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ANALYTICS OF TIME MANAGEMENT STRATEGIES IN
ONLINE LEARNING ENVIRONMENTS: A NOVEL
METHODOLOGICAL APPROACH

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Institute for Language, Cognition and Computation
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Analytics of Time Management Strategies in Online Learning Environments: A Novel Methodological Approach

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In the name of God, the Most Gracious, the Most Merciful

Abstract

The emergence of technology-supported education, e.g., blended and online, has changed the global higher education landscape. Importantly, the new learning modes involve more complex tasks and challenging ways of learning that require effective time management and strong self-regulation skills. In this regard, one of the most prevalent theoretical lenses to understand learning processes is Self-Regulated Learning (SRL). In reference to SRL models, time is a major resource in learning. The way learners schedule, plan, and enact tactics and strategies on their learning time could tremendously impact their academic achievement. However, the assessment of how learners make time-related decisions in learning is a daunting task, particularly given its latent nature and inherent autonomous learning capacity. One way to address this problem is to make use of unprecedented volumes of data collected by digital learning environments that are precisely timestamped records of actions that learners take while studying.

This thesis presents a set of novel learning analytics methods for detecting and understanding time management strategies based on the analysis of digital trace data collected in online learning environments. First, the thesis proposes a new method to detect time management tactics and strategies using a combination of sequence mining and clustering techniques. The thesis also describes how time management tactics and strategies detected with this method are aligned with an SRL model that is used as a theoretical foundation of this thesis. Second, the thesis introduces a novel learning analytics method for the detection of time management tactics and strategies. This method uses a combination of process mining and clustering techniques followed by a complementary process mining technique that has a unique feature to bring insights into the temporal learning processes. This new method also has a strong potential to inform and enhance understanding of how learners make complex decisions about their learning. Third, the thesis investigates mutual connections between time management and learning strategies and their combined connections with academic performance using epistemic network analysis. This analysis provides empirical evidence that supports the proposition that time management is a critical characteristic of effective self-regulated learners. Fourth, the thesis proposes a novel method that integrates computational and visualization techniques to explore the frequency, connections, ordering, and the time of the execution of time management and learning tactics, which usually been done in isolation in the

existing literature. Then, the thesis quantitatively and theoretically compare time management and learning strategies detected with this new method to explore the role of time management and learning strategies in learning as drawing on theories of educational psychology. Fifth, this new method was validated in a study that was conducted on the trace data of different learning modalities and interaction modes, where large cohorts are involved. This final study emphasizes the importance of multivocality approach in the study of time management and other relevant learning constructs. Finally, the thesis concludes with a discussion of practical implications, the significance of the results, and future research directions.

Lay summary

This thesis presents novel methodological approaches for the detection of time management tactics and strategies and other relevant learning constructs in blended and online learning settings. The study presented in this thesis is guided by Philip H Winne and Allyson Hadwin's self-regulated learning theory, complemented by the work of John Dunlosky on the principle of learning. In terms of methodology, we demonstrate a wide range of learning analytics-based methods that can be used to provide richer and meaningful insights into understanding complex learning phenomena and their connections to learning outcomes. To sum up, this thesis offers valid and theoretically-grounded work based on a large scale of digital trace data collected across diverse courses and contexts.

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Declaration of authorship

I declare that this thesis has been composed solely by myself and that it has not been submitted, either in whole or in part, in any previous application for a degree. Except where otherwise acknowledged, the work presented is entirely my own. This thesis also includes five peer-reviewed publications produced under the joint authorship:

1. Ahmad Uzir, N., Gašević, D., Matcha, W., Jovanović, J., & Pardo, A. (2020). Analytics of Time Management Strategies in a Flipped Classroom. *Journal of Computer Assisted Learning*, 36(1), 70–88. doi:<https://doi.org/10.1111/jcal.12392>
2. Ahmad Uzir, N., Gašević, D., Matcha, W., Jovanović, J., Pardo, A., Lim, L.-A., & Gentili, S. (2019). Discovering Time Management Strategies in Learning Processes Using Process Mining Techniques. In *European conference on technology enhanced learning* (pp. 555–569). doi:https://doi.org/10.1007/978-3-030-29736-7_{_}41
3. Ahmad Uzir, N., Matcha, W., Gašević, D., Eagan, B., Jovanović, J., Williamson Shaffer, D., & Pardo, A. (2020). Epistemic Network Analytics to Unveil Links of Learning Strategies, Time Management, and Academic Performance in Flipped Classrooms. *Manuscript submitted for publication to the IEEE Transactions on Learning Technologies*
4. Ahmad Uzir, N., Gašević, D., Jovanović, J., Matcha, W., Lim, L.-A., & Fudge, A. (2020). Analytics of Time Management and Learning Strategies for Effective Online Learning in Blended Environments. *Proceedings of the 10th International Conference on Learning Analytics and Knowledge (LAK '20)*. doi:<https://doi.org/10.1145/3375462.3375493>
5. Ahmad Uzir, N., Gašević, D., Matcha, W., Jovanović, J., Pardo, A., Lim, L.-A., Gentili, S., Pérez-Sanagustín, M., & Maldonado-Mahauad, J. (2020). Theoretically Grounded Analytics of Learning Strategies: A Multivocal Approach. *Manuscript submitted for publication to the IEEE Transactions on Learning Technologies*

I declare that I substantially contributed to all the five publications (i.e., over 50% of the work done) and was involved in all phases of the research process, including study conceptualization, data collection, data analysis, and interpretation, as well as the writing of the final publications.

Nora'ayu Ahmad Uzir

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1

Introduction

Yesterday is gone. Tomorrow has not yet come. We have only today. Let us begin.

— Mother Theresa, *Good stuff for your heart & mind*

ENROLMENT in higher education has shown explosive growth across the globe. It is predicted that globally a total tertiary enrolment is expected to grow from 250.7 million in 2020 to 377.4 million by 2030, and it is forecast to rise to 594.1 million by 2040 (Calderon, 2018). The massification and diversification of the tertiary education sector have increased the need for digital transformation and pedagogical innovations that may promote active learning and improve academic success. The recent 2019 EDUCAUSE Horizon Report (B. Alexander et al., 2019) describes blended learning designs and online learning evolution as the top 10 key trends expected to have a significant impact on how educational institutions approach their core mission of teaching and learning. As digital education advances, there is increasing potential of using complex and unprecedented amounts of data to understand and enhance learning. However, these data would be nothing more than mundane information if higher education institutions failed to see such potential.

One way to decipher meaningful patterns from large sets of data is by using learning analytics. Learning analytics has emerged as a significant area of research related to technology-enhanced learning. Learning analytics involves “*measurement, collection, analysis, and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs*” (Long, Siemens, Conole, & Gasevic, 2011). Since being featured as “Four to Five Years” time-to-adoption horizon in the 2011 New Media Consortium (NMC) Horizon Report (Johnson, Smith, Willis, Levine, & Haywood, 2012), learning analytics has gained widespread attention as a field that offers powerful methods (Shacklock, 2016) to capture and measure academic readiness, learning progress, and other indicators of student success (Johnson et al., 2016) in the higher education context. Recently, the 2019 NMC Horizon Report (B. Alexander et al., 2019) recognized learning analytics as “Mid-Term Trends: Driving Ed Tech Adoption in Higher Education”, thus positioned learning analytics as an important tool for the next five more years.

Table 1. Summary of the datasets used in the thesis

Dataset	Course	Learning Modalities	Year	Course Duration	Total Students	Chapters
Dataset 1	Computer Engineering	Flipped Classroom	2014 — 2016	13 Weeks	1,134	Chapter two Chapter four Chapter six
Dataset 2	Health Science	Blended Learning	2016 -- 2017	13 Weeks	487	Chapter three Chapter six
Dataset 3	Foundation Studies	Blended Learning	2017 -- 2018	13 Weeks	482	Chapter five
Dataset 4	Introduction to Python	MOOC	2017	7 Weeks	368	Chapter six

This thesis examines the affordances and challenges of three learning modalities that have partially or fully adopted web-based educational technologies: (i) *flipped classroom* – commonly involves three explicit components that reiterate on a weekly basis throughout the course timeline. The first component is pre-class preparatory work that is realised through various online modules such as lecture video recordings, reading materials, quizzes, and problem-solving activities in unsupervised study environments. The pre-class activities are used to facilitate the development of lower level cognitive skills such as knowledge (recognising or remembering facts and concepts), comprehension (demonstrating an understanding of facts and concepts), and application (using acquired knowledge in new situations) (Bloom, 1974). The second component involves in-class activities through face-to-face interactions and collaborations with peers guided by the instructor to facilitate higher order thinking skills typically through active participation in the analysis, synthesis, and evaluation (Bloom, 1974) of activities carried out in the preparatory stage. Finally, post-class activities are typically offered in online formats, e.g., formative quizzes undertaken to fully benefit from in-class sessions (Fisher, Ross, Laferriere, & Maritz, 2014; Heinerichs, Pazzaglia, & Gilboy, 2016; Mclean, Attardi, Faden, & Goldszmidt, 2016; Pardo, Gasevic, Jovanovic, Dawson, & Mirriahi, 2018; Porcaro, Jackson, McLaughlin, & O'Malley, 2016), (ii) *blended learning* – the terms blended learning and flipped classroom are often used interchangeably in the literature to describe a combination of face-to-face and online learning. In this thesis, we make a distinction between the two in that the completion of pre-class activities are not mandatory in blended learning. Nevertheless, blended learning recommends learners to regulate their own learning to gain the fundamental knowledge prior to weekly face-to-face sessions, and (iii) *massive open online courses (MOOCs)* – host fully online modules and learning resources such as lecture videos, lecture notes, quizzes, problem-solving exercises, discussion boards, and course assessments. MOOCs are self-paced courses which allow students to freely study any topics and practice any learning materials at their own convenience with the instructor's minimal intervention. This makes the MOOC format a resourceful and powerful (Subbian, 2013), yet demanding learning modality that requires learners to be highly autonomous and responsible for making their own learning decisions to achieve their learning objectives. Accordingly, Table 1 summarizes the datasets that were obtained from the flipped classroom, blended learning, and massive online learning course.

1. INTRODUCTION

Within the context of blended and online education, time management is recognized as a fundamental component that could promote or hinder academic success. Defined as “*behaviours that aim at achieving an effective use of time while performing certain goal-directed activities*” (Claessens, Eerde, & Rutte, 2007, pg. 262), time management is closely related to students’ ability and commitment to plan and regulate their study time to keep up with a wide range of learning tasks throughout their studies. As such, students take an active role in the process of planning for time use in the future, scheduling sufficient study time, spreading time consistently throughout the designated learning duration, completing the learning tasks, and meeting the deadlines (Khiat, 2019; Thibodeaux, Deutsch, Kitsantas, & Winsler, 2017; Xu, Yuan, Xu, & Xu, 2014). This process is essential in the development of students’ self-regulation skills (Van Den Hurk, 2006).

To date, studies of time management are primarily based on theoretical models of self-regulated learning (SRL) (Broadbent, 2017; Douglas, Bore, & Munro, 2016; Eilam & Aharon, 2003; Khiat, 2019; Tabuenca, Kalz, Drachsler, & Specht, 2015; Thibodeaux et al., 2017; Van Den Hurk, 2006; Won & Yu, 2018). In particular, Winne and Hadwin (1998)’s model of SRL (see Figure 1) is arguably the most established and widely-adopted model in the field of learning sciences. Winne and Hadwin (1998) introduce four iterative phases for promoting productive self-regulation that include: (i) *task definition* – represents students’ perceptions of resources and constraints that may affect their studies, (ii) *planning and goal setting* – refers to learning targets that students hope to achieve and the plans they develop to achieve the desired goals, (iii) *tactics and strategies enactment* – refer to students’ engagement with the task by enacting planned operations, and (iv) *metacognition adaptation* – represents students’ ability to review and forecast better forms of learning in the future (Winne, 2017, 2018).

In the literature, it is well established that time management strategies have emerged as important cognitive regulatory aspects of SRL, which is believed to be a key factor of academic achievements (Broadbent, 2017; Thibodeaux et al., 2017). In light of this, we posited that time management tactics and strategies could be used to describe a learning success in blended and online learning environments. Considering that research on time management tactics and strategies in the context of online learning is embryonic, time management tactics are often defined according to a shared definition of a ‘study tactics’, while time management strategies agree on the terminology of ‘learning strategies’ (P. A. Alexander, Graham, & Harris, 1998; Fincham, Gasevic, Jovanovic, & Pardo, 2019; Winne, Jamieson-Noel, & Muis, 2002).

Following Derry (1988), learning strategies are patterns of tactics adopted by learners across study sessions, whereas learning tactics are defined as a sequence of actions that a learner performs in relation to a given task within a learning session (Hadwin, Nesbit, Jamieson-Noel, Code, & Winne, 2007). However, the growing use of the term has led to new definitions of time management tactics and strategies. For example, time management tactics can be define as “*a sequence of time-related decisions and enactment of learning actions during a learning session to meet the requirements*

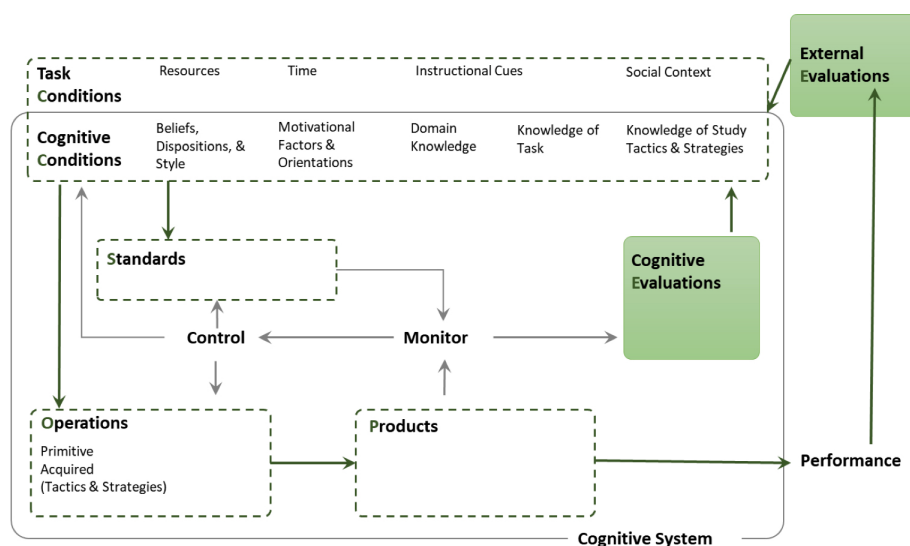


Figure 1. The self-regulated learning (SRL) model (adopted from Winne & Hadwin, 1998)

of specified tasks”, whereas strategies represent “sets of enacted time management tactics made up by selecting, combining, or redesigning those tactics as directed by a learning goal” (Ahmad Uzir, Gašević, Matcha, Jovanović, & Pardo, 2020, pg. 4).

