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Network Analytics to Unveil Links of Learning Strategies, Time Management, and Academic Performance in a Flipped Classroom

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Abstract

Preparatory learning tasks are considered critical for student success in flipped classroom courses. However, less is known regarding which learning strategies students use and when they use those strategies in a flipped classroom course. In this study, we aimed to address this research gap. In particular, we investigated mutual connections between learning strategies and time management, and their combined effects on students' performance in flipped classrooms. To this end, we harnessed a network analytic approach based on epistemic network analysis (ENA) to analyze student trace data collected in an undergraduate engineering course ($N = 290$) with a flipped classroom design. Our findings suggest that high-performing students effectively used their study time and enacted learning strategies mainly linked to formative and summative assessment tasks. The students in the low-performing group enacted less diverse learning strategies and typically focused on video watching. We discuss several implications for research and instructional practice.

Notes for Practice

- We investigated the effects of learning strategies and time management on students' performance.
- Epistemic network analysis (ENA) was used to analyze undergraduates' trace data.
- High-performing students effectively used their study time and enacted learning strategies.
- Learning strategies of high-performing students were linked to formative and summative assessment.

Keywords

Learning analytics, learning strategies, self-regulated learning, time management

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1. Introduction

Many contemporary educators use active learning pedagogies (Freeman et al., 2014) to promote student engagement in a course. As opposed to traditional lecture-only instruction (He et al., 2016), educators who adopt active learning approaches often require students to use a variety of course resources and engage in a number of meaningful learning activities inside and outside the classroom. Many active learning courses include an online component, e.g., a learning management system (LMS), that hosts course resources and instructions for learning tasks.

One of the most commonly used forms of active learning is the flipped classroom. It generally involves two groups of learning activities, pre-class and in-class (Abeysekera & Dawson, 2015), that usually reoccur across different course topics every week. Pre-class learning activities include student engagement in preparatory learning tasks, e.g., video lectures, readings, and online quizzes. These activities are designed to help students develop background knowledge and skills, which enables and fosters in-class learning. In-class activities promote analysis, synthesis, and evaluation (Roehl et al., 2013; Sajid et al., 2016) of what students have studied during the pre-class stage. For this reason, preparatory activities are considered critical for student success in flipped classroom courses.

Because pre-class activities are typically offered online with strict due dates assigned, students need to figure out on their own how and when to engage in studying to complete the activities in a timely manner and harness the affordances of online learning. In this context, students' ability to self-regulate their learning processes becomes critical (Bernard et al., 2014; Cho & Kim, 2013; Cho & Shen, 2013). There are, however, empirically supported concerns that many students may not have a sufficient command of self-regulated learning (SRL) skills to productively study on their own during preparatory activities (Roehl et al., 2013). This may increase the risk of attrition (Lee & Choi, 2011) and hinder the sparsely documented benefits of using flipped classrooms (Abeysekera & Dawson, 2015; Jovanovic et al., 2017; Lin & Hwang, 2018; Thai et al., 2017). For this reason, promoting productive SRL remains an important item in the contemporary educational research agenda and, to this end, educational researchers have increasingly attempted to deepen their understanding of SRL processes and determine ways to promote students' SRL (Ahmad Uzir et al., 2020; Bernacki et al., 2020; Greene, 2020; Jovanovic et al., 2017; Raković et al., 2022).

According to Winne and Hadwin (1998), at the outset of a learning cycle (e.g., course Week 2), productive self-regulated learners evaluate requirements and constraints of a learning task, set goals, and make plans on how to accomplish them. Self-regulated learners then enact learning strategies, a goal-oriented sequence of learning actions, to accomplish their goals. Self-regulated learners also monitor the effectiveness of the learning strategies they chose. At the end of the learning cycle, they reflect on prior learning and adjust learning for the upcoming cycles (Winne & Hadwin, 1998).

Enactment and monitoring of learning strategies are central to productive SRL (Winne, 2013; Winne & Hadwin, 1998). However, effective strategy use is affected not only by students' knowledge of which strategy to choose and when to enact it but also by the overall task requirements. In other words, when managing their learning, productive self-regulated learners consider the broader instructional context, including studying time, learning environment, and academic support (Dent & Koenka, 2016; Pintrich, 2000). In particular, management of studying time is theorized to benefit SRL processing, including learning strategy enactment, and boost learning performance (Weinstein & Mayer, 1983; Winne & Hadwin, 1998). In the context of flipped classroom courses, the time available for pre-class weekly assignments is a critical resource for students to consider in order to successfully complete all preparatory activities for class on time (Abeysekera & Dawson, 2015). This suggests that students' time management skills could be important for their overall success in a flipped classroom course.

In a limited number of studies (Fincham et al., 2018; Gašević et al., 2017; Matcha et al., 2019; Srivastava et al., 2022), researchers have provided empirical evidence supporting associations between the use of particular learning strategies (e.g., self-testing) and academic performance. The relationship between time management and academic performance in online learning is less clear, though indicated in a small group of studies (Douglas et al., 2016; Kizilcec et al., 2017). Moreover, because learning strategies and time management were usually studied independently (but see Ahmad Uzir and colleagues (2020) as an exception), little is known about whether these two constructs may jointly correlate with academic performance in flipped classroom courses.

In the present study, we sought to deepen the understanding of how time management and strategy use in SRL may be associated with academic performance in flipped classrooms. To this end, we identified learning and time management strategies from trace data of undergraduate students in a computer engineering course based on flipped classroom principles. In the analysis, we applied a network analytic approach that allowed us to identify the relationships among multiple time management and learning strategies observed over 12 weeks of the course. Our results suggest that learning strategies and timing of their enactment jointly affect students' examination performance. These findings may inform future development of early warning systems and instructional interventions to promote effective time management and strategy use, toward more productive SRL and improved course performance in flipped classrooms.

2. Background

This section outlines relevant background literature on flipped classrooms, learning strategies, and time management.

2.1 The Flipped Classroom

The concept of flipped classrooms has received much attention recently due to its potential to facilitate active learning. It was initially inspired by the work of Bergmann and Sams (2012), who offered an approach to guiding students toward understanding of learning content through the use of online resources prior to face-to-face classes. Such online preparatory activities are primarily designed to elicit remembering, comprehending, and applying to help students develop the background knowledge required for face-to-face sessions (Heinerichs et al., 2016; Tucker, 2012). Meanwhile, in-class time is typically used to encourage the development of higher-order thinking and promote active learning through analysis, synthesis, and evaluation (Roehl et al., 2013; Sajid et al., 2016).

Instructors in flipped classrooms design opportunities for independent online learning. To this end, they assign pre-class activities such as readings, video lectures, online discussions, summative or formative assessment, or a combination of these. In class, instructors facilitate students' active participation using knowledge acquired during preparation (Gilboy et al., 2015; Heinerichs et al., 2016). Because online preparatory activities are important for students to succeed in flipped classrooms, it is critical for instructors to promote student engagement when they study online. This is, however, often a challenging task, particularly as learning design becomes more complex and the increased workload prevents instructors from regularly monitoring students' pre-class learning progress and providing timely guidance (Lockyer et al., 2013; O'Flaherty & Phillips, 2015).

As a result, students in flipped classrooms often need to take responsibility for their own learning (He et al., 2016; Sun et al., 2018). Under these instructional settings, students' ability to self-regulate their learning becomes critical for maximizing learning gains in pre-class activities and capitalizing on the promises of an active learning approach (Lin & Hwang, 2018; O'Flaherty & Phillips, 2015; Pierce & Fox, 2012; Thai et al., 2017). Specifically, students need to appraise the requirements of weekly preparatory tasks and enact learning strategies that help them acquire background knowledge prior to each lesson. Many students, however, struggle to productively engage in SRL (Pardo et al., 2017; Wolters, 2003), which often hinders their course performance (Lee & Choi, 2011). The problem is further amplified by the rigorous time requirements of pre-class activities in flipped classrooms; i.e., students need to complete the assigned tasks on time every week and come to class prepared. Moreover, knowledge acquired in pre-class activities in each week is often essential to succeed in in-class assignments and examinations in subsequent weeks.

2.2 Learning Strategies, Time Management, and Task Requirements in SRL

According to Winne and Hadwin (1998), studying as SRL encompasses four loosely ordered stages: task definition, goal setting and planning, strategy enactment, and adaptation to future studying. In the task definition stage, the learner surveys internal (e.g., domain knowledge, knowledge of study strategies) and external (e.g., task instructions, available resources, time constraints) task conditions. These conditions affect how the task will be perceived and engaged. After developing the perception of the task in Stage 1, in stage 2 the learner sets goals, often aligned with those set by the course instructor, and develops a plan on how to approach the goals over the period of study (e.g., a lab study session, a week prior to a lecture). The plan includes study strategies, i.e., goal-oriented sequences of actions performed to complete a learning task (Hadwin et al., 2007) (e.g., listening, note taking, self-testing, revisiting), and they are enacted in Stage 3. Self-regulated learners monitor if the studying strategies they chose are sufficient to advance their learning toward goals as planned and often decide to modify a study strategy or a plan (Winne, 2005), e.g., "I want to read the book chapter before I start watching the video lecture, and I will dedicate additional time early next week to complete this activity," or "From the next week, I plan for additional studying time to revisit concepts from previous weeks." Effective time management, i.e., students' ability to plan their study time (Broadbent & Poon, 2015), is theorized to be critical for successful strategy enactment in SRL and improved learning performance (Schunk, 2012; Weinstein & Mayer, 1983; Winne & Hadwin, 1998).

