minutes, 2-7 minutes, 7-16 minutes, 16-21 minutes, 21-35 minutes, and 35-45 minutes. Next, we calculated the frequency of transitions among COPES SRL processes for each learning block (e.g., the frequency of SRL process A occurring after B). Lastly, we grouped learners into high- and low-performing groups based on whether scores fell above the median scores on the essay writing task. The median essay score was 11 (61.1% of the full mark) and so learners who received a score higher than 11 were assigned to the high-performing group (n = 33, M = 14.39, SD = 1.77), while scores lower or equal to 11 were assigned to the low-performing groups (n=33, M = 7.87, SD = 2.39).

3.4 Analysis

3.4.1 Logistic regression. To address RQ1, we applied logistic regression analysis to analyse the influence of the frequency of each transition on learners' performance. To perform the analysis, high-performing groups were assigned a label of 1 while low-performing groups were assigned a label of 0. We used R (Version 4.3.2 [26]) to implement the logistic regression model. The independent variables of the model are the frequency of transitions between different COPES SRL processes and the dependent variable was the performance categorisation of learners.

In this study, we observed several transitions that demonstrated high Variance Inflation Factors (VIFs), indicating high multicollinearity. This was caused by learners performing two SRL processes continuously. For example, learners may perform processes A, B, A, and B again, producing a high correlation between the frequency of transitions from A to B and B to A. This is not surprising since

[1]https://osf.io/4jrva?view_only=074618c2bcd742bcb3dc9a1d9b4d3317

Table 1: The labelling framework based on the COPES model for parsing learning actions to SRL processes.

SRL Facets	SRL processes	Acronym	Definition	Action pattern	Frequency
Conditions	Surveying available resources	C.SAR.1	Learner develops perception of resources for the task (e.g., tools for text annotation).	Table_Of_Content	1275
		C.SAR.2		Try_Out_Tools	305
	Surveying task requirements	C.STR.2	Learner develops perceptions about features of the task.	Task_Overview/ Task_Requirement/ Learning_Goal/ Rubric (first time)	109
	Monitoring for time constraints	C.MTC.1	Learner oversees time left for the task.	Timer	522
	Monitoring for task requirements	C.MTR.2	Learner oversees state task requirements during the learning session.	Task_Overview/ Task_Requirement/ Learning_Goal (after the first time)	182
Operations	Searching	O.S.1	Surveying available sources and information and comparing search entries to the standards.	Search_Annotation	71
		O.S.3		Page_Navigation	222
	Monitoring	O.M.1	Evaluating the match of information to a profile of standards (e.g., highlighted phrase and categorical tag assigned to it)	Label_Annotation	3
		O.M.2		Create_Highlight	100
		O.M.3		Read_Annotation/ Delete_Annotation	136
	Assembling	O.A.2	Learner creates a meaningful composite of two or more units of information.	Write_Essay_Assembling	38
	Rehearsing	O.R.2	Learner creates a copy of information.	Write_Essay_Rehearsing	171
		O.R.3		Pastetext_Essay (single source)	71
	Translating	O.T.2	Learner manipulates input information to output information while preserving critical informational properties (e.g., original meaning is preserved and new related information is inserted)	Write_Essay_Translating	1228
Standards	Adopting/applying standard based on task instructions	S.ASBTS.2	Criteria against which products are monitored (e.g., task instructions and scoring rubric)	Open_Planner	87

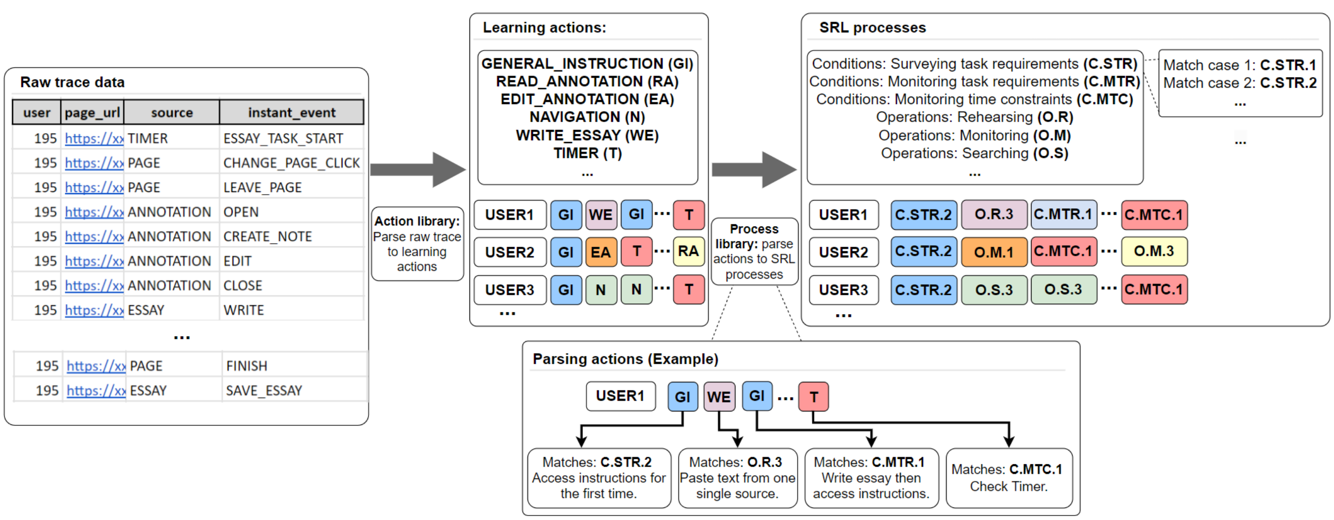

Figure 2: An overview of how the trace parser processes raw trace data into learning actions and subsequently to SRL processes.

the COPES model emphasizes that different processes interact dynamically over time and influence each adaptation [34]. To address this, we implemented an iterative filtering process based on VIFs. In detail, for each iteration, only the transition with the highest VIF value was filtered. This process continued until all transitions had VIFs below 5, indicating minor or no multicollinearity among transitions [19].