Time management strategies are considered as latent constructs that can be inferred by using appropriate analytical methods on trace data. Trace data is recorded evidence of activities undertaken in an online environment. The data usually consists of detailed timestamped records created in a log file. These records provide insights into the time dimension of students’ actions performed in the learning process. Unfortunately time data has been underused (Winne, 2017) and existing research on time management have mainly relied on self-reported instruments (Arguedas, Daradoumis, & Xhafa, 2016; Gayef, 2017; Kelly, 2003; MacCann, Fogarty, & Roberts, 2012; Miller, 2015; Misra & McKean, 2000; Thibodeaux et al., 2017; Van Den Hurk, 2006; van der Meer, Jansen, & Torenbeek, 2010; Won & Yu, 2018). Although self-report research is unequivocally valid to represent students’ perceptions about their learning, it has been criticised for their relative inaccuracy in presenting actual learning processes (Winne & Jamieson-Noel, 2002) and their ineffectiveness to capture latent nature and inherent autonomous learning capacity (Hadwin et al., 2007; Winne & Jamieson-Noel, 2002, 2003).

This gap can be addressed by using more rigorous methods of analysis (Claessens et al., 2007) and making use of the vast amounts of data available in online learning environments. This allows us to develop more data-informed approaches to teaching and learning and improve academic achievement (Hadwin et al., 2007). To this end, *the central idea of this thesis is to make use of a large scale of trace data collected from various learning systems and analyze the trace data by using a wide range of learning analytics methods. The goal is to provide valid, generalizable, and theoretically-grounded evidence about students’ time management tactics and strategies in addition to relevant learning constructs.*

In sum, this PhD thesis presents novel methodological contributions for the detection of time management tactics and strategies and other relevant learning constructs in blended and online learning settings. To serve the purpose of the thesis, three novel methods were proposed. The first method introduces a sequential analysis to detect patterns of tactics used, and unsupervised clustering method to extract time management strategies from patterns of tactics used. The second method makes use of process mining and machine learning algorithm to automatically detect patterns of time management tactics performed during learning sessions. Whereas, hierarchical clustering was used to identify student groups based on the commonalities in the adopted tactics, which are indicative of time management strategies. The third method proposes a new method that integrates two kinds of constructs, which are time management and learning tactics. To detect both time management tactics and learning tactics, we replicated the foregoing tactic detection method by using process mining and machine learning algorithm. Then, we used the epistemic network analysis and hierarchical clustering method to identify strategy groups based on patterns of learning strategies. In this case, learning strategies are characterised by the way a learner incorporates both time management tactics and learning tactics throughout the course. Additionally, we also propose a new method using process mining and network analysis to explore the temporal and sequential dimensions of the learning strategy groups. Taken together, the proposed methods in this thesis provide a comprehensive and holistic approach to the analysis of the integral dimensions of time management and, more broadly, student learning strategies.

1.1 Research goals and questions

The work presented in this thesis is guided by four primary research goals in mind. The first goal is to develop a novel method for the detection of time management tactics and strategies by making use of trace data and learning analytics methods that are theoretically aligned with the Winne and Hadwin (1998) model of SRL. Research into SRL traditionally relied upon self-reported data. However, reliance on self-reports for the measurement of tactics and strategies and other relevant SRL constructs raises concerns about the validity of retrospective reports in terms of capturing latent behaviour and actual learning processes (Winne et al., 2002). Due to these concerns, our analysis focuses on the use of learning analytics methods and digital traces in an attempt to detect time management tactics and strategies. As such, our first research question is formulated as follows:

RESEARCH QUESTION 1:

To what extent can learning analytics methods and trace data about students' interaction with online environments be used to detect theoretically meaningful tactics and strategies of students' time management?

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The effectiveness of strategies is often measured based on students' achievements in the course. Thus, it is necessary to ensure that learning strategies identified by the proposed methods are valid in terms of their association with the course performance. Therefore, our second research question is:

RESEARCH QUESTION 2:

To what extent are learning strategies detected with learning analytics methods from trace data associated with academic achievement?

However, the detection of tactics and strategies alone is not sufficient for informative research into students' behaviour and decision-making. Rather, time management strategies and tactics can be more useful if we can capture how SRL occurs as a temporal event that unfolds over time throughout a learning session. In order to achieve this goal, it is thus essential to develop a method that allows a holistic analysis of the integral dimensions of the learning process, i.e., connection, process, and time to overcome some of the limitations in the temporal analytics research (Chen, Knight, & Wise, 2018). To this end, we explore:

RESEARCH QUESTION 3:

To what extent can a learning analytics methods gauge the temporal dimensions (i.e., process, connection, and time) of students' learning that are grounded in SRL theories?

Recent research, however, posited that there is a paucity of research which integrates prospects of both time management (i.e., time dimension extracted from the timestamps (Hadwin et al., 2007; Winne, 2017, 2018)) and learning tactics (i.e., recorded evidence of learning actions (Howison, Wiggins, & Crowston, 2011; Winne, 2017)) to provide holistic insights into learning strategies (de Barba et al., 2020). Typically, time management and learning tactics are studied in isolation from each other in the literature (Ahmad Uzir, Gašević, Jovanović, et al., 2020; Ahmad Uzir, Gašević, Matcha, Jovanović, & Pardo, 2020; Ahmad Uzir et al., 2019; Fincham et al., 2019; Jovanovic, Gasevic, Dawson, Pardo, & Mirriahi, 2017; Matcha, Gašević, Ahmad Uzir, Jovanović, & Pardo, 2019; Matcha, Gašević, Ahmad Uzir, Jovanović, Pardo, et al., 2019). As our understanding of the complexity of learning matures, it is essential to develop a novel method that can integrate the two kinds of tactics that could add depth to our understandings of students' self-regulation strategies. To offer a valid, grounded in theory, and generalizable methodological contribution, it is vital to evaluate such learning analytics methods across different learning modalities that would allow for generalization from one context to another. As such, the fourth and final research question of this thesis is:

RESEARCH QUESTION 4:

To what extent can learning analytics method be used to incorporate insights from both time management and learning tactics to form valid, generalizable and theoretically-grounded analyses of learning strategies?

1.2 Methodology

The research presented in this thesis is quantitatively and theoretically-grounded work that integrates multiple learning analytics methods and trace data that is collected from blended and online learning environments, namely, flipped classrooms, blended learning courses, and massive open online courses (MOOC). In this remaining section, we described the learning analytics methods used in this thesis according to four research questions (refer to Table 2).

To address research question one (RQ1), two learning analytics methods were proposed to detect time management tactics and strategies. First, we make combined use of sequence analysis and agglomerative hierarchical clustering (AHC) to identify patterns in student behaviour. This process begins with labelling each learning action in each learning session with an appropriate *mode of study* based on its timing with respect to the week's topic as (i) *preparing* – if the learning action was related to the topic the students were supposed to study in the given week; (ii) *ahead* – if the learning action was advance of the schedule; (iii) *revisiting* – if the learning action was related to a behind-the-schedule topic that the student had already studied at some earlier point in time; and (iv) *catching up* – if the student had never accessed activities related to the behind-the-schedule topic. As a result, each learning session was encoded as a sequence of modes of study based on a representation format of the TraMineR R package (Gabadinho, Ritschard, Mueller, & Studer, 2011). Note that the sequences were characterised by considerable heterogeneity, both in terms of their length and the diversity of modes of studies they consisted of. After that, we used AHC based on Ward's algorithm (Hastie, Tibshirani, & Friedman, 2009) to (i) group similar sequences of modes of study in order to detect a pattern of time management tactics; and (ii) identify time management strategies by grouping students with similar patterns of time management tactics indicative of strategy groups.

Table 2. Analytical methods used in the chapters that are presented in this thesis.

Chapter	RQ1			RQ2	RQ3
	Detect Tactics		Detect	Course	Explore
	Time	Learning	Strategies	Performance	Strategies
Chapter 2	SA	-	AHC	KW + MW	-
Chapter 3	FOMM + EM	-	AHC	KW + MW	bupaR
Chapter 4	-	-	-	-	ENA + T-test
	RQ4				
Chapter 5	FOMM + EM	FOMM + EM	ENA + AHC	KW + MW	ENA + bupaR
Chapter 6	FOMM + EM	FOMM + EM	ENA + AHC	KW + MW	ENA + bupaR

**Note: SA = Sequential Analysis, FOMM = First Order Markov Model, AHC = Agglomerative Hierarchical Clustering, EM = Expectation Maximization, ENA = Epistemic Network Analysis, KW = Kruskal Wallis, MW = Pairwise Mann-Whitney U Test, bupaR = Process Mining bupaR, RQ = Research Question

1. INTRODUCTION

Second, we combined three complementary methods, namely First Order Markov Model (FOMM) implemented in the pMineR R (Gatta et al., 2017), expectation-maximization (EM) algorithm (Ferreira & Gillblad, 2009) and AHC based on Ward's algorithm (Hastie et al., 2009) to detect tactics and strategies. FOMM allows for modelling the changing of states based on the probability theory and the assumption that the next state depends only on the current state. In this work, Markov chains mainly were used to model learners' interaction logs as transition probabilities between different modes of studies. As such, Markov chain representation aggregates sequences of modes of study (i.e., ahead, preparing, revisiting, and catching-up) into state transition models, which encode the probability of performing one mode of study after the other. Then, an expectation-maximization (EM) algorithm was used to identify common patterns of modes of study indicative of time management tactics. Once tactics are framed, strategies can be more easily identified. In particular, strategies encompass one or more tactics that learners employ across the course timeline (Derry, 1988). To identify the strategies, we used AHC based on Ward's algorithm to group students with similar usage patterns of time management tactics. Then, the optimal numbers of clusters were inspected from the resulting dendrogram, depicting the cluster results indicative of strategy groups.

To address research question two (RQ2), we used Kruskal Wallis tests followed by pairwise Mann Whitney U tests to examine if there was a significant difference between students who used different learning strategies, identified with our proposed methods, on course performance.

To address research question three (RQ3), we further explored the temporal data based on how tactics been used across identified strategy groups throughout the course timeline by using: (i) process mining method implemented in the bupaR R-package (Janssenswillen, Depaire, Swennen, Jans, & Vanhoof, 2019); and (ii) epistemic network analysis (ENA) implemented in the rENA R-package (Shaffer, 2018). Firstly, we used a process mining method implemented in the bupaR R-package (Janssenswillen et al., 2019) for an easier understanding of the complexity of a learning process. In particular, this process mining method offered useful functions to compute and visualize the process (i.e., transition from one tactic to another), and time dimensions (i.e., interval time between the enactment of one tactic to another). In doing so, we were able to explore and gain insights into the temporal representations of students' learning in terms of the frequency of occurrences of tactics (activity instances), frequency of transitions between consecutive tactics, and idle time (in days) between enactment of one tactic to another, across identified strategy groups.

Secondly, to understand the structure and strength of connections between tactics across strategy groups, we used ENA implemented in the rENA R-package to compute and visualize the network model representing the identified tactics that corresponded to each strategy group. Each resulting ENA network is visualized using two-dimensions plotted along the horizontal axis (x-axis) and the vertical axis (y-axis) defined by a singular value decomposition (svd) with its respective variance (percentages of variance are shown on each axis). In an ENA network, nodes represent individual tactics, and the node size in the visual representation of the network model represents the frequency

Table 3. Overview of the research questions by individual chapters.

Chapter	Title	Research questions			
		RQ 1	RQ 2	RQ 3	RQ 4
Chapter 2	Detection of Time Management Tactics and Strategies	✓	✓		
Chapter 3	Temporal Representation of Learners' Decision	✓	✓	✓	
Chapter 4	Network Representation of Students' Learning			✓	
Chapter 5	Analytics of Time Management and Learning Strategies		✓	✓	✓
Chapter 6	Multivocal Analytics of Learning Strategies		✓	✓	✓

with which tactics occurred in the strategy group. Meanwhile, the thickness of the lines between the nodes indicates the strength of the connections, where thicker lines correspond to stronger relationships (i.e., more frequent co-occurrence) (Shaffer, 2013, 2018). Notably, in Chapter four, we complemented ENA with sample t-test in order to better understand the difference between two polarities of performance groups – high and low performing groups. The sample t-test was carried out to examine the presence of a significant difference in the mean network positions of the two groups in the ENA projection space.

Notwithstanding the importance of appropriate use of tactics and strategies for academic success, comparatively little is known about the effectiveness of time management and learning tactics chosen by learners during online learning. Therefore, to address the final research question (RQ4), we applied a process mining method (FOMM) paired with a clustering method (EM algorithm) to detect: (i) patterns in sequences of the students' modes of study (i.e., ahead, preparing, revisiting, and catching-up), as a manifestation of students' time management tactics, and (ii) patterns in sequences of students' learning actions (i.e., video_play, discussion_post, content_access) as a manifestation of their learning tactics. In both cases, FOMM, implemented in the pMineR R package (Gatta et al., 2017), was used to compute and visualize process models derived from learning sessions.