Researchers have demonstrated that the use of particular learning strategies is associated with improved academic performance in different flipped classroom courses. For instance, Gašević and colleagues (2017) and Matcha and colleagues (2019) found that computing science and engineering students who enacted learning strategies based on formative assessment, e.g., self-testing by using multiple-choice questions (MCQs) and practical tests, performed better in the course examinations than their colleagues who engaged in sparse formative assessment activities throughout the semester. Moreover, Fincham and colleagues (2018), Gašević and colleagues (2017), and Matcha and colleagues (2019) reported that students who enacted diverse learning strategies (e.g., combined lecture video watching, reading, and self-testing) performed better in the course examinations than their colleagues who chose less diverse strategies.

Researchers have also explored the associations between time management and academic success in online learning contexts. In their meta-analysis, Broadbent and Poon (2015) identified six studies that investigated the role of time management in online learning and found significant but weak effects of time management on academic achievements. In line with this is Douglas and colleagues' (2016) position that the connection between time management and student performance in undergraduate education is ambiguous. Limited research, however, has been done to investigate the effects of time management on achievements in flipped classrooms, even though effective use of time is critical for students in those courses, particularly during online preparatory activities, as noted earlier. Moreover, poor time management in online learning is often connected to procrastination and cramming, behaviours that have been shown to hinder performance (Kizilcec et al., 2017; Levy & Ramim, 2012; Michinov et al., 2011). On the other hand, spaced learning practice, e.g., studying new and revisiting previously studied information over shorter and more frequent study sessions throughout the semester, has been shown to improve learning gains across different disciplines (Dunlosky, 2013; Hintzman, 1974; Logan et al., 2012; Soderstrom & Bjork, 2015) and in flipped classrooms (Goedhart et al., 2019).

Even though time management is deemed to affect the use of the SRL strategy, in particular because task conditions (e.g., time constraints) are theorized to set the stage for strategy enactment (Winne & Hadwin, 1998), and also these two constructs together are theorized to promote learning performance (Schunk, 2012; Winne & Hadwin, 1998), limited research has been done to date to empirically examine the combined effects of time management and strategy use on academic achievements. Instead, these constructs were typically studied separately. As an exception, Ahmad Uzir and colleagues (2020) investigated time management and strategy use from student trace data collected in the Foundation Studies blended-learning course and found that not only did high-performing students use diverse learning strategies over the learning period, but they also enacted their strategies at various points in the course timeline, with an average two-day shift from one strategy to another, i.e., the high-performing students spaced their studying out. Building upon Ahmad Uzir and colleagues' (2020) work, we analyzed interactions between learning strategies and time management modes and further investigated their effects on student academic achievements in a different learning setting, i.e., the flipped classroom. Moreover, because SRL is considered a highly contextual set of learning processes (Winne, 2018, 2022), we examined the relationship between learning strategies and time management relative to weekly topics in a course. In this way, we accounted for the change in external SRL conditions (Winne & Hadwin, 1998) throughout the semester. We modelled and examined the relationships between these three entities (i.e., learning strategies, time management modes, and course topics) using epistemic network analysis (ENA; Shaffer et al., 2016). ENA is a network analytical approach that has recently been documented to offer a high-level insight into the complex relationships among different constructs in SRL (Fan et al., 2022), thus adding to analytical approaches previously used in SRL research, e.g., summary statistics and sequence and process mining.

2.3 Research Questions

In summary, the reviewed literature reveals missing links between flipped classroom learning design, student choices of learning strategies (Gašević et al., 2015; Jovanovic et al., 2017), time management, and learning performance (Gašević et al., 2016; McLean et al., 2016). This motivated us to formulate the following two research questions to guide the current study:

RQ1: Which learning strategies do students select, and when, while completing preparatory tasks in a flipped classroom?

RQ2: Are there significant differences between high- and low-performing students in their choices of learning strategies and time management?

3. Methodology

3.1 Context

The study was conducted in an undergraduate flipped classroom course offered at an Australian research-intensive university. We collected trace data from 290 first-year engineering students (18.5% female) in a 13-week-long course on computer systems. Most of the students had limited or no experience with the flipped classroom learning environment. The course consisted of two key components for each week: (i) the pre-class preparation activities, where students were required to complete a set of online activities before their classroom learning, and (ii) face-to-face classroom activities that were designed to promote active learning (Jovanovic et al., 2017; Pardo & Mirriahi, 2017). This study focused on the pre-class preparation activities that were run from Week 2 to Week 12, with the exception of Week 6, when the midterm examination was scheduled. The activities included the following:

Videos with MCQs: The students were provided with short videos that introduce key concepts in the course. The videos were followed by a set of MCQs as a form of formative assessment introduced into the course design to promote simple recall of the concepts explained in the video. The students were immediately informed whether their answers to the MCQs were correct. If the answer was incorrect, the students could request the solution or attempt the MCQs again.

Web pages with embedded MCQs: The students were provided with readings in the form of web pages with embedded MCQs. This activity had a similar purpose as the videos, i.e., MCQs were part of the formative assessment.

Problem-solving activities (exercises): To ensure that the students had prepared for the weekly lecture beforehand, the problem-solving exercises were randomly assigned to students, and their completion counted toward the final course mark. In particular, there were 10 exercise sequences (Weeks 2–5 and 7–12), and each sequence contributed one percentage point toward the final score in the course. These problem-solving exercises served as summative assessments. Students were only given one attempt to complete each problem-solving assessment. After the completion of those assessments and receiving the scores, students could continue re-attempting the problem-solving exercises as many times as they wanted, but, at that point, the completion of the exercises would have no impact on students' marks. In other words, the exercises that students were voluntarily revisiting throughout the course played the role of formative assessments.

The students were provided with a dashboard for real-time feedback that allowed for performance monitoring (Khan & Pardo, 2006). The dashboard presented the level of a student's engagement with the resources. The students could monitor their performance, e.g., scores received in solving MCQs and problem-solving exercises. The students could also compare their performance with the class's overall scores. The data in the dashboard were updated every 15 minutes and were reset each week to include performance data for the current week.

Face-to-face sessions during any given week of the course consisted of a two-hour lecture, a two-hour tutorial, and a three-hour hands-on laboratory session. In face-to-face lectures, four to six problem-solving exercises were introduced. The exercises were related to the videos and problems discussed in the preparation stage. The exercises were also preceded by a brief explanation and then solved in small groups (three or four students). The solutions to the exercises were then discussed by the lecturer. In tutorial sessions, a similar approach was adopted, although the problems were more complex and were worked out in pairs.

There were two exams in the course, a midterm exam (maximum 20 points) and a final exam (maximum 40 points), that were held in Weeks 6 and 13, respectively.

3.2 Data

The trace data were extracted from the clickstreams that recorded students' interaction with online learning resources during the pre-class activities in Weeks 2 to 13. We note that there were no preparatory activities in Week 1. In total, the trace data included 314,494 events for the 290 students. Each event is represented as a tuple comprising event ID, anonymized student ID, type of learning action, course topics, and timestamp. Each event was mapped to a specific learning action (e.g., MCQ_CO, MCQ_IN) following the coding scheme (Table 1) and using the R script published by Jovanovic and colleagues (2017). Course topics are presented in Table 2.

Table 1. Types of Learning Actions Extracted from Trace Data

Action Code	Description
EXE_CO	a correctly solved summative assessment item (exercise)
EXE_IN	an incorrectly solved summative assessment item (exercise)
MCQ_CO	a correctly solved formative assessment item (MCQ)
MCQ_IN	an incorrectly solved formative assessment item (MCQ)
MCQ_SR	a solution requested for a formative assessment item (MCQ)
VIDEO_PLAY	activation of a course video
CONTENT_ACCESS	access to a page containing reading materials
MC_EVAL	access to the dashboard; this is considered a metacognitive evaluation action
MC_ORIENT	access to the schedule and the learning objective pages; this is considered a metacognitive orientation action

3.2.1 Identification of Learning Strategies

In Figure 1 we illustrate the data preparation and the extraction procedure of learning strategies and time management modes. Learning strategies (steps 1 and 2 in Figure 1) were extracted following the methodology proposed by Jovanovic and colleagues (2017), including the reuse of the analysis scripts written in the R language. The methodology included a combination of data pre-processing, exploratory sequence analysis, and clustering. The strategies and their interpretation are presented in Table 3.