Moreover, there were 15 SRL processes observed in the dataset, resulting in 210 possible combinations of the transition. This could lead to sparsity issues in the logistic regression model. To mitigate this, we filtered out transitions performed by less than a certain percentage of learners. We used the percentage value that creates the optimal model indicated by having the lowest corrected Akaike information criterion (AICc) [10]. We found that filtering the transitions that occured for less than 30% of learners created the optimal model. Thus, we used this percentage value for filtering the transitions.

3.4.2 Ordered network analysis. To address RQ2, we employed ordered network analysis (ONA) to identify the SRL processes, which learners frequently transition from or to, that are indicative of their performance. ONA [33] is a method to quantify and visualise the directed connection within coded data derived from Epistemic Network Analysis (ENA) [31]. The key difference between ONA and ENA is that ONA considers the sequential order of the occurrences of codes during the modelling and visualising processes. This enables ONA to analyse the sequential characteristics within coded data [16], allowing analysis of how COPES SRL processes were related to each other by transitioning between them in each learning block.

Regarding the data processing procedures of ONA, ONA starts by accumulating the frequency of the order of codes within *units of analysis* (the subjects of research interest, such as a student) into vectors. This is achieved by iterating through each *line* (i.e., the fundamental unit of meaning of a dataset, such as a line in the event log). When ONA processes each *line*, it examines the codes present in the line along with those in the subsequent *lines*. The codes occurring in the subsequent lines are counted as occurring after the codes in the initial line. Besides, the initial line and subsequent lines collectively form a *stanza window*. Then, the vectors are aggregated across each *conversation* (i.e., collections of meaningfully related *stanza windows*, such as all *stanza windows* in an event log of a learner's access session to Flora) for each *unit of analysis* to acquire cumulative order vectors. Next, a dimensional reduction using Singular Value Decomposition (SVD) or Means Rotation (MR) is applied to the collection of those cumulative vectors to project them as points in a two-dimensional space.

In this study, we used applied MR on the first two dimensions created by SVD to maximise the difference between the high- and low-performance groups on the x-axis of the space. This is achieved by rotating the x-y axes of the two-dimensional space to the direction where the x-axis creates the maximum difference between two groups of data. This is a commonly employed approach to reveal the distinct differences between two groups of comparison [31]. The details of MR can be found in the work of Bowman et al. [9].

After that, ONA networks are visualised in a two-dimensional space. Two representations for each unit of analysis are created in this space: (1) a projected point, representing the location of the projection of the unit's sequential order vector in this space (shown as red or blue points in our study), and (2) a directed weighted network, where nodes correspond to the codes and edges showcase the frequency of directed connection between two codes. The weights of edges are determined by the unit's order vector. Specifically, the node size is proportional to the frequency of its represented code being connected with other codes; and the size of the coloured inner circle of a node is proportional to self-connections. As for the positioning of nodes, the ONA algorithm minimises the distance between the projected points of all units' networks and the centroids of corresponding networks of each point [9]. Consequently, the projected points can be treated as summaries of their corresponding networks, allowing statistical tests on the distribution of these points to compare differences between groups of networks [31, 33]. Moreover, this characteristic of the projected points enables the interpretation of the two dimensions in the projected space based on the locations of the nodes [33]. Similarly, if nodes are positioned on the side of the axis where a specific group of points is clustered, this can suggest that this group tends to create more connections among those nodes. By using COPES SRL processes as nodes, this feature of ONA was used to reveal the SRL processes that learners frequently transition to or from by interpreting the positioning of nodes for addressing RQ2.

Regarding network edges, they consist of a pair of varied size triangles to illustrate the frequency of directed connections. Notably, the ONA network applies a "broadcast" style to represent the order. This means the base points toward the destination of a connection, while the apex of a triangle points at the source of a connection. For ease of inspection, a black chevron is placed on the more frequent side of an edge to support recognising the direction of connections. Regarding the frequency, the bigger and darker a triangle is, the higher the frequency of connections is.

We used the development version (version number: 0.1.1.1684949787) of ONA package[2] [33] in R to perform the analysis. Before conducting ONA, several parameters should be specified, including: *lines*, *conversations*, *stanza windows*, *units of analysis*, and *codes*. In this study, each line in the event log is configured as *lines*. Since the data was related to a 45-minute task, the *lines* of each learner should be all meaningfully related. Thus, we did not further separate the *lines* of each learner into *conversation*. Regarding the size of the stanza window (i.e., the number of lines to consider for accumulating the frequency of order), we used a size of one to reach the same transition matrix as used in logistic regression. Lastly, we configured *each learner* as the *units of analysis*. The same configuration is applied to the analyses of each learning block.