Meanwhile, strategies were characterised by the way a student incorporated time management tactics and learning tactics throughout the course timeline. The rENA R-package for ENA (Shaffer, 2018) was used to compute the co-occurrence of time management tactics and learning tactics in each learning session. Specifically, we presented each student as a vector of the following variables: (i) counts of co-occurrences of a distinct combination of time management and learning tactics. For example, if there are three different time management tactics and four different learning tactics, it creates 12 variables (counts), and (ii) the total count of co-occurrences of time management and learning tactics. Then, such vector-based student representations were normalized and used as an input for the AHC. The distance between students, required for the Ward algorithm (Hastie et al., 2009), was computed as the Euclidean distance of the corresponding vectors. The optimal number of clusters was determined by inspecting dendrograms of strategy groups.

1.3 Thesis structure and overview

To address the four research questions, we organize the thesis into five individual chapters, as shown in Table 3. Each chapter focuses on one or more research questions and includes one peer-reviewed publication that constitutes the core of the chapter. We also provide a short preface and summary to each included publication to describe how a particular publication fits into the overall structure and the topic of the thesis. In the remainder of this section, we provide a brief overview of each chapter and how they contribute to the overall research goals of the thesis.

1.3.1 Overview of chapter two: “Detection of Time Management Tactics and Strategies” (RQs 1 & 2)

To date, research on time management makes extensive use of self-reported instruments (Douglas et al., 2016; Hensley, Wolters, Won, & Brady, 2018; Thibodeaux et al., 2017). Indeed, self-report research is unequivocally valid to represent students’ perceptions about their learning. However, self-reports have been criticised for their limitations to provide insights into actual learning processes (Winne & Jamieson-Noel, 2002) and their ineffectiveness to explore latent nature and inherent autonomous learning capacity (Hadwin et al., 2007; Winne & Jamieson-Noel, 2002, 2003).

Therefore, the use of trace data is suggested to complement self-reports (Winne et al., 2002). Analysis of trace data in the SRL research is a promising approach to mitigating limitations of self-reported measures (Winne, 2010) and could offer actual measures of the use of specific study tactics (Winne & Jamieson-Noel, 2002). Although research related to time management as a general behaviour is relatively well established (Filva, Guerrero, & Forment, 2014; Nguyen, Huptych, & Rienties, 2018; Tang, Xing, & Pei, 2018), research into the detection of time management tactics and strategies from trace data is scarce.

Learning tactics and strategies are considered latent constructs that can be extracted from trace data by using appropriate analytical methods (Fincham et al., 2019; Matcha, Gašević, Ahmad Uzir, Jovanović, & Pardo, 2019). Trace data is recorded evidence of activities undertaken in an online environment, and the data typically consists of detailed timestamped records created in a log file. These records have the potential to support the validity of the time dimension of students’ actions in a learning process and allow for the analysis of timing, sequencing, and patterns of events. Thus, time management tactics and strategies need to be studied further with more rigorous methods of analysis (Claessens et al., 2007) to develop more data-informed approaches to teaching and learning and to improve academic achievement (Hadwin et al., 2007). Accordingly, this study attempts to detect time management tactics and strategies by utilizing students’ trace data collected from learning systems.

Research contributions:

- We provide a new definition for time management tactics and strategies that recognizes the specificity of digital learning environments.
- We develop a new method for detecting time management tactics and strategies from trace data collected from online learning environments by using a combination of unsupervised machine learning and sequence mining methods
- We identify several time management strategies (made-up of a set of enacted tactics) and examined their association with learning outcomes, measured by final grade.
- We show that timestamps available in the trace data are reliable and valid for the interpretation of time management tactics and strategies with respect to the relevant theory of human learning and students' academic performance.

Research output:

1. Ahmad Uzir, N., Gašević, D., Matcha, W., Jovanović, J., & Pardo, A. (2020). Analytics of Time Management Strategies in a Flipped Classroom. *Journal of Computer Assisted Learning*, 36(1), 70–88. doi:<https://doi.org/10.1111/jcal.12392>: A journal article describing our method for detecting time management tactics and strategies using sequential analysis, and their association with course outcomes.

1.3.2 Overview of chapter three: “Temporal Representation of Learners’ Decision” (RQs 1, 2 & 3)

Time management is commonly linked to self-regulation skills (Broadbent, 2017; Thibodeaux et al., 2017) since it is closely related to learners’ decisions about what to study, how long to study, and how to study (Kornell & Bjork, 2007; Winne, 2015, 2017) with minimal instructors’ intervention. In line with the SRL perspective, time management has been recognized as learners’ efforts to effectively use their time while progressing toward set learning goals, whereas time management tactics and strategies refer to how timely students manage their study tactics and strategies (Ahmad Uzir et al., 2019).

Learning analytics methods can extract interpretable and meaningful representations of time management tactics and strategies from trace log data (Chapter two). However, little attention has been paid to precise identification, measurement, and analysis of the temporal features of learning (Chen et al., 2018; Chen, Wise, Knight, & Cheng, 2016). To address this limitation, this chapter demonstrates how process mining methods and machine learning algorithms can be used to: (i) automatically detect time management tactics at the level of learning sessions, and (ii) offer quantitative temporal data about students’ online learning activities indicative of learners’ decision on their time management strategies, on what tactics to use (e.g., how learners modify their tactics to support their learning goal), frequency of tactics use (e.g., the absolute frequency of occurrences of events) and timing of tactic use (e.g., interval time (in days) between one tactic to other tactics).

Research contributions:

- We propose an automated method for the detection of time management tactics that are based on the analysis of students' learning sessions within a blended learning environment.
- We demonstrate that process mining models can detect substantial temporal difference between identified time management strategies, indicative of study decisions that students make in terms of what to study, how long to study, and how to study.

Research output:

1. Ahmad Uzir, N., Gašević, D., Matcha, W., Jovanović, J., Pardo, A., Lim, L.-A., & Gentili, S. (2019). Discovering Time Management Strategies in Learning Processes Using Process Mining Techniques. In *European conference on technology enhanced learning* (pp. 555–569). doi:https://doi.org/10.1007/978-3-030-29736-7_{ }41: A full conference paper discovering time management strategies in learning processes using process mining methods. The paper was presented at the Fourteenth European Conference on Technology Enhanced Learning (EC-TEL 2019) and was awarded the best paper award.

1.3.3 Overview of chapter four: “Network Representation of Students’ Learning” (RQ 3)

Learning strategies and time management are vital components of self-regulated learning (Winne, 2013). However, time management and learning dimensions are typically studied in isolation in the existing literature (de Barba et al., 2020). Methods that commonly used for (statistical) analyses cannot offer sufficient insights into (i) the ways that different learning and time management strategies are interlinked with each other and with course topics, (ii) how these links can qualitatively be interpreted, and (iii) whether there are (statistical) differences in such links among different groups of students. This chapter proposes a network analytic approach – based on ENA (Shaffer, 2018) – to addressing the above limitations in a study that looked at students' ability to modify their learning strategies and manage time while completing online learning tasks. We further apply the same methods to explore the difference between high and low performing groups. The study results show that the use of ENA not only enables us to identify and demonstrate qualitative results, but it also enables us to unveil the quantitative differences among the studied groups.

Research contributions:

- We demonstrate that ENA can be used to analyze interrelations between three constructs — learning strategies, time management, and course topics.
- Our results reveal that the use of ENA allows for qualitative and quantitative comparisons of individuals and groups.

Research output:

1. Ahmad Uzir, N., Matcha, W., Gašević, D., Eagan, B., Jovanović, J., Williamson Shaffer, D., & Pardo, A. (2020). Epistemic Network Analytics to Unveil Links of Learning Strategies, Time Management, and Academic Performance in Flipped Classrooms. *Manuscript submitted for*

publication to the IEEE Transactions on Learning Technologies: A journal article, currently under the review, which describes the use of epistemic network analysis to unveil links among learning strategies, time management, and academic performance.

1.3.4 Overview of chapter five: “Analytics of Time Management and Learning Strategies” (RQs 2, 3 & 4)

Evidence to date indicates that students’ time management and learning strategies are tightly tied to their ability to self-regulate learning (Ahmad Uzir, Matcha, et al., 2020). Recent research into the identification of productive self-regulation in online and blended courses found that effective learning tactics and strategies both in time management (Ahmad Uzir, Gašević, Matcha, Jovanović, & Pardo, 2020; Ahmad Uzir et al., 2019) and learning strategies (Fincham et al., 2019; Jovanovic et al., 2017; Kizilcec, Pérez-Sanagustín, & Maldonado, 2017; Maldonado-Mahauad, Pérez-Sanagustín, Kizilcec, Morales, & Munoz-Gama, 2018; Matcha, Gašević, Ahmad Uzir, Jovanović, & Pardo, 2019; Matcha, Gašević, Ahmad Uzir, Jovanović, Pardo, et al., 2019) were strongly associated with course achievement. Hence, examining both time management and learning tactics and strategies through the perspective of SRL theory could potentially be a promising approach for advancing our understanding of the choices learners make when managing their learning in a blended or online learning environment.

Hence, the focus of this chapter is to propose new methods that allow for the identification and interpretation of SRL in terms of the use of learning strategies characterised by identified tactics – time management and learning tactics in a blended learning setting. To achieve this, we first combine two complementary analytical methods: (i) ENA (Shaffer, 2018) and (ii) AHC based on Ward’s algorithm (Hastie et al., 2009) to identify the strategy groups by integrating both time management and learning tactics. Second, we further combine unsupervised machine learning with network (ENA) and process mining (bupaR) methods to propose a new method that allows us to inspect the role of time management and learning tactics in learning strategies according to relevant principles documented in the educational psychology literature (Dunlosky, 2013; Dunlosky, Rawson, Marsh, Nathan, & Willingham, 2013). In addition, this proposed method also allows for novel insights into learning strategies through the inspection of frequency, order, and timing of time management and learning tactics, and the strength of their connections.

Research contributions:

- We propose a novel method that combines a network analysis method and a hierarchical clustering method to identify and examine strategy groups, starting from the identified tactics – both time management and learning tactics.
- We offer an empirically validated methodological approach to the detection of learning patterns from trace data recorded on digital learning platforms that reflect learners’ (i) time management and learning strategies, and (ii) association with academic achievement in blended

and online courses.

- We offer insights into relevant dimensions (i.e., time, ordering, frequency, and strength of connections) for the understanding of self-regulation in aspects of both time management and learning tactics, which are usually studied in isolation in the literature.
- We propose new methods that allow for a close inspection of the role of time management and learning tactics in learning strategies according to relevant principles documented in the educational psychology literature.

Research output:

1. Ahmad Uzir, N., Gašević, D., Jovanović, J., Matcha, W., Lim, L.-A., & Fudge, A. (2020). Analytics of Time Management and Learning Strategies for Effective Online Learning in Blended Environments. *Proceedings of the 10th International Conference on Learning Analytics and Knowledge (LAK '20)*. doi:<https://doi.org/10.1145/3375462.3375493>: A full conference paper reporting the combined methodology to study on time management and learning tactics as a manifestation of learning strategies. The paper will be presented at the Tenth International Conference on Learning Analytics and Knowledge (LAK '20).

1.3.5 Overview of chapter six: “Multivocal Analytics of Learning Strategies” (RQs 2, 3 & 4)

In Chapter [five](#), we have proposed a new method that combines three complementary methods – AHC, ENA and process mining that allow for (i) the identification of learning strategies by integrating both time management and learning tactics, and (ii) novel insights into learning strategies by studying the frequency of, the strength of connections between, and ordering and time of execution of both time management and learning tactics. This method has been validated in a study that used trace data of two cohorts of first-year undergraduates enrolled in a blended learning course. Although it has been proven to be effective in examining the relationship between time management and learning tactics, however, this new method has not been applied in other learning contexts; thus, its generalizability (i.e., applicability across learning modalities and academic disciplines) is still unexplored.

One way to assess the generalizability of a method is to apply foregoing analysis in different learning settings (Messick, 1995). Thus, the work presented in this chapter is our final investigation into mutual connections between time management and learning tactics and strategies, in which we sought to address the validity and generality constraints of the study presented in Chapter [five](#). In particular, the focus of this chapter is on replicating the proposed methods using a large scale of data obtained from courses of various learning modalities, including flipped classrooms, blended learning, and massive open online course. The purpose is to provide empirical evidence that allows for the generalization of the proposed method across three learning contexts, and validation of multiple learning analytics methods for rigorous evaluation of learning strategies across distinct learning modalities.

Research contributions:

- We replicate the new learning analytics methods proposed in Chapter [five](#) (Ahmad Uzir, Gašević, Jovanović, et al., [2020](#)) to examine learning strategies (made-up of a set of enacted time management and learning tactics) across three learning modalities, namely, flipped classroom, blended learning, and massive open online courses.
- We validate that a combination of multiple learning analytics methods allow for the detection and rigorous evaluation of learning strategies that are meaningful from the perspective of both (i) theory of SRL, and (ii) associations with academic performance.
- This study highlights the importance of time management and learning tactics to promote effective learning strategies and academic success in blended and online learning environments.

Research output:

1. Ahmad Uzir, N., Gašević, D., Matcha, W., Jovanović, J., Pardo, A., Lim, L.-A., Gentili, S., Pérez-Sanagustín, M., & Maldonado-Mahauad, J. (2020). Theoretically Grounded Analytics of Learning Strategies: A Multivocal Approach. *Manuscript submitted for publication to the IEEE Transactions on Learning Technologies*: A journal article, currently under the review, which demonstrates the generalizability of learning analytics methods on time management and learning strategies in online learning environments.

1.3.6 Overview of chapter seven: “Conclusions and Future Directions”

In the final chapter, we examine the impact of the present work concerning the four research questions defined in Chapter [one](#). We also discuss the potential directions for future work as well as for practical applications of the research presented in this thesis. Finally, we conclude with a short overview of the thesis and a summary of its key contributions.