We analyzed learning strategies as they unfolded during a study session. A study session was defined as a continuous sequence of learning actions (refer to Table 1). A period of 30 minutes of inactivity marked the end of a session. We used cluster analysis to categorize a study session as a learning strategy in which an individual student engaged; i.e., we categorized each study session into one of the four learning strategies as suggested by the algorithm as the most suitable number of groups. Clustering allows us to automate the grouping of relevant learning actions into the patterns of learning, because the sequence of learning actions may be reflective of learning strategies used (Jovanovic et al., 2017; Matcha et al., 2019; Saqr et al., 2023; Srivastava et al., 2022). The learning strategies were named according to the pattern of learning actions performed in each learning session. For example, in sessions categorized as S_formative_assess (Table 3), students mainly focused on the formative assessment activities, which were designed to promote recall of the learning content. That is, in these learning

Table 2. Weekly Topics in the Course

Week	Topic	Topic Description
Week 1	T_CST	Course Introduction
Week 2	T_COD	Information Encoding
Week 3	T_DRM	Data Representation and Memory
Week 4	T_CDL	Combinational Digital Logic
Week 5	T_SDL	Sequential Digital Logic
Week 6		Mid-term Examination
Week 7	T_ARC	AVR Architecture
Week 8	T_ISA	Instruction Set Architecture
Week 9	T_ASP	Assembly Programs
Week 10	T_ADM	Addressing Modes
Weeks 11 and 12	T_HLP	High-Level Programming Construct
Week 13		Final Examination

Figure 1. Data Preparation and Extraction of Learning Strategies and Time Management Modes

sessions students aimed to check on their developing understanding of course material, mainly via self-testing. On the other side, S_summative_assess recorded students' use of scored summative assignments provided throughout the semester, i.e., problem-solving exercises. The consistent application of the S_formative_assess and/or S_summative_assess strategy during the course can be considered as "spaced learning" practice. The S_readings and S_videos_and_form_assess indicate that students were highly focused on reading materials or video content, respectively. Further details about the methodology and the identified learning strategies are provided in Jovanovic and colleagues (2017).

3.2.2 Identification of Time Management Modes

Time management modes were identified automatically via time points when the students completed their pre-class activities, as recorded in the student trace data and validated against the course schedule provided by the course instructor (Figure 1). Each week, students were required to study one topic. In our analysis, we differentiated between weeks (i.e., course topics) to account for possible effects of topics on students' learning strategy use and time management.

Table 3. Learning Strategies Identified by the Learning Analytics Method Proposed by Jovanovic et al. (2017)

Learning Strategy	Description
S_formative_assess	Sequences in this learning strategy showed the dominance of formative assessment. Access to the course reading materials was minimally present, mainly toward the beginning of a learning session. Metacognitive activities (e.g., access to the dashboard) mostly occurred toward the end of a learning session.
S_summative_assess	Sequences in this learning strategy were largely dominated by summative assessment activities that more frequently resulted in incorrect than in correct solutions.
S_videos_and_form_assess	Sequences in this learning strategy were mainly video watching. Formative assessment activities were also present, but these activities were gradually superseded by the summative assessment activities toward the end of a session. The presence of metacognitive activities at the beginning of a session in this strategy was also observed.
S_readings	Sequences in this learning strategy were mostly related to access to the reading materials and a small number of formative assessment activities. These sequences appeared to be short, often concluding with video watching.

The algorithm was defined to detect if the students completed their preparatory weekly activities as scheduled (i.e., preparing mode), if they completed their preparatory activities ahead of the schedule (i.e., ahead mode), or if they were accessing their preparatory activities scheduled for the past weeks. In the last case, we further distinguished between the following two modes. If the students accessed a past preparatory activity that they had already completed, the "revisiting" mode was assigned. If the students accessed a past preparatory activity that they had never accessed before (i.e., they fell behind the course schedule), the "catching.up" mode was assigned. Accordingly, each learning action in the trace data was assigned one of the four time management modes (Table 4).

Table 4. Time Management Modes

Time Management Mode	Description
M_preparing	Students completed their preparatory learning activities prior to their weekly face-to-face sessions, as scheduled.
M_revisiting	Students accessed a past preparatory activity that they had already completed.
M_ahead	Students completed their preparatory activities ahead of schedule.
M_catching.up	Students accessed a past preparatory activity that they had never accessed before.

3.3 Network Analysis

Network analytic approaches have already been established in SRL research (Hadwin et al., 2007; Siadaty, 2016; Siadaty et al., 2016; Winne et al., 1994). Networks are often built by creating nodes and connections among the nodes based on temporal sequences of observed learning processes/events (e.g., micro-level SRL processes such as goal setting or planning) or interventions (e.g., software features developed to promote goal setting). In other words, links between nodes are usually established based on temporal co-occurrence of events represented by the nodes. In the networks generated in this way, graph theoretical statistics (Carolan, 2013) are often used to estimate the relative importance of nodes and connections. Although they can produce valuable insights, these analytical methods typically do not allow for quantitative and qualitative comparisons of learning processes across individuals and groups. In the current study, we opted to use ENA (Shaffer et al., 2009), an enhanced network analytic approach that allows for the individual and group comparisons needed to answer our research questions.

ENA is a network analytic technique developed to analyze log data and other traces of individual and collaborative learning (Nash & Shaffer, 2012; Rupp, Gushta, et al., 2010; Rupp, Sweet, et al., 2010; Shaffer et al., 2016; Shaffer & Gee, 2012;

Shaffer et al., 2009). Different learning constructs can be used to create an epistemic network, e.g., learning actions, utterances, and proxies for cognitive processes (e.g., Iqbal et al., 2023; Li et al., 2023). These categories are used to create nodes in an epistemic network. Connections among nodes are established based on co-occurrence of the nodes within a relevant unit of analysis (e.g., two learning actions that co-occur in the same time window as detected in trace data). In this way, the connection weights capture patterns of the different constructs observed.

3.3.1 Data Analysis

We created an epistemic network for each individual student based on the learning actions students enacted throughout the course. To create the ENA space, the unit of analysis, the conversation, and codes must be specified. The nodes in the network depict the codes from three dimensions: (1) learning strategies (four different strategies, Table 3), (2) time management modes (four different modes, Table 4), and (3) course weekly topics (10 topics, Table 2). The edges among the nodes were created based on the co-occurrence of these three dimensions in the dataset. Following this approach, links could only be created between nodes from different dimensions (e.g., a learning strategy and a time management mode) and could not be created between nodes from the same dimension (e.g., two learning strategies). The network thus contained the three types of edges connecting

- learning strategies and time management modes,
- learning strategies and topics, and
- topics and time management modes.

To answer our RQ1, i.e., identify which learning strategies students select, and when, while completing online preparatory tasks in a flipped classroom, we computed the epistemic network showing learning strategies, time management modes, and course topics[1]. Specifically, we first represented a network of each individual student as an adjacency matrix of nodes and the corresponding edges and then aggregated those matrices across all the students to create a cumulative adjacency matrix. Because the matrix obtained in this way was represented in a high-dimensional space, we performed a singular value decomposition (svd), following the approach proposed in Shaffer and colleagues (2016), to reduce the number of dimensions while maximizing the variance our data accounted for. We found that the first two dimensions, i.e., svd1 and svd2, explained the most variance (24% and 19%, respectively) and elected to create a two-dimensional epistemic network for further analysis. The resulting epistemic network thus included x- and y-axes, corresponding to svd1 and svd2, respectively. In the resulting ENA graph, frequently co-occurring nodes were connected with darker and thicker lines, whereas the size of a node was proportional to the frequency of that node in the dataset. The node positions were fixed across the graphs so that the differences among the graphs could be more easily examined. We first created the overall mean epistemic network showing the relationships among four learning strategies, four time-management modes, and 10 course topics for the entire course. We also created a separate network for each week in the course; this approach afforded us the opportunity to observe how students self-regulated their learning by adapting their learning strategies and approaches to time management relative to different topics covered each week.

To answer our RQ2, i.e., identify whether high- and low-performing students tend to choose different learning strategies and time management modes, we projected the epistemic networks[1] (one for each performance group) onto the two two-dimensional spaces. Next, we subtracted these two networks. The new network created in this way, i.e., the subtract network, allowed us to examine the differences between low- and high-performing students in terms of their choice of learning strategies and time management modes. Last, we created an additional ENA space using a mean rotation function of ENA and conducted the two-sample t-test to statistically examine the differences between the low- and high-performing networks. The t-test was conducted using a Bonferroni correction to prevent Type I error.

We note that, in the remainder of this article, we have opted to not show the labels of all the course topics in the ENA diagrams to maximize the readability and reduce the clutter in the figures. We removed the topic labels for all the topics that were not linked to or that had a low number of links with learning strategies and time management modes in an observed week.

4. Results

4.1 RQ1: Strategy Selection and Time Management

The mean epistemic network (Figure 2) visualizes the connections between weekly topics, learning strategies, and time management modes that students utilized in the entire flipped learning course. Overall, we observed that the students used the M_preparing, M_revisiting, and S_summative_assess modes of study more often, as indicated by the size of the corresponding nodes.

[1] The unit of analysis included student ID and week; the conversation included student ID, week, and row ID; the window size was -1.

Due to the high number of variables explored in this study, the labels for the course topics (i.e., T_CST, T_COD, T_DRM, T_ASP) were excluded from the figure. Generally, the *x*-axis corresponds to svd1 and explains 24% of the variability in the network, whereas the *y*-axis represents svd2 and explains 19% of the variability in the network. High values along svd1 represent a higher tendency to use the S_videos_and_form_assess learning strategy and the M_preparing and M_revisiting modes of study. High values along svd2 represent a trend to use the M_preparing and M_ahead modes of study. Low values along both svd1 and svd2 represent a tendency to use S_summative_assess, S_formative_assess, and M_catching.up.