We employed a commonly used approach to identify the prominent differences between high- and low-performing learners [31]. This involved first creating averaged ONA networks by averaging the edge weights of the networks within each group. Then, we subtracted the edge weights of the two groups' averaged networks to generate ONA network subtractions. The created network subtractions used blue colour to represent high-performing learners and red for low-performing learners. Notably, in these network subtractions, if the edge is in red/blue colour, it means that low/high-performing learners have higher edge weights compared to the other. These ONA subtractions were also employed to interpret logistic regression to supplement addressing RQ1, as they highlighted the difference in the frequency of transitions.

4 Results

4.1 Learning block: 0-2 minutes

4.1.1 RQ1. As illustrated in the logistic regression results in the bottom part of Figure 3 (a), three transitions were found that at

[2] https://cran.qe-libs.org/ona/index.html

least 30% of students performed. A likelihood ratio chi-square test showed the logistic regression model fit better than the null model that only contained intercepts at an alpha-level of .05 ($\chi^2(3)$=10.878, p=.012). Out of the three transitions, the transition from the second case of surveying task requirements (C.STR.2) to the first case of surveying available resources (C.SAR.1) was positively and significantly associated with performance grouping (β1=1.08, Z=2.657, SE=.406, p=.007). Moreover, the ordered network subtraction in the top part of Figure 3 (a) illustrates that most of the edges among the nodes were shallow except the one between C.SAR.1 and S.STR.2. The nearly equal-sized triangle indicated that the high-performing group more frequently transitioned between C.SAR.1 and C.STR.2 compared to the low-performing group. This finding matched the logistic regression result. This pair of transitions revealed that surveying the task requirements in the first learning block (0-2 minutes of the task) was associated with high performers compared to low performers.

4.1.2 RQ2. The subplot at the bottom right of ONA subtraction in Figure 3 (a) illustrates the distribution of two groups of learners' projected points. Welch's t-test was performed on projected ONA points along the first dimension (x-axis). This test revealed that the distribution of ONA points of the high-performing group (M=-.113, SD=.189, n=33) was significantly different from the low-performing group (M=.113, SD=.249, n=33) ($t(60)$=4.1, p <.001, Cohen's d=1.021) on the first dimension at the alpha level of .05. This indicated that differences existed in transitions of SRL processes between high- and low-performing groups. Such differences can be identified from the positioning of nodes illustrated in Figure 3 (a). We focused on the node positioning along the x-axis in this figure, as the differences between the two groups were concentrated along the x-axis by performing MR. Moreover, since the projected points of the high-performing group were clustered on the right side and those of the low-performing group on the left, nodes positioned to the left may be indicative of high performance, whereas nodes on the right may be indicative of low performance.

In detail, nodes representing the second case of monitoring (O.M.2) and the first case of surveying available resources (C.SAR.1) were positioned on the left side of the x-axis, suggesting that high-performers more frequently initiated these SRL processes, thus creating more transitions among these SRL processes. According to the patterns in learning actions used for identifying the SRL processes, high-performers more frequently checked the table of contents (C.SAR.1) and used the highlight tool to mark useful information (O.M.2). On the right side, nodes representing the second case of rehearsing (O.R.2), translating (O.T.2), assembling (O.A.2), monitoring for task requirement (C.MTR.2), and the third case of searching (O.S.3) were positioned, suggesting that low-performers more frequently used these processes, demonstrating greater a number of transitions among these SRL processes. Since O.R.2, O.T.2, and O.A.2 are operations related to essay writing, the positioning of these nodes may indicate that low-performers started essay writing at the first learning block. In addition, low performers may also more frequently engage in page navigation (O.S.3) and revisit task requirements (C.MTR,2) during the first 0-2 minutes of the task.

4.2 Learning block: 2-7 minutes

4.2.1 RQ1. As illustrated in the logistic regression result in the bottom part of Figure 3 (b), two transitions were found to occur in at least 30% of learners. A likelihood ratio chi-square test shows the logistic regression model fitted better than the null model at an alpha-level of .05 ($\chi^2(2)$=9.813, p=.007). A significant transition was observed that was negatively associated with performance (β1=-1.164, SE=.471, Z=-2.469, p=.013), which is the transition from the second case of surveying task requirements (C.STR.2) to the second case of translating (O.T.2). Similar to the network for the first learning block, the network in Figure 3 (b) illustrates that most of the edges among the nodes were shallow except the one between C.STR.2 and O.T.2. This also matched with the significant transition in the logistic regression result. This may suggest that exploring the table of contents, finding useful content, and translating the content to essays within 2-7 minutes of starting the task (in the second learning block) can negatively influence task performance.

4.2.2 RQ2. The subplot at the bottom right of the ONA subtraction in Figure 3 (b) illustrates the distribution of two groups of learners' projected points. A Welch's t-test on projected ONA points along the first dimension (x-axis) revealed that the distribution of ONA points of high-performers (M=-.106, SD=.193, n=33) was significantly different from low-performers (M=.113, SD=.180, n=31) ($t(62)$=4.7, p <.001, Cohen's d=1.179). Notably, two low-performers did not perform any SRL process in this learning block, leading to only 31 projected points for low-performers. The similar rationale applies to the results in the following sections when n was less than 33. As illustrated in Figure 3 (b), although nodes representing monitoring (O.M.1 and O.M.2), assembling (O.A.2), searching (O.S.1), rehearsing (O.R.2), and monitoring task requirement (C.MTR.2) presented on the left side, their small size and shallow related edges suggest that only minor differences between the two groups exist for these nodes. On the right side, there were nodes representing the first case of surveying available requirements (C.SAR.1), the second case of translating (O.T.2), and the third case of monitoring (O.M.3), showing that high-performers more frequently performed the transitions related to these SRL processes. These transitions suggest that low-performers tended to check through the table of contents (C.SAR.1) or annotation and highlighting (O.M.3) to find the content to translate the information into their essay content (O.T.3).