2

Detection of Time Management Tactics and Strategies

Your greatest resource is your time.

— Brian Tracy, *Charge Your Life: How to Get Everything You Ever Want in Life*

2.1 Introduction

THE idea of learners taking control of their learning through a cyclical process based on internal (i.e., prior knowledge, experience) and external standards (i.e., feedback from instructor) is well known as to the notion of self-regulated learning. The capacity of learners to plan and invest time in learning, follow a highly structured schedule, and proactively balance the use of time are essential parts of self-regulation (Macan, Shahani, Dipboye, & Phillips, 1990; Thibodeaux et al., 2017). Although it has been well established that self-regulation is linked to learners' time management, which, in turn, can contribute to learners' success in online and blended learning (Broadbent, 2017; Hensley et al., 2018; Nguyen et al., 2018), only a few empirical studies have examined the link between SRL and actual time management practices in online learning settings using digital trace data (Cicchinelli et al., 2018; Kizilcec et al., 2017; Tabuenca et al., 2015). Traditionally, research on time management makes extensive use of self-reported data, commonly collected through surveys (Arguedas et al., 2016; Hensley et al., 2018; Lahmers & Zulauf, 2000; Ruiz, Charleer, Fernández-castro, & Duval, 2016; Wolters, Won, & Hussain, 2017). While this data provides invaluable information about learners' perception of their own learning, it fails to measure how learners employ learning tactics and strategies (Winne et al., 2002) in learning processes, due to immature skills of self-reflection among learners (Zhou & Winne, 2012).

To overcome this limitation, we use trace data (also known as digital traces or log data) collected from LMS as fine-grained behavioural traces, which are proximal to actual learning experiences (Zhou & Winne, 2012). Trace data can help us discover patterns of students' learning experiences (Gašević, Dawson, Rogers, & Gasevic, 2016) and understand learning strategies that learners adopt (Winne et al., 2002). To the best of our knowledge, this is the first study that exploits the capacity of learning analytics methods to identify and interpret the learners' time management tactics and

strategies based on digital traces that are captured from learning management systems. Thus, this chapter aims to provide evidence and a solid understanding of how learners enact specific time management tactics and strategies when interacting with online learning environments in addition to the association of time management tactics and strategies with course performance.

2.1.1 Chapter overview

Recently, a considerable amount of research has been conducted to extract representations of learning strategies using digital trace data (Fincham et al., 2019; Jovanovic et al., 2017; Kizilcec et al., 2017; Maldonado-Mahauad et al., 2018; Matcha, Gašević, Ahmad Uzir, Jovanović, & Pardo, 2019; Matcha, Gašević, Ahmad Uzir, Jovanović, Pardo, et al., 2019). However, there is a remarkable scarcity of research examining the effectiveness of its use on identifying time management strategies. Like learning strategies, time management tactics, and strategies in online learning contexts are latent constructs that can only be extracted using appropriate analytics methods or machine learning algorithms. If these analytic methods could be used robustly to identify learning tactics and strategies, we posit that they can also be used to discover time management tactics and strategies.

In line with this interest, we utilise a sequence mining method called optimal matching of state sequences and agglomerative hierarchical clustering (Jovanovic et al., 2017) to extract latent representations of learners' time management behaviour which can be interpreted across two theoretically inspired levels: time management tactics, and time management strategies (characterised by the enacted tactics) (Ahmad Uzir, Gašević, Matcha, Jovanović, & Pardo, 2020). We first examined time management by looking at times when online activities were carried out by the learners, as evidenced in trace data, and checked against the course schedule provided by the course instructor. In particular, in each week, learners were required to study one topic. Next, the corresponding mode of study (i.e., ahead, preparing, revisiting, and catching-up) was assigned to each action based on the time that action was carried out (timestamps), which allowed us to analyse the progress and achievement behaviour of learners. The resulting sequences of the modes of study were then segmented into a learning session where each session corresponded to a particular tactic. After that, the sequences of these tactics were then generated for each learner for the entire duration of the course and were clustered to identify a set of time management strategies.






Our findings indicate that time management patterns, as manifested in students' time management tactics, can be detected from a combination of learning sessions. The observed time management patterns further contribute to the discovery of several strategy groups indicative of time management strategies. Subsequently, we demonstrate that the identified strategy groups are significantly associated with the course performance. The main contribution of the present work is a new method that provides interpretable representations and offers practical insight into learning processes and outcomes (Gašević, Kovanović, & Joksimović, 2017).

2.2 Publication: Analytics of Time Management Strategies in a Flipped Classroom

The following section includes the verbatim copy of the following publication:

Ahmad Uzir, N., Gašević, D., Matcha, W., Jovanović, J., & Pardo, A. (2020). Analytics of Time Management Strategies in a Flipped Classroom. *Journal of Computer Assisted Learning*, 36(1), 70–88. doi:<https://doi.org/10.1111/jcal.12392>

Analytics of time management strategies in a flipped classroom

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Abstract

This paper aims to explore time management strategies followed by students in a flipped classroom through the analysis of trace data. Specifically, an exploratory study was conducted on the dataset collected in three consecutive offerings of an undergraduate computer engineering course ($N = 1,134$). Trace data about activities were initially coded for the timeliness of activity completion. Such data were then analysed using agglomerative hierarchical clustering based on Ward's algorithm, first order Markov chains, and inferential statistics to (a) detect time management tactics and strategies from students' learning activities and (b) analyse the effects of personalized analytics-based feedback on time management. The results indicate that meaningful and theoretically relevant time management patterns can be detected from trace data as manifestations of students' tactics and strategies. The study also showed that time management tactics had significant associations with academic performance and were associated with different interventions in personalized analytics-based feedback.

KEYWORDS

flipped learning, learning analytics, self-regulated learning, time management

1 | INTRODUCTION

Within the higher education context, the transition from traditional education to online and blended courses provides students with a great opportunity to access learning resources conveniently. However, it also introduces a tremendous challenge for students to maintain motivation and active engagement aligned with designated academic goals. This is particularly the case in the flipped learning context, where students are required to actively participate both in online preparation (pre-class) and face-to-face (in class) activities (He, Holton, Farkas, & Warschauer, 2016). However, students are often unprepared, struggling with regulation of their time and effort, especially during pre-class activities (Heinerichs, Pazzaglia, & Gilboy, 2016). Recent research reveals that ineffective time management and low self-regulation skills are the most commonly

cited combination of unsuccessful learning factors (Petersen, Craig, Campbell, & Taffioovich, 2016; Thibodeaux, Deutsch, Kitsantas, & Winsler, 2017).

From self-regulated learning (SRL) perspective, students should be able to adjust and adapt their learning strategies and time use after reflecting on their performance (Thibodeaux et al., 2017). According to the Winne and Hadwin's four-phase model of SRL (Winne & Hadwin, 1998), students manage their learning by making a clear definition of the task at hand, by setting up goals, and by choosing strategies to achieve those goals. This is followed by enacting the tactics and strategies chosen to conduct their learning and, finally, by evaluating the effectiveness of their learning strategies based on internal (e.g., prior knowledge and experience) and external standards (e.g., feedback from teacher) for future improvement (Winne, 2014). Hence, the capacity of students to plan and invest time in learning, to follow

a highly structured schedule, and to balance proactively the use of time are essential parts of self-regulation (St, Macan, Dipboye, & Phillips, 1990; Thibodeaux et al., 2017). The need for strong self-regulation and time management skills has also been recognized by studies that found their significant positive associations with academic performance (Hensley, Wolters, Won, & Brady, 2018; Nguyen, Hupitych, & Rienties, 2018; Thibodeaux et al., 2017). All this clearly points to the relevance of time management skills.

There has been a lacuna in research that aims to understand how students manage their time in online preparation activities within the flipped classroom context. Even if particular approaches to time management can be identified, there is equally limited research on the extent to which such differences are associated with academic success. To address these two gaps in the literature, the objective of the current study is to propose and empirically demonstrate the value of a learning analytics-based methodology for identification of tactics and strategies of time management. This is achieved by making use of trace data recorded by digital learning environments and analysing these data with advanced data science methods. As such, the proposed methodology overcomes the limitations of self-reported measures of time management and SRL including their static nature and inherit bias (Jovanović, Gašević, Pardo, Dawson, & Whitelock-Wainwright, 2019; Winne & Jamieson-Noel, 2003; Zhou & Winne, 2012).

The presented analytics-based methodology builds upon recent research in learning analytics that proposed methodologies for detection of learning tactics and strategies. According to Fincham, Gasevic, Jovanovic, and Pardo (2019) and Matcha, Gašević, Uzir, Jovanović, and Pardo (2019), learning tactics are reflective of students' cognitive routines used for performing specified tasks, whereas learning strategies look into how students use several tactics over the course timeline. Furthermore, existing research shows that learning tactics and strategies, detected using analytics-based approaches, are associated with course performance and satisfaction (Fincham et al., 2019; Jovanovic, Gasevic, Dawson, Pardo, & Mirriahi, 2017; Matcha et al., 2019; Pardo, Gasevic, Jovanovic, Dawson, & Mirriahi, 2018) and can be used as a sound foundation for providing analytics-based personalized feedback at scale (Pardo, 2019). We posit that time management tactics and strategies have equal potential to yield useful information in the form of feedback to improve future learning. However, based on our knowledge, the current literature offers very limited evidence of time management tactic and strategies that students employ in the flipped model. Therefore, this study aims to contribute to this line of research.

The value of feedback for promoting effective time management practices in flipped classrooms is still underexplored (Pardo, 2017). To our knowledge, there has been limited work on large quantitative investigations of the role of learning analytics-based feedback in promoting effective time management practices. Thus, by employing digital traces and learning analytics methods to examine students' time management practices in relation to the received feedback, the current study is expected to provide evidence and contribute to better understanding of actual time management practice and how it can be advanced through feedback provision. In educational research, feedback is documented as one of the most powerful intervention

strategies to optimize student learning progress and performance (Evans, 2013; Hattie & Timperley, 2007). The challenge for time management feedback is to provide meaningful and actionable messages to students as they seek external feedback from expert agents such as teachers, peers, or groups (Hattie & Timperley, 2007) to support productive SRL (Azevedo et al., 2013; Winne & Hadwin, 2013). The current study addresses this gap by leveraging the principles of external educational feedback to help learners optimize their time management practices.

2 | LITERATURE REVIEW

2.1 | Time management and flipped classrooms

Flipped classroom is a pedagogical model that requires students' active participation in both pre-class and in-class learning activities (He et al., 2016). It involves online (pre-class) and face-to-face (in-class) components repeating in a back-and-forth manner on a weekly basis throughout the course. Pre-class activities allow students to make use of the independent learning time to gain foundational knowledge and skills, whereas during in-class sessions, students can actively engage in the learning process and receive individualized support (Brewer & Movahedazarhouli, 2018). By providing students with online learning resources, available before and/or after the class time, the flipped classroom model offers students an opportunity to become self-regulated in preparing their learning, for example, to explore materials such as videos, readings, or exercises at their own pace (He et al., 2016), to catch up with missed lecture (Loch & Borland, 2015), or review course materials after the class time (Bergmann & Sams, 2012).

The flipped classroom model offers much flexibility (Thai, De Wever, & Valcke, 2017), but to fulfil the potentials of this pedagogical model, time management skills and self-regulation are needed (Broadbent & Poon, 2015; Carson, 2011; He et al., 2016; Puziferro, 2008; Richardson, Abraham, & Bond, 2012). In the literature, time management is defined as "behaviours that aim at achieving an effective use of time while performing certain goal-directed activities" (Claessens, Van Eerde, Rutte, & Roe, 2007, p. 262). From the SRL perspective, effort and time management are behavioural aspects that involve students' decisions and intentions about how they allocate and control time and effort invested into studying (Pintrich, 2000; Winne, 2015). For instance, in a flipped learning context, students need to ensure that they can manage their time to complete weekly pre-class activities prior to face-to-face learning sessions, so that they can have sufficient knowledge to contribute during in-class sessions that involve interactions with peers and instructors. Overall, students need to deliberately allocate time to both online preparatory activities and face-to-face components because both hours of class attendance and hours of study out-of-class have proven to be predictors of academic success (Brint & Cantwell, 2010; Jaclyn Broadbent, 2017; He et al., 2016; Loch & Borland, 2015).

2.2 | Measurement of time management

The literature demonstrates that the interpretation of students' time management is often theoretically grounded in models of SRL (Eilam & Aharon, 2003; Van Den Hurk, 2006). Models of SRL attempt to explain how metacognitive, cognitive, motivational, and contextual factors influence the learning process (Pintrich, 2000; Winne & Hadwin, 1998; Zimmerman, 2001). This research effort is grounded in the work of three leading researchers in the field of SRL as the intention was to follow the tenets of the prevailing philosophy. According to Pintrich (1991), time management is the ability of students to schedule, plan, and manage their personal study time (Pintrich, 1991). He highlighted that setting realistic goals, allocation of study time, and effective use of study time should not be carried out in isolation but need to be carefully integrated. This is in line with the SRL perspectives of Winne (2014) and Zimmerman (1998) that see students as independent and proactive agents who are capable to construct their own goals, to engage in strategic planning, to enact the plans, to monitor their performance, and to balance various learning activities by reflecting on information available in the internal (e.g., prior knowledge) and external (e.g., time) environment.