As presented in Figure 2, the modes of time management were located on the same quadrant except for M_catching.up. According to Ahmad Uzir and colleagues (2020), M_preparing, M_revisiting, and M_ahead were considered effective time management strategies, whereas M_catching.up was considered the ineffective time management strategy. Learning strategies were located in different quadrants. Two practical exercises including S_summative_assess and S_formative_assess were located in the same quadrant. The S_readings and S_videos_and_form_assess are located in opposite directions. We note that the connections between S_summative_assess node and M_preparing, M_ahead, and/or M_catching_up nodes identified in the ENA indicate that the summative assessment activity was graded, whereas the connections between the S_summative_assess node and the M_revisiting node indicate that the summative assessment activity was not graded. This may explain a particularly high co-occurrence of the summative assessment strategy and the preparing time management mode, i.e., students tended to engage in more preparatory learning activities when practical summative exercises following those activities were graded.

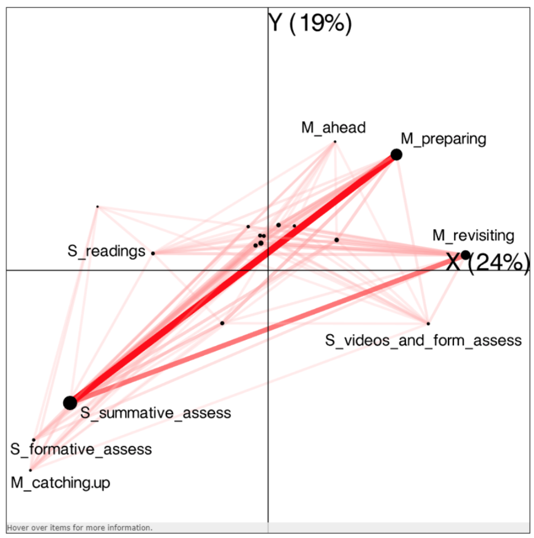

Figure 2. The Overall Mean Epistemic Network of Weekly Topics, Time Management Mode of Study, and Learning Strategy for the 12 Weeks Included in the Study

To understand how the time management modes of study and learning strategies changed over the course timeline, we created individual epistemic networks for each week in the course. Networks with approximately similar patterns were grouped in Figures 3 and 4, respectively, to facilitate the interpretation. In Figure 5 we show networks from the weeks in which the examinations happened. Initially, in Week 2, students mainly focused on M_preparing and S_summative_assess (Figure 3 (a)), and no action on revisiting was observed since the course had just commenced (i.e., Week 1 did not cover any specific topic but rather it introduced the course).

Starting in Week 3, the pattern, changed as shown in Figure 4. The model highlights dominant connections between summative assessment (S_summative_assess) and both the topic of the current week (T_DRM) and the topic of the previous week (T_COD). For instance, students prepared for T_DRM (Week 3) and then revisited the same topic in the subsequent week (Week 4). Apart from that, links of weekly topics and time management modes with the other three learning strategies (video watching, reading, and formative assessment) were low. As is evident in the epistemic networks (Figure 4), these scenarios were consistent in most of the subsequent weeks that featured some preparation activities (i.e., Weeks 4, 5, 7, 8, 9, and 11).

The approach to learning in Weeks 10 and 12 (Figure 3 (b) and (c)) was somewhat similar to that of Week 2, in which students predominantly focused on preparatory activities prior to the face-to-face session and little revision work was done after that. The topics of Weeks 10 and 12 (T_ADM and T_HLP) seemed to be found by the students to be highly important given that they kept intensively preparing for them and revisiting them later on, as shown by the networks in Figure 3 (b–c), Figure 4, and Figure 5 (b).

Rather different patterns in learning approaches were observed in epistemic networks for Weeks 6 and 13 (Figure 5 (a)

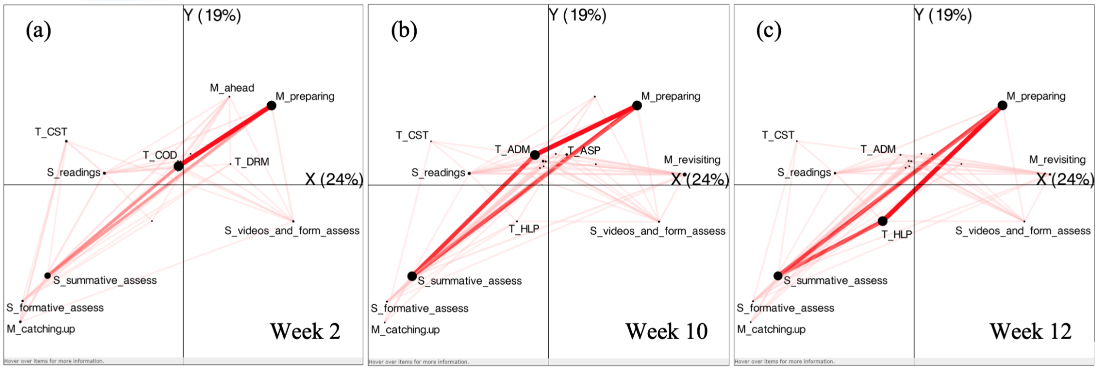

Figure 3. Epistemic Networks for Weeks 2, 10, and 12

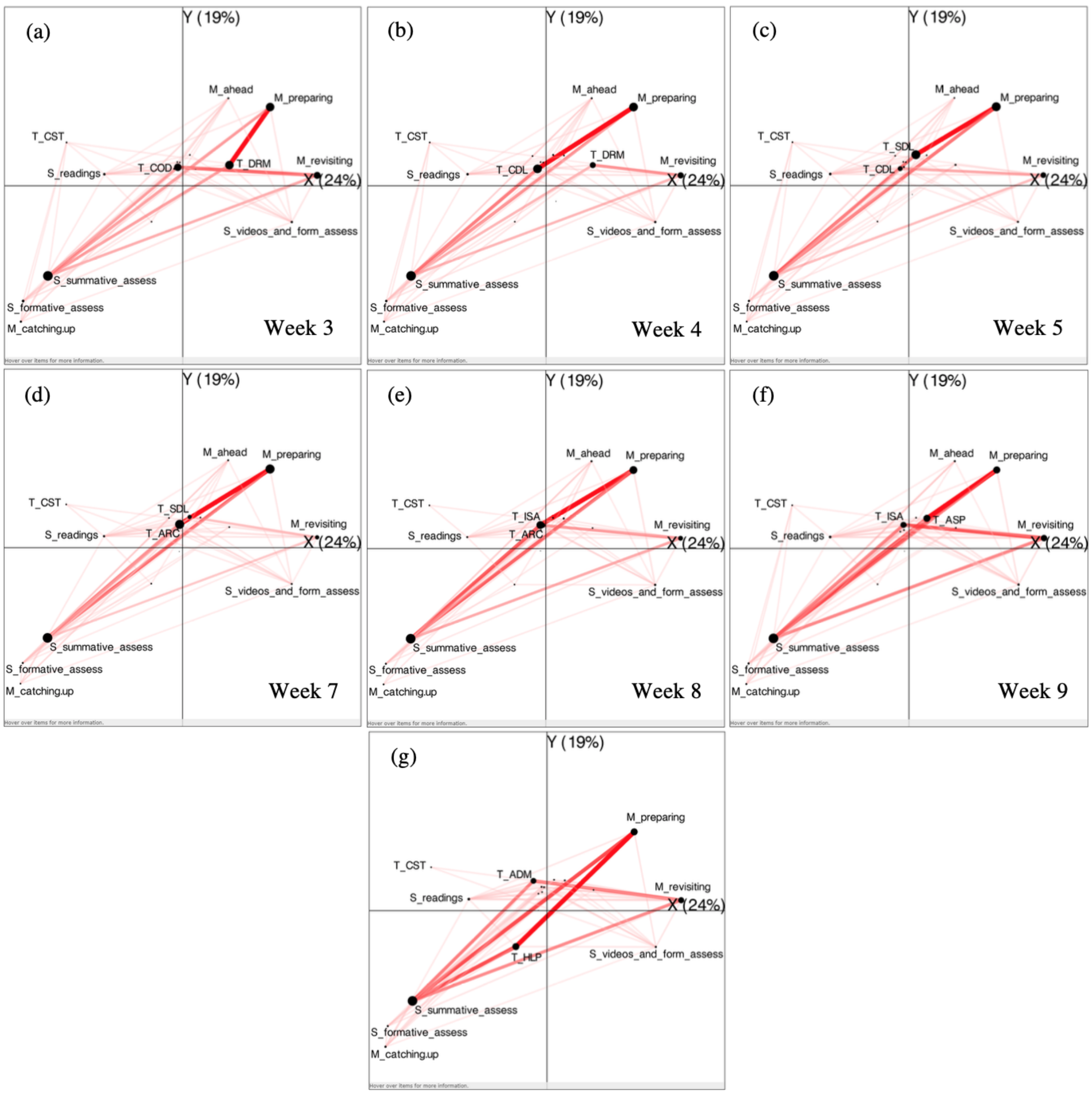

Figure 4. Epistemic Networks for Weeks 3, 4, 5, 7, 8, 9, and 11

and (b)), in which students worked only on the preparation for the midterm and final examinations, respectively. The ENA showed that the students' attention mainly focused on revisiting every topic that they had worked on in the previous weeks, and no work on the preparation activities was observed, as was expected according to the course design. In these weeks, students made extensive use of exercises (originally provided as summative assessment) as practice opportunities to prepare for the