4.3 Learning block: 7-16 minutes

4.3.1 RQ1. As illustrated in the logistic regression result in the bottom part of Figure 3 (c), four transitions were demonstrated by at least 30% of learners. A likelihood ratio chi-square test showed the logistic regression model did not fit better than the null model at an alpha level of .05 ($\chi^2(4)$=8.165, p=.085). None of the four transitions were found to significantly influence task performance (ps >.05).

4.3.2 RQ2. Regarding ordered network analysis, a Welch's t-test on projected ONA points along the first dimension (x-axis) revealed that the distribution of ONA points of high-performers (M=-.112, SD=.191, n=32) was significantly different from low-performers (M=.119, SD=.185, n= 30) ($t(61.488)$=4.618, p <.001, Cohen's d=1.23).

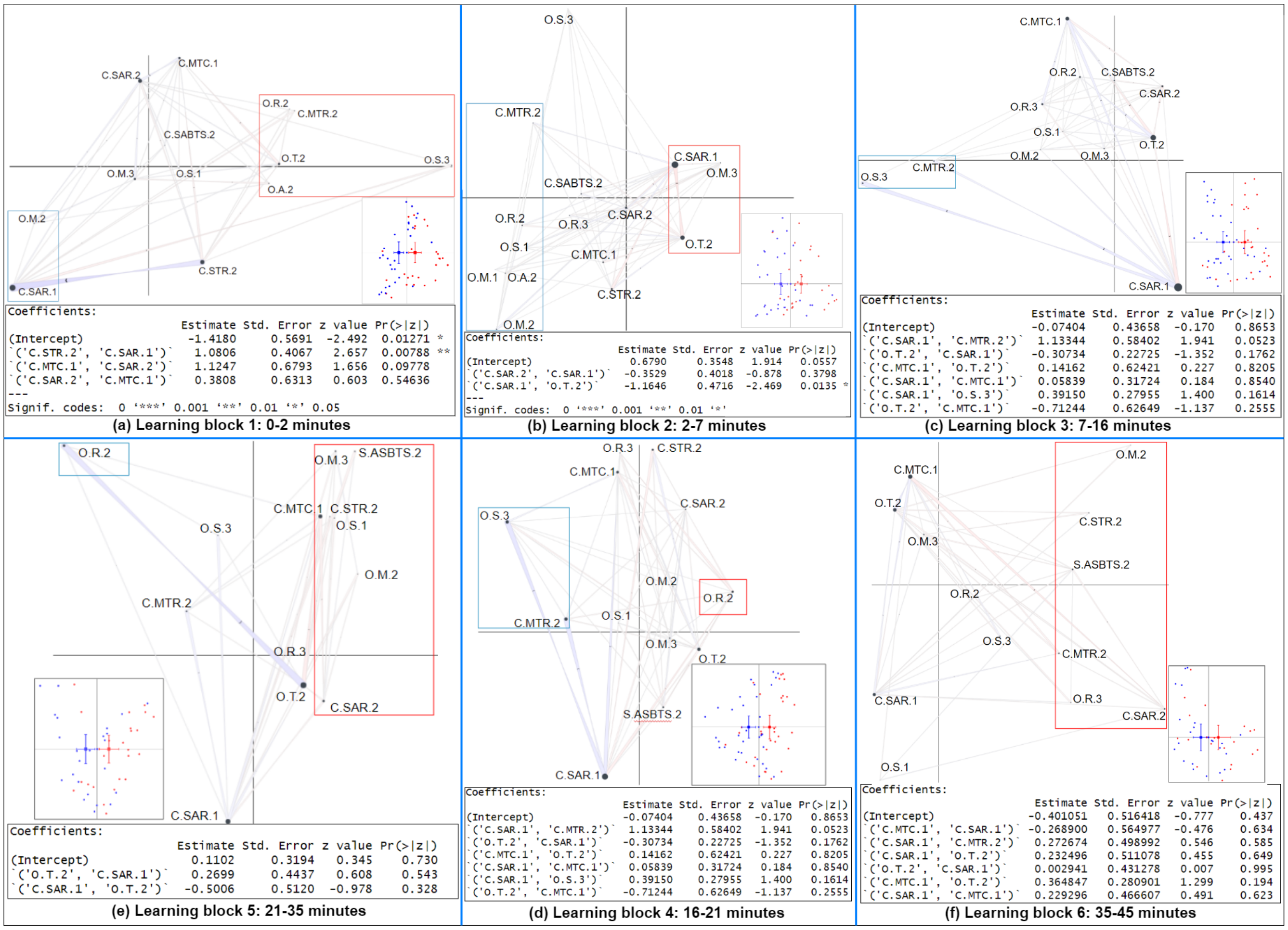

Figure 3: Averaged ordered network subtractions for high-performing (blue edges) and low-performing (red edges) students with logistic regression on the bottom for six learning blocks. The blue rectangle in each network highlights SRL processes that can potentially distinguish high-performing students, while the red rectangle highlights those that may distinguish low-performing students. The plot at the bottom right (or left) of the ONA network subtractions shows the distribution of the projected network points for high-performing (blue points) and low-performing (red points) students, with confidence intervals along both the x-axis and y-axis.