Research on SRL makes extensive use of self-report instruments. According to Azevedo (2015), self-reports, in addition to classroom discourse, are the only proven approach that can be used for the measurement of cognitive, metacognitive, affective, and motivational constructs of student engagement. The Motivated Strategies for Learning Questionnaire (MSLQ) is a survey instrument that is frequently used to measure time management of students as part of their SRL aptitudes in tertiary education (Pintrich, Smith, Garcia, & McKeachie, 1993). The MSLQ is the most comprehensive self-reported instrument (Jaclyn Broadbent, 2017) that was constructed to measure three major components of SRL including cognitive, metacognitive, and resource management strategies (Pintrich, 1991; Pintrich, 2000). The MSLQ has a subsection focused on time management, called time/study environment (Pintrich et al., 1993). The time management and study environment subscales consist of eight items specifically to measure time regulation like "I make good use of my study time for this course" and "I have a regular place set aside for studying." Recently, a number of researchers who adopted the MSLQ instrument to assess the SRL aspects in relation to the academic achievement reported that a student's self-efficacy score is the strongest predictor of course performance, whereas the student's scores on specific regulatory scales of effort regulation and time and study environment proved to be the next most significant predictors of academic achievement (Al-Harthy, Was, & Isaacson, 2010; Jackson, 2018; Kitsantas, Winsler, & Huie, 2008; Lynch & Trujillo, 2011; Miller, 2015). Therefore, understanding the time management behaviours that students exhibit during their learning process is of key importance towards improving future learning experience and academic success.

Validity of self-reported measures of SRL and time management is often questioned, and the use of trace data is suggested to either replace or complete self-reports. Winne and Jamieson-Noel (2002)

showed that learners are inaccurate in calibrating their self-reported and actual measures of the use of specific study tactics. According to Zhou and Winne (2012), this inaccuracy in self-reports is likely due to poor learner reflection. They also empirically showed that self-reported data measured students' intentions whereas trace data measured realized intentions and allowed for collection of finer grain data points, which were more proximal to the actual learning experiences. Likewise, Filva, Guerrero, and Forment (2014) affirmed that self-reports insufficient to track or capture latent behaviour of students in online learning spaces. Trace data are suggested in the SRL research as a promising approach to mitigating limitations of self-reported measures (Winne, 2010). Trace data can offer temporally proximal accounts of the actual events of SRL. Furthermore, trace data do not suffer from biased memories of learners and self-selection bias (He et al., 2016) as trace data are collected unobtrusively while learning unfolds (Gasevic, Jovanovic, Pardo, & Dawson, 2017; Jovanović et al., 2019). Trace data also comprise many measurement points based on which the enactment of learning actions can be replayed (Winne, 2017). Finally, trace data are shown to have stronger associations with learning outcomes than self-reported measure (Zhou & Winne, 2012).

2.3 | Trace data and time management

This study relies upon the capacity of data analytics methods to uncover patterns and trends in students' time management practices based on the trace data captured by a learning management system. The advantage of analytics approaches is in their reliance on trace data that can be captured without significant interference with the actual learning process and with low risk of bias that traditional data collection methods are often susceptible to. Moreover, patterns extracted from trace data can be scrutinized to develop more complex accounts of learning (Winne, 2015).

Recently, a number of studies have begun to use learning analytics methods in examining students' time management practices in online learning settings. For instance, Il-Hyun, Kim, and Yoon (2015) used log data from a learning management system to examine adult learners' time management strategies in a commercial e-learning course. This 1-month course consisted of 12 modules and involved 200 participants. Il-Hyun et al. extracted the total login time, login frequency, and regularity of login intervals as predictors of online performance. As a result, they concluded that the regularity of the login interval is a strong indicator of adult learners' learning achievement. In addition, a recent study by Montgomery, Mousavi, Carbonaro, Hayward, and Dunn (2019) examined trace data collected from 157 undergraduates of Bachelor of Education programme who enrolled in blended classroom. This study groups the SRL skills into three categories, that is, activating, sustaining (e.g., based on Learning Management System (LMS) access time), and structuring learning (e.g., based on time management of LMS access time in terms of regularity). They found that access regularity, identified through LMS data, is the most significant indicator of SRL behaviour, also having a significant

correlation with academic achievement. Meanwhile, other types of SRL skills examined in this study have a moderate significant relation with students' academic performance.

In another work, Jovanovic, Mirriahi, Gašević, Dawson, and Pardo (2019) used learning trace data from three consecutive offerings of a flipped learning course to examine students' regularity of pre-class learning activities and its association with the course performance. Two indicators were used: generic and course-design-specific indicators. The results showed that the generic indicators of time management of pre-class activities were significantly associated with the final exam score in all three course offerings.

2.4 | Analytics of time management

This study is unique in its focus on exploring latent behaviour of students related to time management, that is, it focuses on detecting patterns in study time as manifestation of students' time management tactics. We further posit that the inspection of observable patterns in applied time management tactics can lead to the detection of time management strategies and several strategy-based student groups. In defining time management tactics and strategies, we rely on the literature on study tactics and study strategies. In the literature, study tactics are described as cognitive routines that sequences of learning actions oriented towards specified tasks, whereas strategies are defined as sets of enacted tactics made up by selecting, combining, or redesigning tactics as directed by a learning goal (Alexander, Graham, & Harris, 1998; Fincham et al., 2019; Winne, 2001; Zimmerman, 1998). Accordingly, *time management tactics can be defined as a sequence of time-relevant decisions and enactment of learning actions during a learning session to meet the requirements of specified tasks, whereas strategies represent sets of enacted time management tactics made up by selecting, combining, or redesigning those tactics as directed by a learning goal.*

In the recent years, a large and growing body of literature has focused on the use of analytics-based methods (e.g., a combination of techniques from process or sequence mining with those from unsupervised machine learning) for the study of learning strategies including detection of learning tactics, strategies, and strategy-based student profiles (Fincham et al., 2019; Jovanovic et al., 2017; Kovanović, Gašević, Joksimović, Hatala, & Adesope, 2015; Lust, Elen, & Clarebout, 2013; Matcha et al., 2019; Pardo et al., 2018). For example, Fincham et al. (2019) proposed a method that automatically detects students' learning tactics by calculating the percentages of different kinds of learning actions (e.g., exam_correct, video_start) at the level of study sessions and using them as inputs for building a hidden Markov model. After identifying study tactics as the states of the hidden Markov model, a sequence of such states was created for each student according to the chronological order of the student's sessions. Then, these sequences were clustered using agglomerative hierarchical clustering, based on Ward's method, to identify student groups based on the commonalities in the adopted learning tactics.

The results of clustering confirmed the existence of distinct patterns in student learning behaviour as manifestations of students' learning strategies.

Meanwhile, Matcha et al. (2019) proposed a novel approach that combines process mining and clustering to detect learning tactics and strategies from trace data. The analysis of trace data about students' online activities in a flipped classroom was examined at the level of study sessions using first-order Markov models (FOMM) followed by clustering of sessions via the expectation maximization algorithm in order to identify study tactics. Finally, agglomerative hierarchical clustering of the detected tactics, based on Ward's algorithm, was applied to identify student strategy groups. The findings showed five learning tactics that were combined in three different learning strategies. The identified learning strategies allowed for explaining (a) how the students enacted learning tactics over the course timeline and (b) academic performance in the course. The learning strategies were well aligned with approaches to learning (Biggs, 1987; Entwistle, 1991; Marton & Säljö, 1976) with high-engagement students following deep learning approach and having high academic performance, whereas low-engagement students employed surface approach to learning and had relatively low performance. In the same vein, Jovanovic et al. (2017) examined students' learning sessions as sequences of learning actions by using sequence analysis. The study used agglomerative hierarchical clustering method to (a) group similar learning sequences to detect patterns in the students' learning behaviour and (b) group students based on the detected behavioural patterns that were considered manifestations of the students' learning strategies.

Like analytics of learning strategies, time management tactics and strategies in online learning contexts are latent constructs that can only be inferred based on the patterns identified in student trace data. Their detection and interpretation can lead to increase awareness of (a) educators to improve their teaching and course design and (b) learners to improve their future learning. If these analytic methods could be used robustly to identify learning tactics and strategies, we posit that they can also be used to discover time management tactics and strategies. Application of analytics-based methods have a potential to facilitate research into how students modify their time management tactics over time. It could also allow for more accurate assessment of how different interventions impact on students' time management strategies than it could be done with self-reported data collected at the start of a course. To explore the efficacy of learning analytics to detect time management tactics and strategies, we defined our first (RQ1) and second (RQ2) research questions as follows:

RQ1: Can we detect theoretically meaningful tactics and strategies of students' time management from trace data about students' interactions with online preparatory learning activities in a flipped classroom?

RQ2: What is the association between time management strategy groups identified in an online component of a flipped classroom course and their course performance?

2.5 | Feedback

The literature reports on numerous interventions that have been designed to improve time management behaviour of students, including time management seminars (Misra & McKean, 2000), trainings (Häfner, Stock, Pinneker, & Ströhle, 2014; Nadinloyi, Hajloo, Garamaleki, & Sadeghi, 2013), counselling services (St et al., 1990), and sending reminders based on the student progress (Nawrot & Doucet, 2014). The rapid growth of new pedagogical approaches and diversification of student population in higher education have imposed new challenges in promoting time management. Hence, it is necessary for the educators to find cost-effective initiatives to provide support to their students. To date, several studies have investigated feedback and its importance in promoting effective learning and overall academic achievement. Feedback is seen as a crucial way to facilitate students' development as independent learners who are able to monitor, evaluate, and regulate their own learning (Azevedo et al., 2013; Winne & Hadwin, 2013).

As posited in the Conditions, Operations, Products, Evaluations, and Standards (COPES) model of SRL (Winne, 2013), learners evaluate their learning products and the effectiveness of learning strategies based on internal and external standards. Internal standards are described as internal qualities of learners (e.g., experience and prior knowledge) that autonomously guide their own learning (Winne, 2013). However, in some cases, students need to seek external feedback from expert agents such as instructors, peers, or groups (Hattie & Timperley, 2007) to decrease discrepancies between their current learning state and intended learning outcomes (Butler & Winne, 1995; Ramaprasad, 1983). In addition to this, Winne posits that students often require an optimal external support before they are able to gain their own cognitive footing (Winne, 1995), especially at the freshmen level. In spite of claims about the power of external feedback to produce positive learning effects, there are concerns regarding the proper timing of a feedback intervention, as it may significantly influence the learning outcomes (Thornock, 2016).

Several studies have attempted to explain timing of feedback on students' learning experiences. For instance, Khan and Pardo (2006) presented students with an insight into their weekly engagement with the course activities through a real time updated learning analytics dashboard in the context of flipped learning course. In particular, the dashboard provided feedback, on a weekly basis, about the students' engagement with preparatory learning activities throughout the course (12 weeks). This study identified four student clusters based on dashboard view patterns: (a) in the middle of a study session, (b) at the beginning of a study session, (c) in the middle of a long study session, and (d) near the end of a study session. The study found that most students preferred to use the dashboard in the middle of study sessions and the number of accesses to the dashboard decreased as the semester advanced. Nevertheless, the study found no statistically significant relation between the use of the dashboard and the students' academic performance. Similarly, Zimbardi et al. (2017) explored the use of feedback by a large cohort of students. In this study, students were provided with different modalities of feedback (e.g., audio

and typed feedback) available through an online platform. Overall, this study suggests that feedback provision is more efficient during early stages of a course as students are likely to benefit from the feedback to perform unfamiliar tasks. However, students tend to less frequently access the feedback as the familiarity with the required task increases. Based on these studies, students tend to profit from feedback in earlier stages of learning.

Recent research has recognized the important role that learning analytics may have in the provision of personalized feedback at scale (Dawson, Jovanovic, Gašević, & Pardo, 2017; Pardo, Jovanovic, Dawson, Gašević, & Mirriahi, 2017), provided that feedback interventions are based on the existing body of research on feedback. Considerable work on learning analytics-based personalized feedback has been done by Pardo, Poquet, Martinez-Maldonado, and Dawson (2017). Their approach consists of combining digital trace data, captured by a computer-based learning platform, with pedagogical knowledge to provide an elaborated and personalized feedback to individual learners in an instructional and timely manner. In particular, the approach presented by Pardo, Jovanovic, et al. (2017) included the formation of feedback messages that were parametrized based on the indicators obtained by applying learning analytics methods on digital traces. The selection, personalization, and dispatching of suitable feedback messages were done by an algorithm based on the students' level of engagement with learning activities. This way, students were provided with personalized feedback on a weekly basis throughout the course.

Accordingly, Pardo, Jovanovic, et al. (2017) explored the use of elaborated personalized feedback at scale. The study was conducted with first-year undergraduate engineering students enrolled in a computer systems course with a blended learning design across three consecutive years (2013–2015). Students were provided with personalized comments emailed by the instructor based on their engagement and learning progress with the activities proposed for Weeks 2–5 of the 2015 edition of the course. By comparing students' academic performance in the two course editions without personalized feedback and the edition when the feedback was available, the study found a positive association of the feedback and the students' performance. Furthermore, the elaborated feedback (EF) messages had a positive association with the students' satisfaction with feedback. In the same line of research, Van Der Kleij, Eggen, Timmers, and Veldkamp (2012) investigated the effects of different types of written EF in a computer-based assessment on academic performance. In this study, students were randomly assigned to one of three experimental groups and were subjected to an assessment for learning with different kinds of feedback, such as immediate knowledge of correct response (KCR) with EF, delayed KCR with EF, and delayed knowledge of results. In particular, immediate responses were the feedback provided to the students right after the assessment, whereas delay responses were the feedback given after students have completed the entire assessment for learning. The study found that the students perceived immediate KCR with EF as the most useful for learning. In addition, the students appreciated the feedback more when they received KCR with EF rather than knowledge of results only. However, no significant relation was found between the feedback and the students' academic performance.

Even though feedback has received a considerable interest by the educational research community, there has been a dearth of empirical studies of learning analytics-based feedback aimed to promote effective time management behaviour in student learning or to provide clear guidelines on the ideal time frame to send feedback to the learners. Furthermore, there is a need for an exhaustive evaluation on the effects of feedback on student learning process (Dawson, 2017; Pardo, Jovanovic, et al., 2017; Pardo, Poquet, et al., 2017). Aiming to contribute to this line of research, we propose to investigate that the desirable duration of feedback (i.e., how long learning analytics-based feedback related to the students' time management practices) should be given to the learner to support SRL skills and to promote positive academic outcome:

RQ3: To what extent is feedback duration (i.e., feedback given in the first half of the course vs. feedback distributed throughout the entire course) associated with the students' time management strategies?