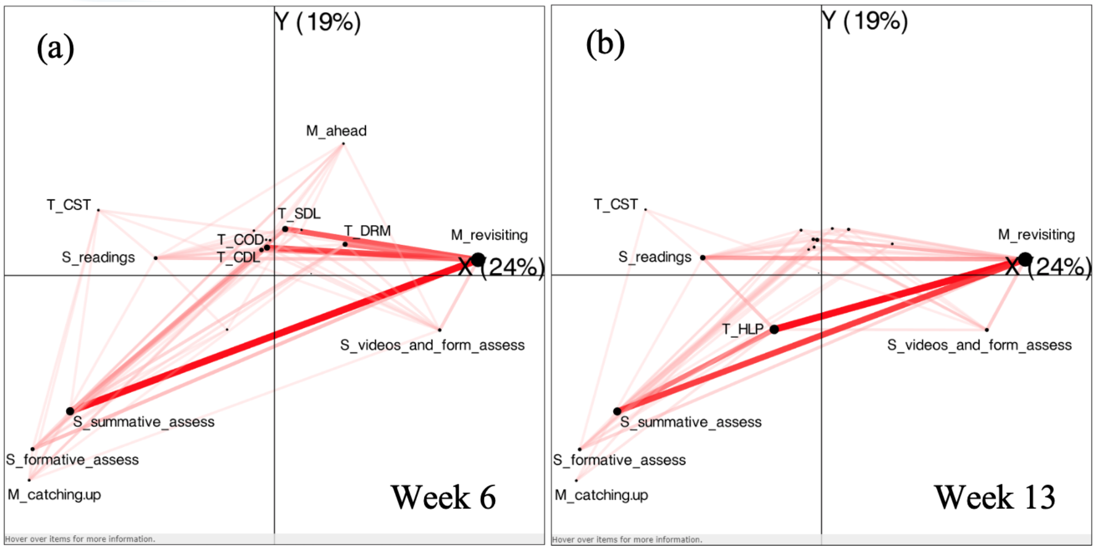

Figure 5. Network Models for the Weeks in Which No Preparatory Activities Were Planned and When the Midterm (Week 6) (a) and Final (Week 13) (b) Examinations Happened

examinations. The use of exercises was also combined with some reading activities. Since completing the exercises in the examination weeks could not contribute to the students' final marks (their deadlines had passed in the previous weeks), these exercises played the role of formative assessments.

The epistemic networks also revealed that the M_preparing (T_HLP, T_COD, T_CDL, and T_SDL) and M_revisiting (T_COD, T_DRM, and T_SDL) time management modes had dominant links with other nodes in the network, in contrast to the other two modes—M_catching.up and M_ahead.

4.2 RQ2: Comparison between High- and Low-Performing Students

To address research question 2, we examined students with the highest and the lowest scores on the midterm exam and the final exam. We extracted the high-performing groups by selecting students with exam (midterm or final) scores in the 90th percentile, and for the low-performing groups, the students with exam scores below the 25th percentile. The latter groups were extended (25th instead of 10th percentile) to obtain comparable samples of high- and low-performing students in several learning sessions. The group with midterm scores above the 90th percentile included 23 students ($N_{above90th} = 23$), whereas the group with midterm scores below the 25th percentile included 63 students ($N_{below25th} = 63$). There were 27 students with final exam score above the 90th percentile ($N_{above90th} = 27$), and 73 students with the score lower than the 25th percentile ($N_{below25th} = 73$).

4.2.1 Midterm Performance

A new ENA space was created to investigate the difference between high- and low-performing students on the midterm and final exams. Figure 6 displays the centroids of the epistemic networks of the low- (red nodes) and high- (blue nodes) performing students. The square shapes represent the mean networks, and each square is surrounded by a rectangle representing the confidence interval. The figure shows that the mean values of the two networks are located close to each other.

We further explored the networks of both the low- and high-performing students, as shown in Figure 7. The networks in Figure 7 do not contain the nodes representing course topics since, as indicated in RQ2, we primarily wanted to study the association of academic performance with learning strategy and time management. The *x*-axis corresponds to svd1 and explains 18% of the variability in the networks, whereas the *y*-axis represents svd2 and explains 17% of the variability in the networks. Overall, higher values along svd1 represent a higher tendency to use the M_revisiting mode of study. Higher values along svd2 represent a trend to use the M_preparing mode of study. Lower values along both svd1 and svd2 represent a tendency to use S_summative_assess.

Similar patterns in the epistemic network structure were observed for both high- and low-performing students. That is, both networks in Figure 7 reveal a relationship between M_preparing and S_summative_assess. These networks are indicative of time management in the sense that students were mostly in the preparation mode. The main learning strategy in both student groups was focused on summative assessment activities, which comprised exercises and problem-solving activities that counted toward the final course mark. Another noticeably strong relationship is the connection between M_revisiting and S_summative_assess. M_revisiting represents the mode in which students revisited topics from the previous weeks. Recall that after face-to-face

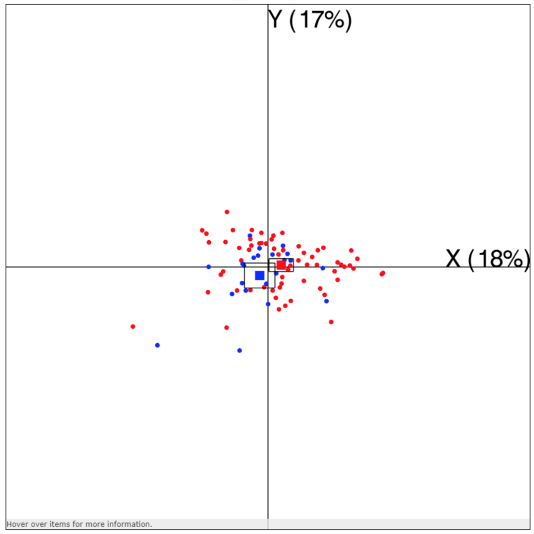

Figure 6. Comparison of Network Centroids for Each of Low- (Red) and High- (Blue) Performing Students on the Midterm Exam

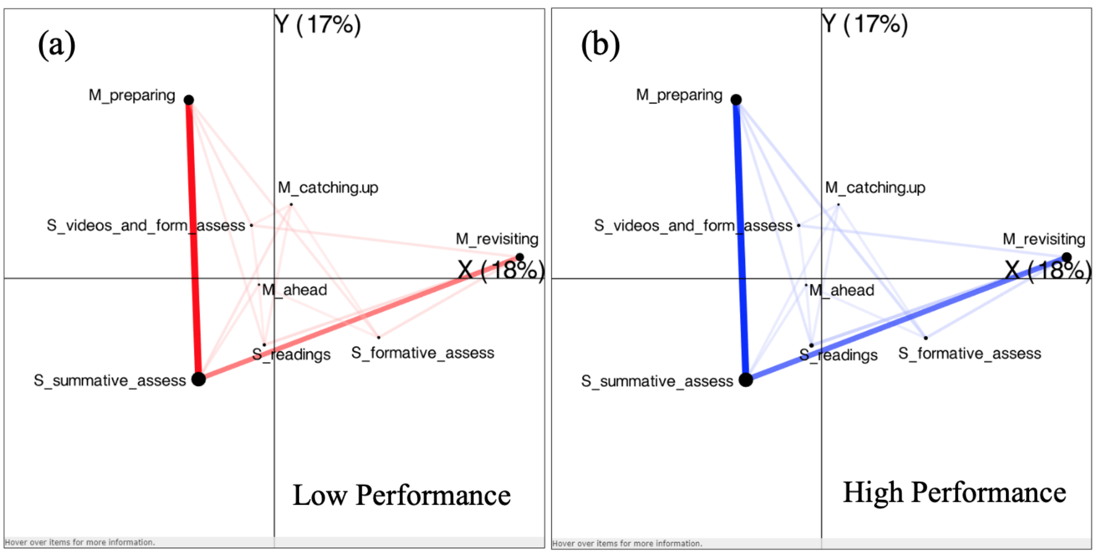

Figure 7. Mean Epistemic Networks for Low (a) and High Performers (b)

sessions in a particular week were completed, further work on the summative assessment activities of that week would no longer count toward the final course mark. Still, the students kept undertaking those activities. This suggests that students revisited their lessons by re-doing the problem-solving activities. The connections between other learning strategies, i.e., reading, video watching, and formative assessment, and time management modes observed in this study were weaker. This finding indicates that students appeared to combine those learning strategies less often than the summative assessment strategy, which appeared to be frequently combined with other strategies during the weeks preceding the midterm exam.