From the node positioning illustrated in Figure 3 (c), it can be observed that surveying available requirements (C.SAR.1 and C.SAR.2) and translating (O.T.2) were positioned on the right side. However, O.T.2 and C.SAR.1 were connected with both blue and red edges. This may suggest that whether the connections related to these two were indicative of learners' performance was uncertain. Regarding C.SAR.2, the edges connected to it were mostly red. This may indicate that low-performing students tended to attempt to use some of the tools for the first time in this learning block (C.SAR.2). On the left side, there are the nodes for searching (O.S.3) and monitoring task requirement (C.MTR.2), indicating the high-performing learners tended to perform the page navigation (O.S.3) and revisit the requirements more during this learning block (C.MTR.2) compared to low-performing learners.

4.4 Learning block: 16-21 minutes

4.4.1 RQ1. As illustrated in the logistic regression result in the bottom part of Figure 3 (d), there are two transitions that at least 30% of learners performed. A likelihood ratio chi-square test showed the logistic regression model did not fit better than the null model at an alpha-level of .05 ($\chi^2(2)$=1.020, p=.6). Neither of the two transitions was found to significantly influence task performance (ps >.05).

4.4.2 RQ2. Regarding the ordered network analysis, a Welch's t-test on projected ONA points along the first dimension (x-axis) revealed that the distribution of ONA points of high-performing learners (M=-.102, SD=.225, n=31) was statistically significantly different from low-performing learners (M=.105, SD=.231, n=30) (t(58.783)=3.54, p <.001, Cohen's d=.907). Specifically, Figure 3 (d) illustrates that high-performing learners tended to focus on rehearsing (O.R.2), while low-performing learners tended to perform a variety of SRL processes, including monitoring article content (O.M.2 and O.M.3) and time constraint (C.MTC.1), applying standard based on task instructions (S.ASBTS.2), surveying task requirement (C.STR.2), searching created annotation (O.S.1), and surveying available resources (C.SAR.2). This may indicate that low-performing learners tended to more frequently survey the materials (S.ASBTS.2, C.STR.2, C.SAR.2, and O.S.1) and highlighting the useful resource (O.M.2), while high-performing learners learners more focused on rehearing the materials to write the essay (O.R.2).

4.5 Learning block: 21-35 minutes

4.5.1 RQ1. As illustrated in the logistic regression results in the bottom part of Figure 3 (e), there are eight transitions that at least 30% of learners performed. Alikelihood ratio chi-square test shows the logistic regression model did not fit better than the null model at an alpha-level of .05 ($\chi^2(6)$=10.198, p=.116). None of the six transitions were found to significantly influence task performance (ps >.05).

4.5.2 RQ2. Regarding the ordered network analysis, a Welch's t-test on projected ONA points along the first dimension (x-axis) revealed that the distribution of ONA points of high-performing learners (M=-.112, SD=.185, n=31) was significantly different from low-performing learners (M=.119, SD=.216, n=33) ($t(61.488)$=4.618, p <.001, Cohen's d=.801). The ordered network subtraction in Figure 3 (e) illustrates that on the left side, almost only blue edges were connected to the nodes representing the third case of searching (O.S.3) and the second case of monitoring task requirement (C.MTR.2), while primarily red edges were connected to the node for the second case of rehearsing (O.R.2). This indicates that low-performing learners tended to focus more on rehearsing the found materials (O.R.2). On the other hand, high-performing learners tended to navigate across pages to find useful materials for writing (O.S.3) while keeping track of task requirements (C.MTR.2). This may indicate that high-performing learners acquired material for writing with more variety.

4.6 Learning block: 35-45 minutes

4.6.1 RQ1. As illustrated in the logistic regression result in the bottom part of Figure 3 (e), a likelihood ratio chi-square test shows the logistic regression model did not fit better than the null model at an alpha-level of .05 ($\chi^2(6)$=3.718, p=.714). None of the six transitions were found to significantly influence task performance (ps >.05).

4.6.2 RQ2. Regarding the ordered network analysis, a Welch's t-test on projected ONA points along the first dimension (x-axis) revealed that the distribution of ONA points of high-performing learners (M=-.083, SD=.197, n=25) was significantly different from low-performing learners (M=.104, SD=.274, n=20) ($t(33.429)$=2.57, p=.014, Cohen's d=.801). The ordered network subtraction in Figure 3 (f) illustrates that both blue and red edges were connected to the nodes on the left side, suggesting no indicative nodes were found for high-performing learners. On the right side, despite the nodes' sizes being small, low performers had slightly more frequent second cases of monitoring task requirements (C.MTR.2), surveying task requirements (C.STR.2), monitoring highlights of materials (O.M.2), applying standards based on task instructions (S.ASBTS.2), surveying available resources (C.SAR.2), and third case of rehearsing (O.R.3), compared to high performers. From these SRL processes, low-performing learners more frequently refer to the planner (S.ASBTS.2) and task requirements (C.SAR.2 and C.MTR.2) to find (O.M.2) and copy the useful content from reading materials (O.R.3) than high-performing learners. Notably, low-performing learners performed C.SAR.2 in this learning block. Since C.SAR.2 can only be detected when students check the instructions after 5 minutes, this indicates that several low-performing learners did not check the task requirement until the last ten minutes of the writing task compared to the high-performing learners, possibly suggesting unproductive SRL.