3 | METHODS

To address the research questions, an exploratory study was conducted considering that we could find priory research on detection of time management strategies and tactics, and thus, we could not hypothesize what tactics/strategies we could find and how they could be associated with academic performance and feedback.

3.1 | Data

This study relied on two main sources of data: (a) trace data collected from the course LMS and (b) course performance scores. Trace data were obtained from three consecutive student cohorts enrolled in years 2014, 2015, and 2016 ($N_{2014} = 290$, $N_{2015} = 368$, and $N_{2016} = 476$) in a first-year computer engineering undergraduate course at an Australian university. The course duration was 13 weeks (one semester) with 10 course topics. One course topic was covered in each week except Weeks 6 and 13 when midterm test and final exam were conducted. Particularly, this course adopted a flipped classroom design that required students to (a) complete online learning activities provided via the institutional LMS on a weekly basis prior to the face-to-face classroom sessions and (b) participate in active learning sessions with the instructor that took the form of collaborative problem-solving tasks. This study focused on the online learning activities that were designed to prepare students for the face-to-face sessions. A set of online learning tasks were available from Weeks 2 to 13 and consisted of (a) videos with multiple-choice questions, (b) reading materials with embedded multiple-choice questions, and (c) problem solving tasks (exercises). Each set of weekly exercises accounted for 2% of the final score. As the course was designed with 10 course topics taught over 10 weeks, the exercises contributed a maximum of 20% to the student's

final score grade. Meanwhile, in face-to-face setting, in each week, students were required to attend a 2-hr lecture, a 2-hr tutorial, and a 3-hr hands-on laboratory session working on a collaborative project. The second data source was derived from the scores of the midterm test and the final exam. The midterm test accounted for 20% whereas the final exam accounted for 40% of the final course marks. The midterm test was administered in Week 6, whereas the final exam was in Week 13. Both were conducted in a conventional setting. The scores data were used to differentiate between high- and low-performing students so that their time management practices can be examined and compared.

In this study, time management was analysed by looking at times when the students completed the pre-class online activities, as evidenced in the trace data and validated against the course schedule provided by the course instructor. In each week, students were required to study one topic. An algorithm was defined to associate learning actions with appropriate time management modes of study based on the time students perform the actions in the LMS. The algorithm began by comparing the course topic that a learning action was associated with against the scheduled learning topic for the given week to identify if the student was on the topic that they were supposed to study in the given week (*preparing*), or was ahead of the schedule (*ahead*), or was accessing a topic that was scheduled for one of the previous weeks. In the last case, the number of attempts was taken into account: If the student had visited and completed the required activities for the behind-the-schedule topic at some earlier point in time, then the *revisiting* mode was assigned. The *catching-up* mode was used if the student had never accessed activities related to the behind-the-schedule topic. These study modes were used in further analysis as indicators of the students' time management (see Table 1). By examining the students' time management modes of study, we expected to obtain insights that could inform the proposed research in several ways such as providing feedback based on students' progress, detection of procrastination behavioural patterns, and time management patterns associated with academic performance.

TABLE 1 Indicators of the students' time management, labelled as modes of study

Mode of study	Description
Preparing	Students completed learning actions prior to their weekly face-to-face sessions and in the week when the course topic associated with the learning action were scheduled.
Revisiting	Students returned to course topic in a future week after they had completed them as part of the preparation.
Ahead	Students completed some of the course topic ahead of the weeks in which the course topic were scheduled.
Catching up	Students completed the course topic after the schedule time (catching up), but without completing them in the scheduled week as that was the case for the revisiting activities.

3.2 | Procedure

In the context of the studied flipped classroom course, in each week, students were provided with feedback on their engagement with the week's online learning activities. The intervention was implemented in two forms. The first type of feedback available across the three studied cohorts was in the form of a learning dashboard. The learning dashboard provided students with information about their own and the overall class engagement with the online pre-class activities on a weekly basis, thus allowing students to monitor their progress. The second type of feedback was in the form of personalized analytics-based feedback messages available over different time periods. In year 2014, no personalized feedback messages were given to the students, and they only had access to the learning dashboard. In year 2015, in addition to the dashboard, students received personalized analytics-based feedback messages in the first half of the course (Weeks 2–5), whereas students in year 2016 received personalized feedback messages throughout the entire semester. Personalized feedback messages were parametrized based on the indicators derived from the students' learning traces. In particular, an algorithm selected suitable feedback options for individual learner based on their level of engagement with pre-class learning activities and sent a personalized message to the student's personal email. For example, "Good initial work. However, you should try again and make sure you fully understand how memory works. Choose those answers that you don't understand why they are correct and post them in the forum." More details are given in Pardo, Jovanovic, et al. (2017).

3.3 | Analysis

This section explains the data analysis methods used in the study.

3.3.1 | Detection of time management tactics and strategies

Figure 1 illustrates the method applied for detecting time management tactics and strategies. To address our first research question (RQ1), time management tactics were detected from sequences of study modes based on the students' learning sessions. This learning sessions consisted of successive learning actions where any two consecutive actions are within 30 min of one another (Jovanovic et al., 2017; Khan & Pardo, 2006). Each learning action was labelled with an appropriate *mode of study* based on its timing with respect to the week's topic as (a) preparing, if the learning action was related to the topic the students were supposed to study in the given week; (b) ahead, if the learning action was advance of the schedule; (c) revisiting, if the learning action was related to a behind-the-schedule topic that the student had already studied at some earlier point in time; and (d) *catching up*, if the student had never accessed activities related to the behind-the-schedule topic. As a result, each learning session was encoded as sequence of modes of study based on a representation format of the TraMineR R package (Gabadinho, Ritschard, Mueller, & Studer, 2011) and resulted in sequences of the following format:

- [1] (catching.up,7)
- [2] (catching.up,30)
- [3] (catching.up,28)

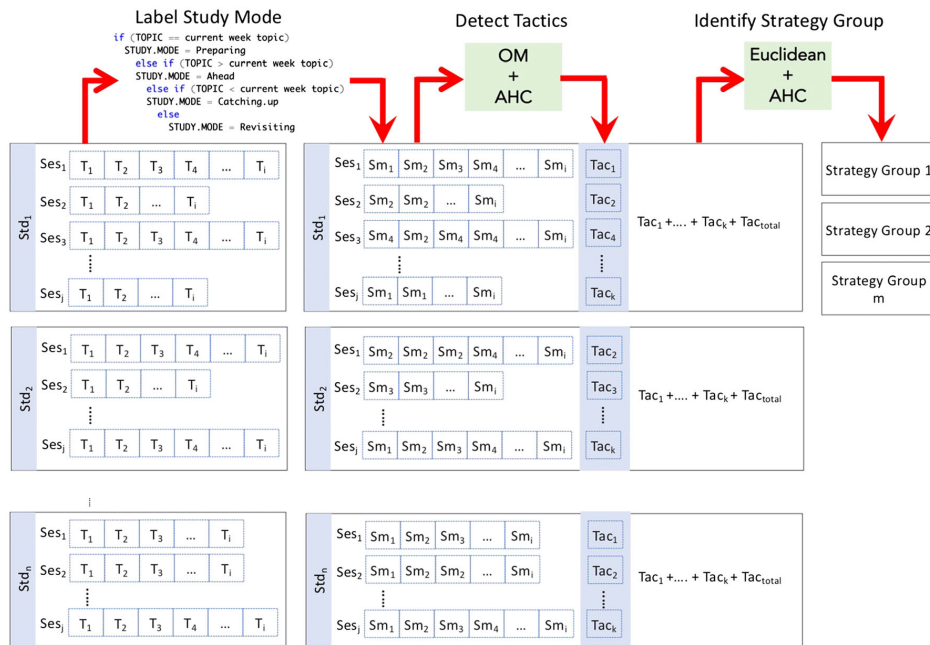


FIGURE 1 Methodology for detecting time management tactics and strategies [Colour figure can be viewed at wileyonlinelibrary.com]

[4] (revisiting,2) - (catching.up,7) - (revisiting,3) - (catching.up,15) - (revisiting,7) - (catching.up,27)

As the example indicates, the resulting study mode sequences varied, both in terms of their length (sequence [1] vs. sequence [2]) and the composition of modes of study (sequence [3] vs. sequence [4]). We removed outliers, that is, those sessions (i.e., sequences) that were above 95th percentile in terms of the number of events as well as sessions that composed of only single events. Next, we used agglomerative hierarchical clustering based on Ward's method to identify *time management tactics* by grouping similar study mode sequences. Similarity of sequences was determined using the optimal matching technique (Gabadinho et al., 2011), which is a variant of Levenshtein's edit distance (Levenshtein, 1966). By inspecting the dendrogram, the optimal number of clusters was determined. The identified clusters reflect patterns in the sequences of study modes and can be considered manifestation of students' time management tactics.

Furthermore, time management strategies were inferred from the way a student employed time management tactics; that is, strategies were characterized by one or more tactics (Derry, 1988). The applied clustering technique has already been used for identification of learning strategies (Jovanovic et al., 2017; Pardo et al., 2018). Relying on this existing practice, agglomerative hierarchical clustering based on Ward's algorithm (Hastie, Tibshirani, & Friedman, 2009) was used to identify time management strategies by grouping students with similar patterns of time management tactics. To identify such student groups, we represented each student as a vector of the following variables: (a) counts of instances of the identified time management tactics followed by the student (one variable per time management tactic) and (b) the total number of instances of time management tactics. The distance between students, required for Ward's algorithm, was computed as the Euclidean distance of the corresponding vectors. The optimal number of clusters was determined by inspecting dendrograms.

In addition, we used process mining to further explain time management tactics identified through clustering. A FOMM was generated for each time management tactic. FOMM allows for modelling the changing of states based on the probability theory and the assumption that the next state depends only on the current state. The pMineR R package was used to compute and visualize FOMMs (Gatta et al., 2017).

3.3.2 | Association with academic performance

To examine if there was a significant difference between the identified strategy groups on midterm and final exams, and thus address our second research question (RQ2), we used Kruskal-Wallis tests followed by pairwise Mann-Whitney *U* tests.

3.3.3 | Association with feedback changes

To address the third research question (RQ3), a chi-squared test was carried out to examine the relation between year and student strategy

groups. This allowed us to explore whether there was an association between different feedback interventions and time management strategies followed by the students.

4 | RESULTS

4.1 | Time management tactics

Cluster analysis of sequences of study modes (Table 1) led to the detection of four clusters indicative of the students' time management tactics. Figure 2 represents some of the characteristics of the four clusters, namely, probability of certain action types (*y*-axis) given the length of sessions (*x*-axis). In addition, Figure 3 shows proportions of most frequent sequences accounted for by their different lengths. The clusters are characterized as follows:

1. *Tactic 1—mixed and short* ($N = 35,460$, 66.32% of all sequences). This was the largest cluster, comprising the shortest learning sequences among all clusters. Sequences in this cluster included all kinds of study modes (Table 1).
2. *Tactic 2—revisiting* ($N = 8,549$, 15.99%). Sequences in this group were clearly focused on revisiting learning activities after initially studying them as part of the preparation.
3. *Tactic 3—short preparing* ($N = 7,792$, 14.57%). This group was predominantly focused on short preparing activities. This cluster had the highest frequency of *preparation* activities compared with all other clusters.
4. *Tactic 4—long preparing* ($N = 1,668$, 3.12%). This was the smallest cluster, comprising the longest sequences mainly focused on preparation work.

Meanwhile, Figures 4–7 show the resulting FOMMs of each of the four time management tactics. States in the models correspond to study modes, whereas edges with the associated transition probabilities indicate how often one study mode was followed by the other modes in each tactic. The obtained process models provide the following insights about the identified tactics:

1. *Tactic 1—mixed and short*: There was a high probability that a learning session began with either revisiting ($p = .57$) or preparing ($p = .34$) actions. It is interesting to note that students tended to stick to the same study mode throughout a session. This is evident in high transition probabilities associated with self-loops in Figure 4, ranging from .81 for revisiting to .92 for ahead study modes.
2. *Tactic 2—revisiting*: Sessions corresponding to this tactic almost always started with a revisiting action ($p = .97$). When a session started with the revisiting study mode, it often continued in the same mode for the entire duration of the session (probability of self-loops was .97).
3. *Tactic 3—short preparing*: This tactic was strongly linked to the preparation study mode ($p = .89$). There was a high probability of

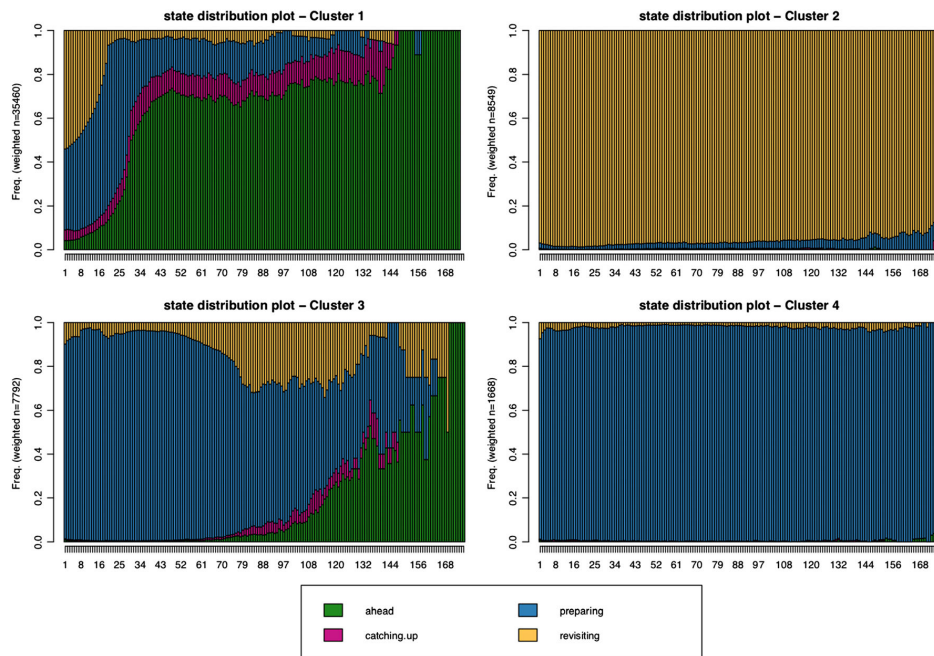


FIGURE 2 State distribution diagram of study mode sequences indicative of the detected time management tactics [Colour figure can be viewed at wileyonlinelibrary.com]