To examine the differences between the networks of high- and low-performing students, we subtracted one cumulative adjacency matrix from the other and plotted the resulting network graph, as shown in Figure 8. Blue lines indicate stronger connections for the high-performance group; red lines represent stronger connections for low-performance students. The thickness of lines reflects the differences between two networks.

The high-performance students had stronger connections in almost every activity except for M_catching.up–S_summative_assess and M_catching.up–S_videos_and_form_assess. As a reminder, M_catching.up refers to performing learning actions after the due date has passed (i.e., performing preparation activities for a face-to-face session after the session). Hence, the results suggest that the students with low performance tended to procrastinate more on problem solving and exercises that counted toward the final course mark. They also procrastinated more in watching videos and doing the associated formative MCQs.

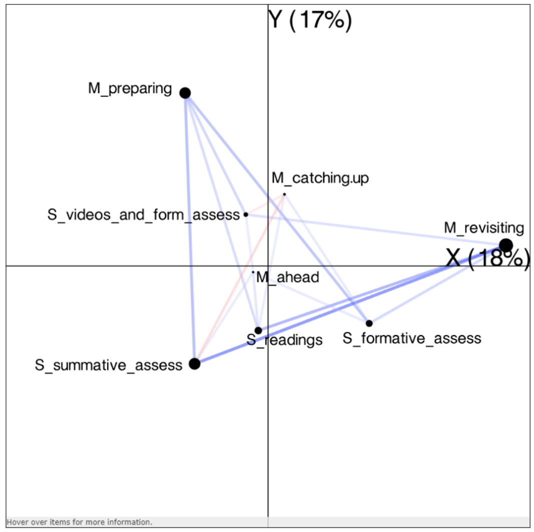

Figure 8. Subtracted Epistemic Networks of the Low- (Red) and High- (Blue) Performing Students on the Midterm Exam

However, no significant difference was observed between these two mean networks on the network dimensions (X and Y) shown in Figure 8 (X dimension, $t = -1.766$, $p = 0.083$, Cohen's $d = -0.388$; Y dimension $t = 1.577$, $p = 0.123$, Cohen's $d = 0.412$). Even though the differences in learning strategy selection between low- and high-performing students based on their midterm performance were detected in the network model, the differences were not statistically significant.

4.2.2 Final Exam Performance

Figure 9 plots the centroids of individual students, where the red nodes represent low-performing students and the blue ones represent high-performing students based on their final exam score. The squares represent the mean centroids of the two networks, and the rectangles around them confidence intervals. Meanwhile, to explore the differences between the two performance groups, their mean epistemic networks were further studied and are shown in Figure 10. Similar to the case of the midterm exam, the x-axis corresponds to svd1 and explains 18% of the variability in the networks, whereas the y-axis represents svd2 and explains 17% of the variability in the networks. Overall, higher values along svd1 represent a higher tendency to use the M_revisiting mode of study. Higher values along svd2 represent a trend to use the M_preparing mode of study. Lower values along both svd1 and svd2 represent a tendency to use the S_summative_assess mode.

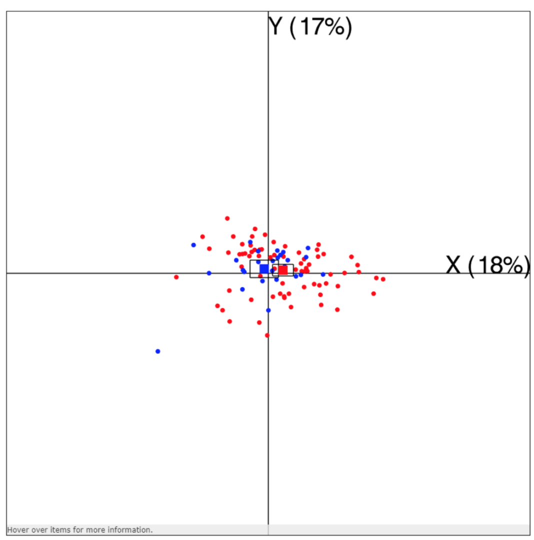

Figure 9. Centroids of the High- (Blue) and Low- (Red) Performing Students on the Final Examination

Similar to the case of the midterm exam, the link between M_preparing and S_summative_assess was the strongest for both groups. The second strongest connection is M_revisiting–S_summative_assess. To check for the differences between the two networks, we applied subtract equiload. Subtract equiload is a function to superimpose the two networks to allow for

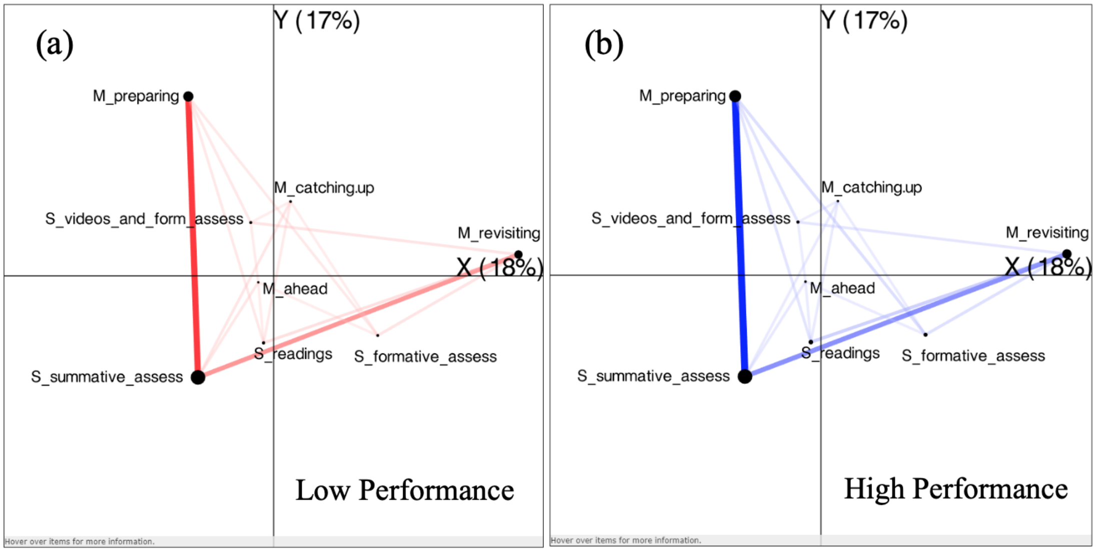

Figure 10. Mean Epistemic Networks for Low- (a) and High- (b) Performing Students on the Final Examination

meaningful comparison of the patterns of connections in two networks. The subtracted network is in Figure 11.

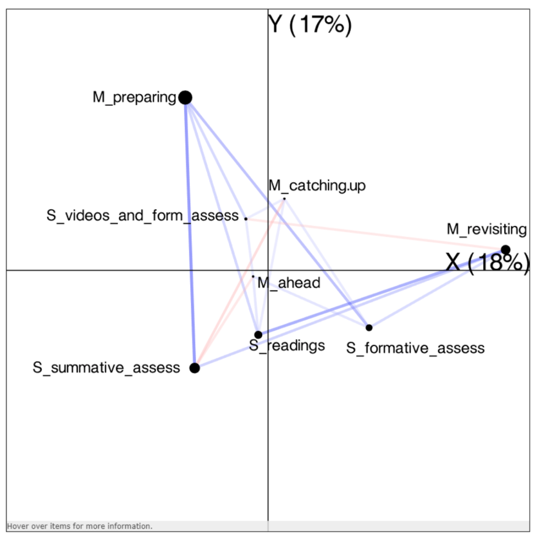

Figure 11. Subtracted Epistemic Network between the Low- (Red) and High- (Blue) Performing Students for the Final Exam

The subtracted mean network reveals that high-performing students (blue lines) had more dominant links between almost all pairs of learning strategies and time management modes than their low-performing peers. However, low-performing students (red lines) showed dominant connections between M_catching.up–S_summative_assess, M_revisiting–S_videos_and_form_assess, and M_ahead–S_summative_assess. Although the low-performing students tried to complete some of the summative assessments ahead of the schedule, their attempts mostly resulted in incorrect responses. The low-performing students also demonstrated dominant links related to watching videos while revising. t-tests showed significant differences between the two networks in Figure 11 on dimension X ($t = -2.163$, $p = 0.035$, Cohen's $d = -0.451$) but not so for dimension Y ($t = -0.256$, $p = 0.799$, Cohen's $d = -0.056$).

Since the choices of time management of the two groups proved to be rather different, we decided to further investigate the role of time management. Specifically, we aimed to explore how students managed their time when studying each of the course topics. The relationships between time management mode of study and topics are presented in Figure 12. The figure shows the networks that are presented in a different epistemic network space to highlight time management in connection to the topics studied by the students included in the study.