5 Discussion

The objective of this study was to evaluate the frequency and sequential transition between multiple COPES SRL processes identified using automated SRL detectors during an essay-writing task with the Flora platform. Learners were assigned to groups based on the quality of their essay responses. ONA and logistic regression analysis were used to evaluate the relationships among the sequential transitions among COPES processes on task performance.

In summary, the analysis results in this study revealed several transitions between SRL processes, where the frequency was associated with task performance. Regarding RQ1, transitions that significantly contribute to high or low performance were only identified from the first two learning blocks. Specifically, we found that high-performing learners tended to transition between checking the content table (C.SAR.1) and surveying the task requirement (C.STR.2). This aligns with findings of SRL that checking the task requirements at the beginning of the task to build an understanding of the condition of the task can contribute to task performance [11, 37]. In the second learning block, the transition between translating material content to essay content (O.T.2) and checking the content table (C.SAR.1) (operation→condition) was negatively associated with task performance. This transition may suggest that low-performing learners conducted essay writing in the early learning blocks of the task. This aligns with the finding in previous studies that "read first, write later" tends to be a more effective strategy than conducting writing in the early stage [32].

Regarding RQ2, the statistical tests showed that the distribution of ONA networks' projected points was significantly different between high- and low-performing learners across all learning blocks. From the positioning of the nodes, we identified several SRL processes that high- and low-performing learners tended to transition to (or from) more frequently. Specifically, high-performing learners tended to revisit task requirements more frequently during the task, indicated by the positioning of the monitoring task requirement (C.MTR.2) on the left in learning blocks 2, 3, 4, and 5. We suspect that some low-performing learners may not realise the importance of task requirements and delay accessing them until the latter half of the task. This is suggested further by the C.STR.2, which represents accessing the task requirement for the first time, being positioned on the right side and most edges connected to it are red in the last three learning blocks. This is also aligned with prior findings, which suggest that the importance of monitoring task requirements is critical for building an understanding of the condition to guide self-regulation during a task [11, 37, 38].

Moreover, the positioning of the nodes can also suggest that the overall strategy of high-performing learners tended to be read-first and write-later, aligning with the findings in the work from Srivastava et al. [32]. Specifically, in the first three learning blocks, high-performing learners more frequently performed monitoring operations (O.M.1 or O.M.2) that represent highlighting or annotating reading materials. This suggests that high-performing learners focused more on reading, leading to a higher frequency of annotations and highlights in the first part of the task. In the last three learning blocks, O.M.1 and O.M.2 shift to the right side, suggesting that high-performing learners spend less effort on reading and potentially more on writing in later learning blocks.

5.1 Practical implication

This study has direct implications for researchers and practitioners for detecting multiple SRL processes automatically with an online learning platform. Specifically, we found that the frequency of transitions between specific SRL processes was associated with high performers compared to low performers and vice versa. These insights can be utilised to drive adaptive scaffolding with online learning systems, such that if a learner is infrequently transitioning between specific SRL processes (e.g., operations→conditions), it may be indicative of unproductive SRL that harms task performance. Yet, researchers rarely examined the impact of transitions of SRL processes on performance currently. More research is needed to confirm the impact of these transitions and confirm whether the findings can transfer to other learning environments and learning tasks.Moreover, the method that combines ONA with logistic regression presents an approach to interpret network subtraction edges with statistical evidence, providing more insight into the relationships among SRL process transitions. Researchers may consider adopting this approach to interpret edges when applying similar quantitative ethnography methods, such as epistemic network analysis [31].

5.2 Limitation and future work

This study is not without limitations. First, the learning blocks explored in this study were determined empirically according to the previous study [21]. While the learning tasks and time limit were the same as in the prior study, there were differences in the participants' educational levels, the reading materials, and the task requirements. Therefore, the expected behaviours in each learning block may be different [21]. Consequently, the learning blocks in our study are used solely as temporal blocks to explore differences in the transitions demonstrated by high- and low-performers. Studying the more appropriate learning blocks for secondary school learners can be meaningful future work.

Second, the dataset in this study may be insufficient to fully reveal the interesting transitions from logistic regression analysis in the last four learning blocks. This issue becomes apparent when comparing the logistic regression results and ONA results, as several recognisable directed connections appear in the ONA subtractions while not significant in the logistic regression result. We inspected the frequency of transitions in such cases and found that only a few learners performed these transitions more frequently than others in the same group, leading to such situations. Whether such cases are outliers or driven by individual differences (e.g., prior knowledge, personality, gender, motivation, emotions) should be explored more in future work. Enriching trace data with other data channels, such as physiological signals (e.g., [28]), facial recognition, or data-driven interviews [5] may provide more insight into individual-level factors that influence SRL process transitions and their relation to task performance.

Lastly, although we identified several transitions that are indicative of learners' task performance, whether these transitions can be used to drive monitoring prompts or adaptive scaffolding tools that effectively facilitate productive SRL is an area we aim to explore in future research.

6 Conclusion

In summary, we presented a method that combines logistic regression and ONA to analyse the transitions between SRL processes. The results revealed several transitions between SRL processes that can be indicative of high- and low-performers in different temporal learning blocks. Our method and the findings hold implications for developing adaptive scaffolding tools to facilitate learners to engage in productive SRL that benefit task performance with digital learning platforms.

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References

[1] M. Alewiwi, C. Orencik, and E. Savaş. 2016. Efficient top-k similarity document search utilizing distributed file systems and cosine similarity. *Cluster Computing* 19 (2016), 109–126.