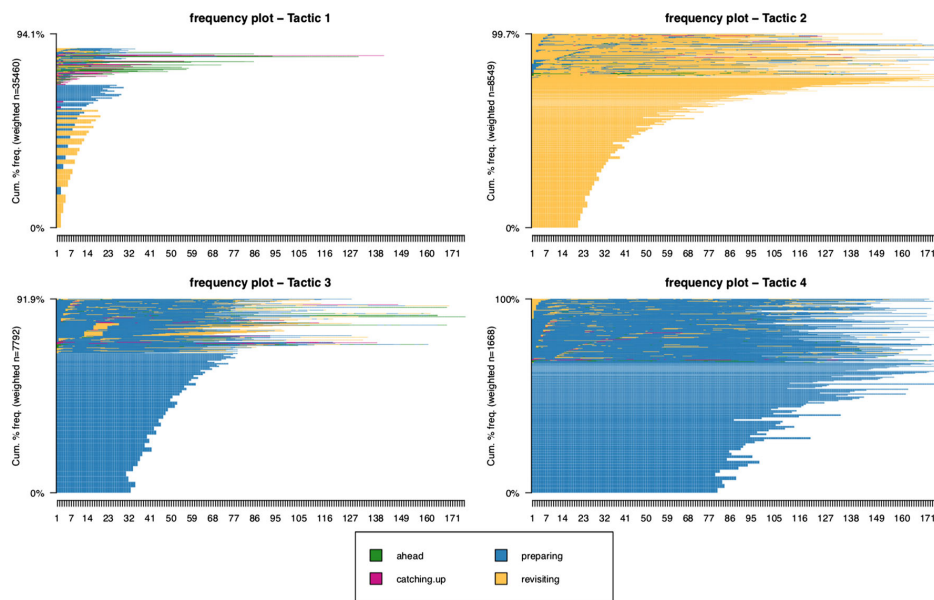


FIGURE 3 Frequency diagram of study mode sequences indicative of the detected time management tactics [Colour figure can be viewed at wileyonlinelibrary.com]

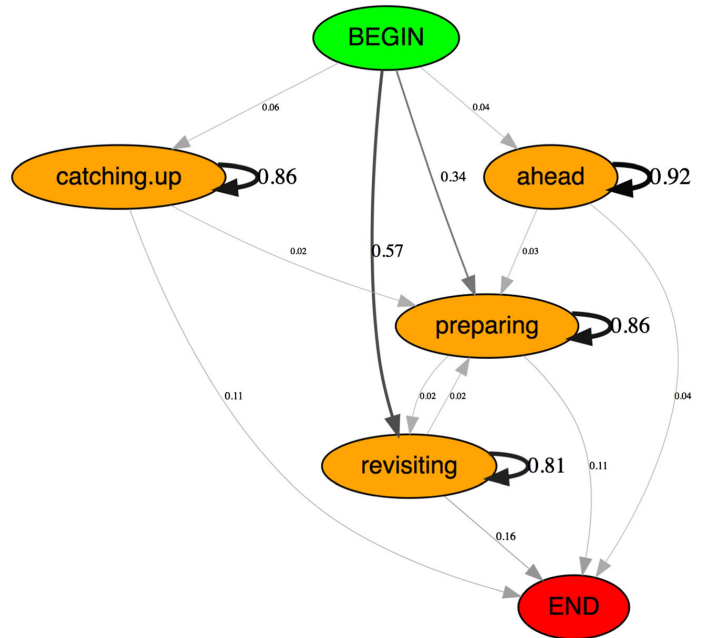


FIGURE 4 Process mining graphs for Tactic 1 (mixed and short) [Colour figure can be viewed at wileyonlinelibrary.com]

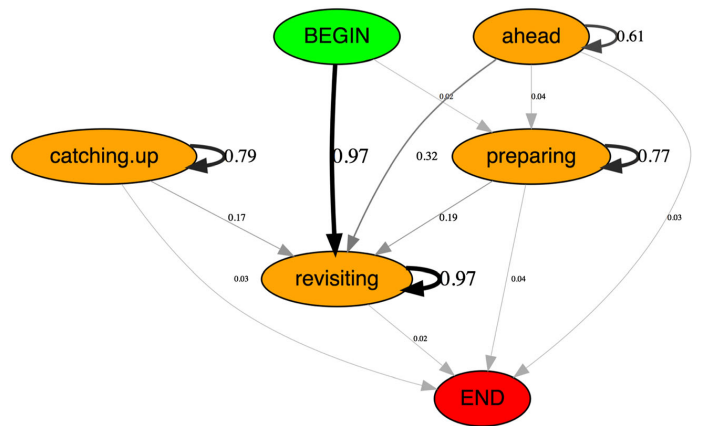


FIGURE 5 Process mining graphs for Tactic 2 (revisiting) [Colour figure can be viewed at wileyonlinelibrary.com]

preparing self-loops (.97), as well as repetitions of revisiting modes ($p = .86$) and catching up ($p = .84$). The most notable transitions were from ahead to preparing ($p = .18$) and the shift from the catching up to preparing mode ($p = .11$; Figure 6).

4. *Tactic 4—long preparing*: Learning sessions in this group almost always started with the preparing mode ($p = .90$) and remained in the same mode for the entire duration of the session (probability of self-loops is.99). Meanwhile, this tactic showed high probability of transition from the ahead to preparing modes ($p = .28$), followed by the shift from the catching up and revisiting to the preparation mode with probabilities of.24 and.19, respectively.

4.2 | Time management strategy groups

Three time management strategy groups were detected based on the counts of the four identified time management tactics and the total number of study mode sequences. Table 2 provides descriptive statistics for the three strategy groups of students. To better understand the detected time management strategies, we examined, for each strategy group, how the use of time management tactics changed throughout the course timeline. Figure 8 shows that for each strategy group, median number of different tactics was applied in each week of the course. Based on these insights, the strategy groups can be described as follows:

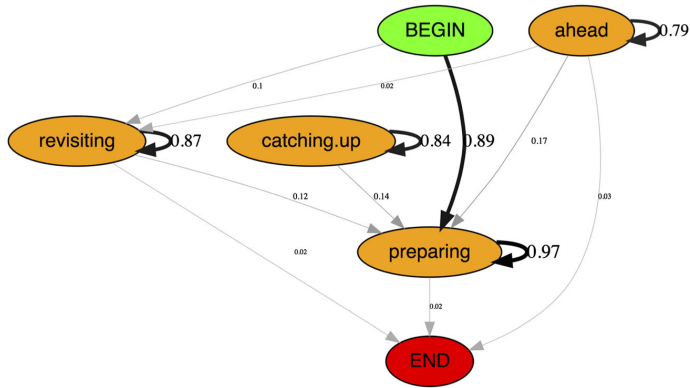


FIGURE 6 Process mining graphs for Tactic 3 (short preparing) [Colour figure can be viewed at wileyonlinelibrary.com]

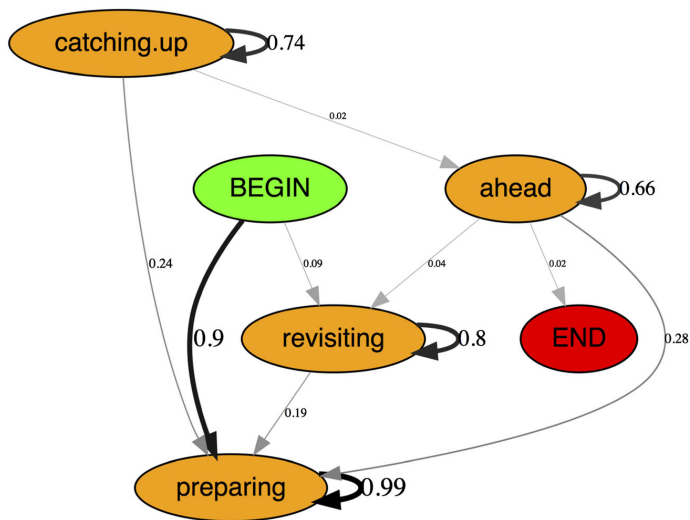


FIGURE 7 Process mining graphs for Tactic 4 (long preparing) [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 2 Summary statistics for the three time management strategy groups: Median, 25th and 75 percentiles

Strategy group	Comprehensive	Selective	Limited activity
Total students	457 (40.30%)	471 (41.53%)	206 (18.20%)
seq.clus.1: mixed and short	42 (30, 57)	24 (17, 34)	14 (8, 21)
seq.clus.2: revisiting	9 (6, 13)	7 (4, 10)	3 (1, 4)
seq.clus.3: short preparing	8 (6, 10)	7 (6, 8)	3 (1, 5)
seq.clus.4: long preparing	3 (2, 4)	0 (0, 1)	0 (0, 1)
seq.total	62 (50, 78)	40 (31, 48)	21.5 (15, 29)
Midterm test score	16 (13, 18)	14 (11, 16)	12 (10, 16)
Final exam score	23.7 (16, 32)	18 (13, 26)	17 (11, 26)

1. Strategy Group 1—comprehensive (N = 457, 40.30% of all students) was the most active group. Students in this group were the most comprehensive in their use of the time management tactics—they tended to use a variety of tactics (i.e., revisiting and short preparing) while interacting with the pre-class learning activities. Still, they highly emphasized the use of Tactic 1 (mixed and short) with the median value of 42.
2. Strategy Group 2—selective (N = 471, 41.53%) is the most populated group. Compared with the comprehensive strategy group, this group showed a low use of Tactic 1 (mixed and short) particularly after midterm test (Week 6), and almost no use of Tactic 4 (long preparing).
3. Strategy Group 3—limited activity (N = 206, 18.20%) is the smallest group consisting of students who concentrated predominantly on Tactic 1 (mixed and short) for the entire duration of the course

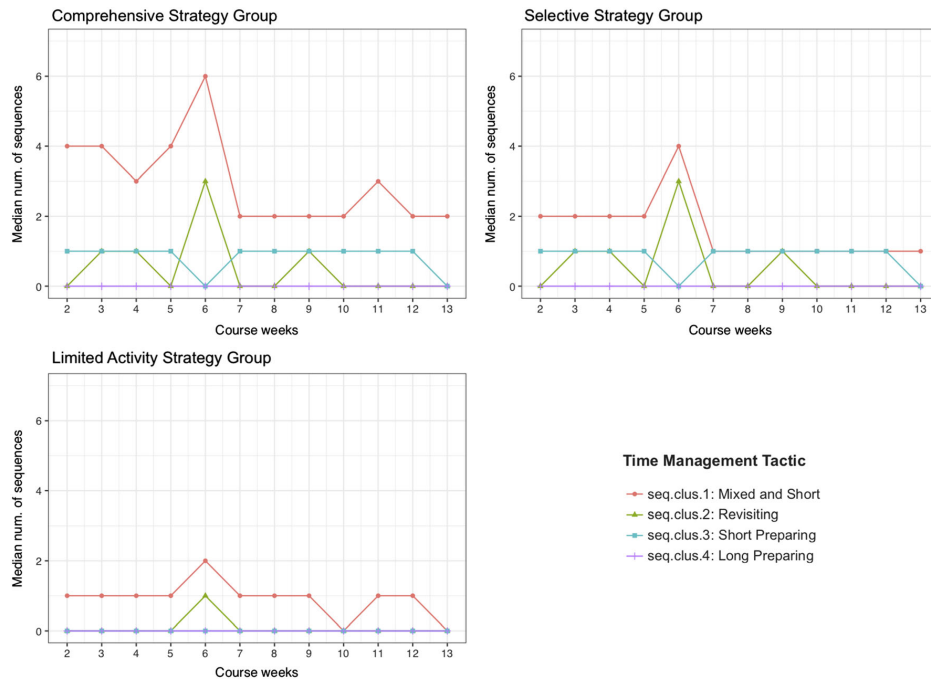


FIGURE 8 The dynamics of time management tactics for each identified strategy group [Colour figure can be viewed at wileyonlinelibrary.com]

but not as intensively as the previous two groups. All other tactics (i.e., revisiting, short preparing, and long preparing) were very rarely used by this group

4.3 | Associations with academic performance

To explore the association between the detected time management strategies and the students' academic performance (RQ2), Kruskal-Wallis tests were carried out. The results showed a significant association between the identified students' strategy groups and the students' course performance ($p < .0001$ for both midterm test and final exam scores). To further inspect these associations, pairwise tests were carried out to compare the identified strategy groups with respect to the scores on the midterm test (Table 3) and final examination (Table 4). All pairs were significantly different (after applying false

TABLE 3 Pairwise comparison of student clusters with respect to the students' midterm test scores

Cluster 1	Cluster 2	Z	p	α	r
Limited activity	Comprehensive	8.0217	.000	.017	.31
Comprehensive	Selective	7.0722	.000	.033	.23
Selective	Limited activity	3.2845	.001	.050	.13

TABLE 4 Pairwise comparison of student clusters with respect to the students' final exam scores

Cluster 1	Cluster 2	Z	p	α	r
Limited activity	Comprehensive	7.3052	.000	.017	.28
Comprehensive	Selective	6.5203	.000	.033	.21
Selective	Limited activity	2.8731	.004	.050	.11

discovery rate correction to account for multiple comparisons) with effect sizes (r) ranging from small to medium. Combining the results of the statistical tests with the descriptive statistics for the midterm test and final exam scores of each group (Table 2), we found the following:

1. *Strategy Group 1—comprehensive (high performing)*: This group represents the students with the highest median value for both midterm test and final exams.
2. *Strategy Group 2—selective (mid performing)*: The students in this group received lower grades on the midterm test and final exams compared with the students in the comprehensive strategy group, whereas their scores were higher than those of the limited activity group.
3. *Strategy Group 3—limited activity (low performing)*: This group represents the students with the lowest median value for both midterm test and final exam scores compared with the other two groups.