Figure 13 shows the ENA space comparing the time management modes and the topic of high- and low-performance students. The network reveals that the low-performing group (red lines) completed more activities ahead of time (M_ahead)

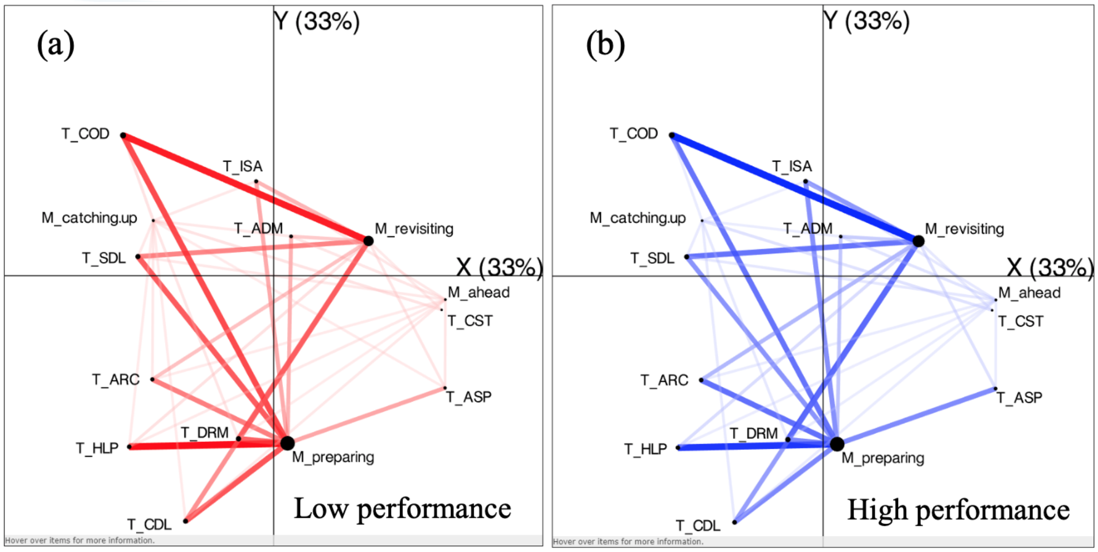

Figure 12. Mean Networks for Time Management Mode of Study and Topic for Low- (a) and High- (b) Performing Students

in only two topics (ASP and HLP) than their high-performing peers, who did so for a few other topics. The low-performing students tended to complete relevant activities on time for three topics only, namely topics CST, DRM, and CDL, which were introduced in Weeks 1, 3, and 4, respectively. It should be noted that CST was not an actual course topic; rather it represented the course introduction, a description of available resources, and expectations. The high-performing students exhibited less catching-up behaviour, especially toward the end of the course. They did not have any catching-up behaviour in relation to topics ARC, ASP, and HLP, which belonged to Weeks 7, 9, and 11–12, respectively.

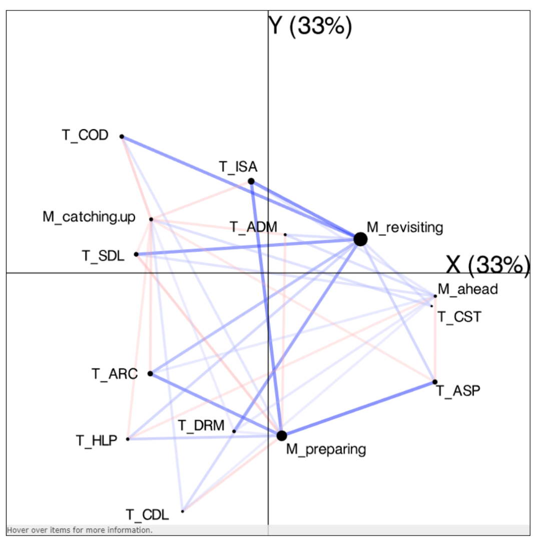

Figure 13. Subtracted Network of Time Management Modes and Topics between Low- (Red) and High- (Blue) Performing Students

4.2.3 Mean Comparison

To further explore the difference between high- and low-performing students, we created an additional ENA space using a mean rotation function of ENA. Specifically, mean rotation is used to create a model of multiple networks (Figure 14), where each network is represented as a point (i.e., network centroid). The distance between centroids represents a measure of the difference between the corresponding networks. This ENA network model explains 26.8% of the variance in coding co-occurrences along the *x*-axis and 31.5% of the variance on the *y*-axis. Figure 14 (b) uses the same ENA space as the one used in Figure 14 (a) to represent the mean plot for each week (i.e., Week 2 until Week 13) comparing the high- (blue) and low- (red) performing groups. The high-performing group consisted of 15 students ($N_{above90th} = 15$) with the midterm and final exam scores above the 90th percentile, whereas the low-performing group counted 31 students ($N_{below25th} = 31$) in the 25th percentile for both midterm and final exam.

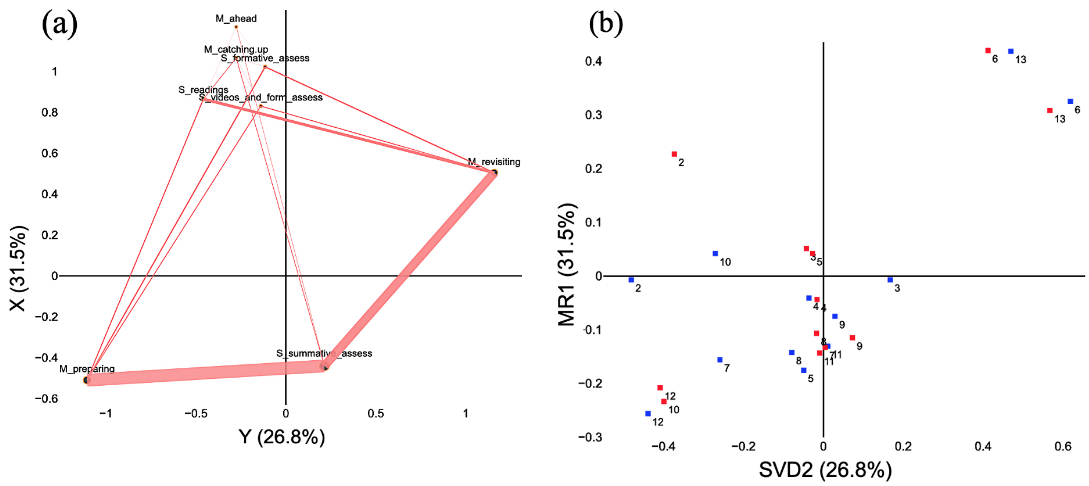

Figure 14. (a) The Network Model Generated Using the Mean Rotated Function of ENA; (b) Position of the Mean Plots (Shown as Squares) of High- (Blue) and Low- (Red) Performing Groups Based on 12 Active Weeks (Week 2–Week 13).

We performed a series of two-sample t-tests examining the statistical difference between the high- and low-performing students over the 12 weeks of the course (Figure 14 (b); Table 5). We found a statistically significant difference between the two groups of students in Week 2 ($t = 0.486$, $p = 0.028$, Cohen's $d = 0.972$), Week 3 ($t = 0.373$, $p = 0.039$, Cohen's $d = 0.747$), Week 6 ($t = 0.291$, $p = 0.010$, Cohen's $d = 0.583$), and Week 7 ($t = 0.468$, $p = 0.006$, Cohen's $d = 0.936$). These differences were detected relative to the x-axis (mr1) and computed as the d effect sizes (Cohen, 1992). We also detected statistically significant differences relative to the y-axis (svd2) in Week 5 ($t = 0.365$, $p = 0.045$, Cohen's $d = 0.730$), Week 6 ($t = 0.147$, $p = 0.048$, Cohen's $d = 0.295$), and Week 10 ($t = 0.610$, $p = 0.038$; Cohen's $d = 1.221$).

Table 5. Weekly Topic Covered in the Course

Week	MR1 (p)	Cohen's d	SVD2 (p)	Cohen's d
Week 2	0.0282*	0.486	0.0927	0.199
Week 3	0.0386*	0.972	0.6571	0.110
Week 4	0.8313	0.014	0.9812	0.037
Week 5	0.8290	0.026	0.0454*	0.225
Week 6	0.0104*	0.583	0.0481*	0.295
Week 7	0.0056*	0.936	0.8370	0.434
Week 8	0.5438	0.335	0.7318	0.104
Week 9	0.6518	0.254	0.7157	0.645
Week 10	0.0570	1.045	0.0381*	1.221
Week 11	0.8220	0.068	0.8978	0.205
Week 12	0.4749	0.096	0.5264	0.501
Week 13	0.2618	0.519	0.3687	0.730

Note: * indicates $p < 0.05$; $Cohen'sd$ indicates effect size.

5. Discussion

5.1 Interpretation of the Results

Even though theoretical assumptions of SRL have been extensively studied (c.f. Dent and Koenka, 2016), few researchers have empirically investigated the hypothesized relationship between time management, learning strategy use, and learning performance (Schunk, 2012; Winne & Hadwin, 1998). To fill this gap, we investigated (i) how students select and modify learning strategies and manage their study time while completing online preparatory tasks in a flipped classroom and (ii) how these strategies and time management modes jointly affect student achievement in the midterm and final exams. To this end, we harnessed the potential of ENA, the network analytical approach that has been shown in prior research to provide a comprehensive overview of SRL constructs and their connections (Fan et al., 2022) across different achievement groups, both at one point of observation and longitudinally (Ahmad Uzir et al., 2020). We observed four types of learning strategies and four modes of time management using student trace data recorded in an online learning environment. Further, we created an epistemic network for each student to examine the relationships between their learning strategies and time management throughout the semester and investigated the effects on academic achievement.