[2] R. Azevedo. 2015. Defining and Measuring Engagement and Learning in Science: Conceptual, Theoretical, Methodological, and Analytical Issues. *Educational Psychologist* 50, 1 (2015), 84–94. https://doi.org/10.1080/00461520.2015.1004069 arXiv:https://doi.org/10.1080/00461520.2015.1004069

[3] R. Azevedo, F. Bouchet, M. Duffy, J. Harley, M. Taub, G. Trevors, E. Cloude, D. Dever, M. Wiedbusch, F. Wortha, et al. 2022. Lessons learned and future directions of metatutor: Leveraging multichannel data to scaffold self-regulated learning with an intelligent tutoring system. *Frontiers in Psychology* 13 (2022), 813632.

[4] R. Baker, D. Xu, J. Park, R. Yu, Q. Li, B. Cung, C. Fischer, F. Rodriguez, M. Warschauer, and P. Smyth. 2020. The benefits and caveats of using clickstream data to understand student self-regulatory behaviors: opening the black box of learning processes. *International Journal of Educational Technology in Higher Education* 17 (2020), 1–24.

[5] R. S. Baker, S. Hutt, N. Bosch, J. Ocumpaugh, G. Biswas, L. Paquette, J. A. Andres, N. Nasiar, and A. Munshi. 2023. Detector-driven classroom interviewing: focusing qualitative researcher time by selecting cases in situ. *Educational technology research and development* (2023), 1–23.

[6] M. Bannert and C. Mengelkamp. 2008. Assessment of metacognitive skills by means of instruction to think aloud and reflect when prompted. Does the verbalisation method affect learning? *Metacognition and Learning* 3 (2008), 39–58.

[7] M. Bannert, P. Reimann, and C. Sonnenberg. 2014. Process mining techniques for analysing patterns and strategies in students' self-regulated learning. *Metacognition and learning* 9 (2014), 161–185.

[8] C. Borchers, J. Zhang, R. S. Baker, and V. Aleven. 2024. Using think-aloud data to understand relations between self-regulation cycle characteristics and student

performance in intelligent tutoring systems. In *Proceedings of the 14th Learning Analytics and Knowledge Conference*. 529–539.
[9] D. Bowman, Z. Swiecki, Z. Cai, Y. Wang, B. Eagan, J. Linderoth, and D. W. Shaffer. 2021. The Mathematical Foundations of Epistemic Network Analysis. In *Advances in Quantitative Ethnography*, A. R. Ruis and S. B. Lee (Eds.). Springer International Publishing, Cham, 91–105.
[10] M. J. Brewer, A. Butler, and S. L. Cooksley. 2016. The relative performance of AIC, AICC and BIC in the presence of unobserved heterogeneity. *Methods in Ecology and Evolution* 7, 6 (2016), 679–692.
[11] D. L. Butler and S. C. Cartier. 2004. Promoting effective task interpretation as an important work habit: A key to successful teaching and learning. *Teachers college record* 106, 9 (2004), 1729–1758.
[12] G. L. Callan and S. S. Shim. 2019. How Teachers Define and Identify Self-Regulated Learning. *The Teacher Educator* 54, 3 (2019), 295–312.
[13] A. L. Dent and A. C. Koenka. 2016. The relation between self-regulated learning and academic achievement across childhood and adolescence: A meta-analysis. *Educational Psychology Review* 28 (2016), 425–474.
[14] J. Du, K. F. Hew, and L. Liu. 2023. What can online traces tell us about students' self-regulated learning? A systematic review of online trace data analysis. *Computers & Education* 201 (2023), 104828. https://doi.org/10.1016/j.compedu.2023.104828
[15] Y. Fan, M. Rakovic, J. van der Graaf, L. Lim, S. Singh, J. Moore, I. Molenaar, M. Bannert, and D. Gašević. 2023. Towards a fuller picture: Triangulation and integration of the measurement of self-regulated learning based on trace and think aloud data. *Journal of Computer Assisted Learning* 39, 4 (2023), 1303–1324. https://doi.org/10.1111/jcal.12801 arXiv:https://onlinelibrary.wiley.com/doi/pdf/10.1111/jcal.12801
[16] Y. Fan, Y. Tan, M. Raković, Y. Wang, Z. Cai, D. W. Shaffer, and D. Gašević. 2023. Dissecting learning tactics in MOOC using ordered network analysis. *Journal of Computer Assisted Learning* 39, 1 (2023), 154–166. https://doi.org/10.1111/jcal.12735
[17] Y. Fan, J. van der Graaf, L. Lim, M. Raković, S. Singh, J. Kilgour, J. Moore, I. Molenaar, M. Bannert, and D. Gašević. 2022. Towards investigating the validity of measurement of self-regulated learning based on trace data. *Metacognition and Learning* 17, 3 (2022), 949–987.
[18] S. Hutt, J. Ocumpaugh, J. Ma, A. L. Andres, N. Bosch, L. Paquette, G. Biswas, and R. S. Baker. 2021. Investigating SMART Models of Self-Regulation and Their Impact on Learning.. In *Proceedings of the 14th International Conference on Educational Data Mining (EDM)*. ERIC.
[19] J. H. Kim. 2019. Multicollinearity and misleading statistical results. *Korean journal of anesthesiology* 72, 6 (2019), 558–569.
[20] T. Li, Y. Fan, Y. Tan, Y. Wang, S. Singh, X. Li, M. Raković, J. Van Der Graaf, L. Lim, B. Yang, et al. 2023. Analytics of self-regulated learning scaffolding: effects on learning processes. *Frontiers in psychology* 14 (2023), 1206696.
[21] L. Lim, M. Bannert, J. van der Graaf, Y. Fan, M. Rakovic, S. Singh, I. Molenaar, and D. Gašević. 2024. How do students learn with real-time personalized scaffolds? *British Journal of Educational Technology* 55, 4 (2024), 1309–1327. https://doi.org/10.1111/bjet.13414
[22] L. Lim, M. Bannert, J. van der Graaf, I. Molenaar, Y. Fan, J. Kilgour, J. Moore, and D. Gašević. 2021. Temporal assessment of self-regulated learning by mining students' think-aloud protocols. *Frontiers in Psychology* 12 (2021), 749749.
[23] M. L. McHugh. 2012. Interrater reliability: the kappa statistic. *Biochemia medica* 22, 3 (2012), 276–282.
[24] C. Paans, I. Molenaar, E. Segers, and L. Verhoeven. 2019. Temporal variation in children's self-regulated hypermedia learning. *Computers in Human Behavior* 96 (2019), 246–258.
[25] R. Pérez-Álvarez, J. Maldonado-Mahauad, and M. Pérez-Sanagustín. 2018. Tools to Support Self-Regulated Learning in Online Environments: Literature Review. In *Lifelong Technology-Enhanced Learning*, V. Pammer-Schindler, M. Pérez-Sanagustín, H. Drachsler, R. Elferink, and M. Scheffel (Eds.). Springer International Publishing, Cham, 16–30.
[26] R Core Team. 2023. *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/
[27] M. Raković, S. Iqbal, T. Li, Y. Fan, S. Singh, S. Surendrannair, J. Kilgour, J. van Der Graaf, L. Lim, I. Molenaar, et al. 2023. Harnessing the potential of trace data and linguistic analysis to predict learner performance in a multi-text writing task. *Journal of Computer Assisted Learning* 39, 3 (2023), 703–718.
[28] M. Raković, Y. Li, N. M. Foumani, M. Salehi, L. Kuhlmann, G. Mackellar, R. Martinez-Maldonado, G. Haffari, Z. Swiecki, X. Li, G. Chen, and D. Gašević. 2024. Measuring Affective and Motivational States as Conditions for Cognitive and Metacognitive Processing in Self-Regulated Learning. In *Proceedings of the 14th Learning Analytics and Knowledge Conference* (Kyoto, Japan) *(LAK '24)*. Association for Computing Machinery, New York, NY, USA, 701–712. https://doi.org/10.1145/3636555.3636934
[29] N. Reimers and I. Gurevych. 2019. Sentence-BERT: Sentence Embeddings using Siamese BERT-Networks. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing*. Association for Computational Linguistics. https://arxiv.org/abs/1908.10084
[30] J. Saint, Y. Fan, D. Gašević, and A. Pardo. 2022. Temporally-focused analytics of self-regulated learning: A systematic review of literature. *Computers and Education: Artificial Intelligence* 3 (2022), 100060. https://doi.org/10.1016/j.caeai.2022.100060
[31] D. W. Shaffer, W. Collier, and A. R. Ruis. 2016. A tutorial on epistemic network analysis: Analyzing the structure of connections in cognitive, social, and interaction data. *Journal of Learning Analytics* 3, 3 (2016), 9–45. https://doi.org/10.18608/jla.2016.33.3
[32] N. Srivastava, Y. Fan, M. Rakovic, S. Singh, J. Jovanovic, J. Van Der Graaf, L. Lim, S. Surendrannair, J. Kilgour, I. Molenaar, et al. 2022. Effects of internal and external conditions on strategies of self-regulated learning: A learning analytics study. In *LAK22: 12th international learning analytics and knowledge conference*. 392–403.
[33] Y. Tan, A. R. Ruis, C. Marquart, Z. Cai, M. A. Knowles, and D. W. Shaffer. 2023. Ordered Network Analysis. In *Advances in Quantitative Ethnography*, C. Damşa and A. Barany (Eds.). Springer Nature Switzerland, Cham, 101–116.
[34] P. H. Winne. 2017. Cognition and metacognition within self-regulated learning. In *Handbook of self-regulation of learning and performance*. Routledge, 36–48.
[35] P. H. Winne. 2023. *Roles for Information in Trace Data Used to Model Self-Regulated Learning*. Springer International Publishing, Cham, 175–196.
[36] P. H. Winne and D. Jamieson-Noel. 2002. Exploring students' calibration of self reports about study tactics and achievement. *Contemporary Educational Psychology* 27, 4 (2002), 551–572.
[37] P. H. Winne and R. W. Marx. 1982. Students' and teachers' views of thinking processes for classroom learning. *The Elementary School Journal* 82, 5 (1982), 493–518.
[38] Z. Yan. 2020. Self-assessment in the process of self-regulated learning and its relationship with academic achievement. *Assessment & Evaluation in Higher Education* 45, 2 (2020), 224–238. https://doi.org/10.1080/02602938.2019.1629390 arXiv:https://doi.org/10.1080/02602938.2019.1629390
[39] J. Zhang, J. M. A. L. Andres, S. Hutt, R. S. Baker, J. Ocumpaugh, N. Nasiar, C. Mills, J. Brooks, S. Sethuaman, T. Young, et al. 2022. Using machine learning to detect SMART model cognitive operations in mathematical problem-solving process. *Journal of Educational Data Mining* 14, 3 (2022), 76–108.