We documented a strong overall engagement of learners in pre-class preparatory activities. As well, we found that many learners tended to revisit the topics studied in previous weeks. This suggests that learners strove to ensure they had developed sufficient background knowledge to successfully engage in in-class activities and perform well in subsequent examinations, conforming to the instructional requirements of flipped classrooms (Grosas et al., 2014; Heinerichs et al., 2016; Luo et al., 2016; Roehl et al., 2013; Tucker, 2012).

Our results also indicate that many students in the flipped classroom enacted the assessment-based study strategies that are considered effective across domains and courses (Dunlosky, 2013). For example, students used the summative assessments provided in each week to prepare for weekly face-to-face sessions (preparation mode of time management) and also reengaged in those same assessments in the following weeks (revisiting mode of time management), even though those assessments were not among the required pre-class activities in the following weeks. Importantly, this finding suggests that students have possibly engaged in judgment of learning at multiple points throughout the semester and adapted their studying strategies to the emerging context of a learning task, evidence of metacognitive monitoring and control, which are processes central to SRL (Winne, 2018; Winne & Azevedo, 2014; Winne & Hadwin, 1998).

The high- and low-performing students differed in terms of their time management, especially during Weeks 2 through 7 (Figure 13). The high-performing students tended to begin the coursework on time, i.e., in Week 2 or 3, and engage in spaced learning practice (Dunlosky, 2013), i.e., the consistent revisiting of previously studied information over shorter and more frequent study sessions throughout the semester. This is indicated by the strong connections observed in the high-performing student network between the revisiting time management mode and weekly topics, allowing us to detect how students adapted their revisiting behaviours over the course of the semester. This finding further conforms to prior research that documented spaced learning as an effective learning strategy that contributes to improved learning performance (Dunlosky, 2013; Hintzman, 1974; Logan et al., 2012; Soderstrom & Bjork, 2015). The high-performing students thus regularly opted for a summative assessment strategy prior to each face-to-face session and a formative assessment strategy to revisit the previously studied course content, and they did so more consistently throughout the semester than their low-performing colleagues. In particular, many high-performing students might have benefited from self-testing with retrieval practice, the opportunities provided by the formative assessment tasks in this course. In other words, the students may have been repeatedly using the questions from previous assignments to self-test for recall of previously studied information, a studying approach that has been widely documented to boost learning performance, e.g., Carpenter and colleagues (2008) and Roediger III and Karpicke (2006). In addition, the high-performing students used the whole range of learning strategies observed in this study, in both preparing and revisiting modes of time management, which corroborates previous findings that enactment of diverse learning strategies benefits learning performance (Fincham et al., 2018; Gašević et al., 2017; Matcha et al., 2019). Our results indicate that high-performing students were aware of the emerging requirements in a flipped classroom course, e.g., the need to study for the upcoming class and the need to revisit some materials from previous weeks to succeed in the subsequent classes and examinations. To this end, they effectively used their study time and enacted appropriate learning strategies and hence appeared to productively self-regulate learning (Yamada et al., 2017) and perform well in the course exams. This further confirms the existing theoretical assumptions that effective learning strategies alone are often not sufficient to boost learning gains. Rather, the choices that students make both about what strategies to use and about when to enact them can jointly benefit learning performance (Weinstein & Mayer, 1983; Winne & Hadwin, 1998).

On the other hand, the students in the low-performing group enacted less diverse learning strategies, typically focusing on video watching, interweaved with sparse formative assessment. Additionally, we found that the low-performing students exhibited more catching-up behaviours than their high-performing colleagues. For instance, they tended to use less diverse learning strategies early in the course (e.g., Weeks 2 and 3) and maintained the same set of strategies until the beginning of Week 5. After that, they used summative assessment to support revisiting of the course materials prior to the midterm exam. These inconsistent patterns of studying activities may be one of the reasons for students' low academic performance, as indicated in Bos and Brand-Gruwel (2016). Moreover, procrastination and delayed revision until later in the course might be another reason for poor performance, resonating with the previous research that connected procrastination and cramming with poor performance in online learning (Klassen et al., 2008; Steel, 2007).

5.2 Limitations and Future Work

We acknowledge the following limitations of our study. We studied learning strategies, time management, and academic performance by using trace data collected during preparatory online activities in a flipped classroom. We note that there is an additional group of factors that could not be captured by the trace data collected in this study, but that could have affected our results. These factors include student participation in in-class activities (e.g., face-to-face group discussions) and individual differences among students (e.g., personal learning goals, prior knowledge, motivation, and overall approaches to learning; Bos and Brand-Gruwel, 2016; Gašević et al., 2017; Jovanovic et al., 2017; Winne and Hadwin, 1998). Future research should thus include data that account for both online and offline learning activities and students' internal factors to get a more comprehensive picture of studying in flipped classrooms.

We also note that, even though we included course topics in our analysis to account for external conditions theorized in SRL (Winne & Hadwin, 1998), we acknowledge that course topics are typically determined by a course instructor/instructional designer, and self-regulated learners may not have control over this factor. Also, in the present study, we did not specifically explore whether our analytical approach may be biased toward particular demographics (e.g., students of a particular gender and economic status). Even though our data were collected in authentic university courses, we posit further analyses, e.g., those using sampling strategies, will need to be conducted in the future to ensure that the trace-based analysis of learning strategies, time management, and academic performance is not biased toward a particular student population.

Next, it should be noted that this study was exploratory and correlational in nature. Therefore, any causal inferences are unwarranted. The network-based interpretations in this study should be validated in future research against additional data channels and methods, e.g., by asking students to reflect back on their preparatory activities during a flipped classroom course. Moreover, because we deemed 314,494 events to be a sufficient data sample for our analysis, we did not examine the stability of the network. In future research, data-sampling techniques, e.g., bootstrapping, may be harnessed to gain a deeper insight into the stability of the ENA networks created. To test the generalizability of the reported results, this study should be validated in courses with flipped classroom designs that involve subject domains different from the one we studied. We also note that the topical codes used in the present study (Table 2) are course specific, and a broader repository of topical codes spanning different courses may need to be developed to improve generalizability and data sharing across future studies.

Even though detrimental effects of procrastination on learning achievements were documented in previous research (Klassen et al., 2008; Steel, 2007), we note that not every form of procrastination is unproductive. For instance, a deliberate delay in studying, known as active procrastination, could improve learning performance (Chun Chu & Choi, 2005; Kim et al., 2017). In future research, we aim at collecting additional data to distinguish between passive and active procrastination, toward better understanding of when and how procrastination can have positive effects on learning.

6. Conclusions and Implications

Drawing upon the model of SRL proposed in Winne and Hadwin (1998), we studied the joint effects of learning strategy use and time management on student achievements in a computer engineering course based on flipped classroom principles. Up to now, learning strategies and time management were usually studied independently. We identified learning and time management strategies from student trace data collected over 12 weeks of the course and applied a novel network analytic approach to shed light on the relationships among learning strategies and time management modes, unveiling how such relationships are associated with the students' academic performance.

In sum, our results indicate that the high-performing students used diverse learning strategies and more consistently engaged in summative and formative assessment throughout the semester than their low-performing colleagues. The high-performing students typically used their time to prepare for face-to-face classes each week and to revisit course materials studied in previous weeks. The students in the low-performing group enacted less diverse learning strategies and exhibited more catching-up behaviours throughout the semester than the high-performing students. The findings of this study may support the existing theoretical assumptions that the choices students make about both what strategies to use and when to enact them can jointly benefit learning performance.

From a research perspective, this study proposed a novel methodology based on the epistemic network analytical approach and trace data to efficiently monitor students' progress by simultaneously tracking their time management and learning strategies related to different course topics. This provides a foundation for personalized feedback and an early warning system to detect students who need support.

This study could help instructors to provide their students with evidence-based advice on the learning strategies that can work well for them and on the most effective ways to manage their studying time during the semester, e.g., take summative assessment before class and revisit the course content after class, and set aside multiple time slots each week to regularly revisit course materials.

From a learner perspective, this study could help to support students to alter their learning behaviours to increase their likelihood of success in a course, e.g., by effectively regulating their learning time and strategy use, particularly in terms of revisiting their learning.

In conclusion, the results of our study may contribute to the future refinements of instruction in flipped classrooms because they highlight learning strategies and time management practices that can lead to productive SRL and boost academic achievement, toward addressing the documented challenges many students face in engaging in productive SRL in flipped classrooms (Roehl et al., 2013). Our findings may particularly support students who are at risk of underperforming in demanding flipped classroom courses by providing personalized guidelines during preparatory activities. For example, a personalized learning analytics dashboard may be created to show a network of learning strategies and time management approaches that a learner used during the week and compare this network to the network of high-performing colleagues from the same week in previous course offerings, thus giving the learner an opportunity to reflect on their own studying approaches and adapt those approaches to increase learning productivity.

Declaration of Conflicting Interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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