4.4 | Associations with feedback changes

A chi-square test, done to answer our third research question (RQ3), found a significant association, $\chi^2(4, N = 300) = 12.4, p < .01$, between time management strategy group and the year of the course offering. Figure 9 illustrates the comparison of the identified time management strategy groups across the 3 years that saw different feedback interventions (see Section 3.2). Taken together, these results indicate a significant change in the distribution of students across strategy groups from the first year (2014, no personalized feedback messages) to the second year (2015, personalized feedback messages in the first half of the semester only), but minimal changes from the second to the third (2016) year. In the first year (2014), there was a similar number of students in high-performing (comprehensive) and low-performing (limited activity) groups. The proportion of the mid-performing group (selective) was nearly equal to the proportion of high-performing (comprehensive) and low-performing (limited activity) groups put together. In the second year (2015), the top-performing group (comprehensive) grew by 20%, the highest proportion overall (46.20%) of all the years, whereas the proportion of moderate-performing (selective) and low-performing (limited activity) groups notably declined. Similar to the second year, the third-year (2016) students also received feedback messages except that they kept receiving them for the entire duration of the course. The distribution of students across the three strategy groups in 2016 and 2015 proved to be very similar.

5 | DISCUSSION

5.1 | Time management tactics and strategies

Even though trace data were successfully used to identify patterns indicative of learning strategies (e.g., Jovanovic et al., 2017), there has been a scarcity of documented research on using trace data to investigate students' time management behaviour. The results of the

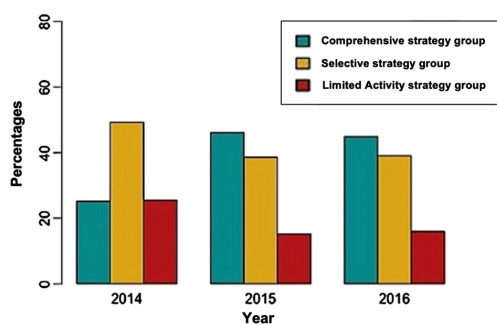


FIGURE 9 Distribution of time management strategy groups stratified by year [Colour figure can be viewed at wileyonlinelibrary.com]

present study, further discussed in this section, offer some relevant insights related to time management, especially in flipped classroom settings.

The reported study has methodological similarities with the work reported in (Jovanovic et al., 2017) on the detection of distinct learning strategies. However, there are two important methodological differences: (a) this study clustered learning sessions based on the study modes (i.e., indicators of students' time management behaviour, Table 1) instead of using types of activities and (b) study tactics were further investigated with FOMM in this work.

The results of cluster analysis of sequences of study modes (see Section 4.1) indicate that meaningful time management patterns can be detected from data about students' learning sessions. As manifestations of students' time management tactics, the detected clusters provide insights into how students made use of their time when interacting with the online preparatory activities. In particular, the study identified four distinct time management tactics adopted by the students—mixed and short, revisiting, short preparing, and long preparing. Time management tactics differed in the way students began their learning sessions within the learning environment. Based on the process mining results, students who opted for Tactic 1 (mixed and short) typically started their learning in the preparing or revisiting mode, that is, by engaging with the activities required for the week's face-to-face session or by revisiting the learning activities they have previously done as a part of preparation tasks. Furthermore, students who opted for Tactic 1 (mixed and short) showed the ability to time manage by not sticking to one mode of study but using different modes interchangeably to suit to the course requirements. Tactic 2 (revisiting) shows high probability of revisiting events performed by the students for the entire course. Tactic 3 (short preparing) is distinguished by high probability of preparing events throughout the course. Similarly, Tactic 4 (long preparing) is strongly focused on preparation events throughout the duration of the course, but unlike Tactic 3, preparation events tended to form long learning sessions.

The study results related to the detection of time management strategies showed that, throughout the course, the students employed distinct patterns of tactics while regulating their learning process within online spaces (see Section 4.2). The analysis of the identified patterns suggested that these can be considered manifestations of the students' time management strategies. In particular, three different strategy groups were detected, namely, comprehensive, selective, and limited activity. The comprehensive strategy group is the most active group in regulating their use of time management tactics. It showed high adoption of Tactic 1 (mixed and short) consistently paired with Tactic 3 (short preparing), as well as deliberate use of Tactic 2 (revisiting) throughout the course. From the self-regulation viewpoint, preparing paired with revisiting activities can be characterized as competent time management strategy (Cicchinelli et al., 2018; Winne, 2015; Zimmerman, 2008). In particular, students study learning materials in order to monitor their comprehension and then go back and restudy any of course material; this restudying is a regulatory strategy (Dunlosky, Rawson, Marsh, Nathan, & Willingham, 2013). The fact that students in the comprehensive strategy group recorded

highest level of engagement in Week 6 is indicative of careful alignment of their study tactics according to the course structure and their maintenance of level of motivation (regulation strategies) while progressing towards certain learning goal. The adequate capacity to judge their own learning point to the learners' internal qualities (e.g., prior knowledge and experience) that enable them to regulate their own learning (Butler & Winne, 1995).

The selective strategy group was applying relatively similar tactics as the comprehensive strategy group. The difference between these groups seems to be twofold. First, students from the comprehensive group might have realized they needed more time to invest as they were possibly more accurate in judging their learning than those in the selective group. Second, the comprehensive group might have been more motivated to invest more time on learning. Meanwhile, the limited activity group was probably associated with lower levels of motivation and self-regulation, in particular, in terms of their judgement of learning. In other words, they might have been inaccurate in their self-assessments of how much they knew and thus how much time they needed to put into their study.

The time management strategy used by the most academically successful group of students proved to be combinations of tactics that were consistent with the recommendations for effective learning. Those tactics are indicative of the interleaved practices that were proven consistently, in numerous studies, to enhance learning performance (Dunlosky et al., 2013). Specifically, the comprehensive strategy group mostly used the mixed and short tactic. These students also demonstrated how to use effectively spaced practice (Tactic 2—revisiting) and combined that with tactics focused on preparation only (Tactics 3 and 4).

5.2 | Associations with academic performance

Findings of previous studies have confirmed that students with effective time management strategies performed better in examinations (Jaclyn Broadbent, 2017; He et al., 2016; Lai & Hwang, 2016; Nguyen et al., 2018). Nevertheless, there has been almost no empirical work that explained how time management tactics and strategies adopted by students during the learning process affected their performance. The results of the current study suggest that time management strategies adopted by students were related to academic performance (Section 4.3). Our analysis suggests that students with higher academic performance were characterized by consistent efforts and diverse time management tactics throughout the entire course (comprehensive) compared with mid-performing (selective) and poorly performing students (limited activity). It seems that the comprehensive strategy group had a strong sense of control over their time as well as willingness to invest more time to study, particularly before (preparing) and after (revisiting) the scheduled time. This finding is in line with empirical findings in the domain of SRL, which suggest that students who experiment with different tactics and strategies tend to be engaged in more metacognitive monitoring and more active self-regulation of learning (Hadwin, Nesbit,

Jamieson-Noel, Code, & Winne, 2007), which in turn leads to better academic results (Bannert, Reimann, & Sonnenberg, 2014; Broadbent & Poon, 2015).

By contrast, students who exhibited low engagement and limited use of time management tactics (limited activity) were associated with low academic performance. Those students were focused mainly on Tactic 1 (mixed and short) throughout the entire course, practically abandoning all other tactics. One potential explanation could be that this group involved students who were aware of the need to complete learning tasks but failed to motivate themselves to perform the activities within the desired or expected time frame (Senécal, Koestner, & Robert, 1995) and were inconsistent in the pursuit of their learning goals. Future research should investigate the reasons for this inadequate time management. The passive versus active distinction of procrastination may be another relevant approach to understand the observed behaviour (Chun Chu & Choi, 2005). Passive procrastination is observed in students who have hard time to make many different decisions in a timely fashion, while recognizing that this is detrimental to their learning. This leads them to feel guilty and depressed. In contrast, active procrastinators intentionally delay their activities to balance their work with other competing tasks. They generally feel highly confident in their time management abilities and do not regret about their time management choices. Therefore, it is essential for future research to develop methods that can distinguish between active and passive procrastinators through the analysis of trace data (Choi & Moran, 2009).

5.3 | Associations with feedback changes

Proper timing of feedback interventions significantly influences learning outcomes (Thornock, 2016). However, a majority of research on feedback timing has revolved around the quality of immediate and delayed feedback given to students to enhance learning process and performance (Shute, 2008). This is the first study that sought to investigate the desirable timing and duration of feedback to be given to students to improve their time management. In particular, the present study addressed a need for an exhaustive evaluation of the effects of feedback on student learning outcomes (Dawson, 2017; Pardo, Poquet, et al., 2017), with the ultimate goal of providing clear guidelines on the ideal timeframe and amount of feedback to send to learners (Attali & van der Kleij, 2017; Tanes, Arnold, King, & Remnet, 2011).

In this study, the feedback intervention was phased in over 3 years (as explained in the Section 3.2). Therefore, we could have expected a significant change from the first to the second year and smaller changes from the second to the third year in terms of the students' time management behaviour and overall grades. Table 2 and Figure 9 provide partial support for this hypothesis: comparing year one (2014) and year two (2015), there was a significant increase in the proportion of students in high-performing group (comprehensive) and a drop in the proportion of mid-performing students (selective) and poorly performing students (limited activity). One potential

explanation could be that the increase in the proportion of high achieving students indeed coincided with the introduction of personalized feedback messages in the first half of the course. The intervention helped some students to more effectively manage their time and thus also increase their academic success. However, further studies with stronger experimental design are warranted to test this observational claim.

Similar to the second year, the third year (2016) students also received feedback messages except that they kept receiving them each week for the entire duration of the course. However, proportions of students in all three strategy groups in years 2015 and 2016 were very similar with only small differences. This result suggests that the feedback intervention in the first half of semester was equally effective in supporting students' time management as was the feedback intervention during the entire course. A potential explanation could be that students required an external support at the start of the course to be able to employ optimal tactics and strategies (Winne & Jamieson-Noel, 2003). However, they did not additionally benefit from prolonged feedback once they gained their own cognitive footing (Butler & Winne, 1995) and became familiar with required task (Khan & Pardo, 2006). It is however important to further examine this as well as to study whether there are other benefits (e.g., satisfaction) from the provision of prolonged feedback rather than those related to academic performance.

6 | CONCLUSIONS AND IMPLICATIONS

In conclusion, the methodology proposed in this paper allows for identifying patterns in students' time management behaviour on the basis of learning sessions. In particular, our findings indicated that time management patterns, as manifestation of students' time management tactics, can be detected from students' learning sessions. Such observable patterns in learning behaviour further led to the detection of several strategy-based student groups. Second, a significant association between students' time management strategies and academic performance was identified. Consistent with previous research, we found that more active and directive time management strategies promoted effective self-regulation and positive association with academic performance. Third, a significant association between learning analytics-based feedback and time management behaviour was revealed. The study pointed out that feedback intervention in the first half of the semester was adequate to promote positive academic outcome, whereas extended feedback for the entire duration of the course did not have additional contribution towards the improvement of time management strategies.

The implications of this study are multifold. First, from a research perspective, this study contributes to the literature by offering an approach to detecting time management tactics and strategies adopted by students in a flipped classroom environment, through a combined use of trace data and analytics techniques. The state of the art in time management research is mainly based on self-reports (Claessens, Eerde, & Rutte, 2007), while very little attention was

given to getting insights through analytics techniques. Thus, the adoption of learning analytics techniques, and in particular the proposed methodology, could help both researchers and practitioners improve the interpretation of their results related to time management behaviour. Furthermore, our research clearly points towards the need for learning analytics researchers to take time management aspects into consideration while modelling effects of feedback.

From an instructor perspective, this study makes a step forward to translate time management into actionable feedback. Our findings highlight effective time management behaviour as a vital element for self-regulation as well as a strong predictor of academic success. By having a solid understanding of how students enacted specific time management tactics and strategies while progressing in learning, an instructor would be in a better position to generate feedback to guide learners towards the achievement of their learning goals (Zimbardi et al., 2017). Better incorporation of time management into provision of feedback affords a potential for the student to exercise metacognitive control and monitoring that adapts engagement in mid task (Winnie & Perry, 2000). The study also suggests that for instructors to promote effective time management strategies, they can provide personalized analytics-based feedback to the students in the first half of a semester on a weekly basis rather than providing the feedback throughout the entire duration of a course. This recommendation has been tested on the typically 12-week-long courses, and future research needs to study feedback practices in other course formats.

From a learner perspective, this study could offer practical guidelines for making necessary adaption and adjustment of their timing of engagement based on a different set of time management tactics, to effectively regulate their learning time, especially during the preparation for face-to-face sessions. The findings suggest that the mixture of preparation of new content and revision of the previously studied one in short, frequent sessions (Tactic 1 coupled with other three tactics) tends to lead to the best learning outcomes. This time management strategy is consistent with the spaced and interleaved study practice (Dunlosky et al., 2013).

There are some limitations of the current study that need to be carefully considered in future research. First, our study was conducted within the context of a specific flipped learning environment, which could limit the generalizability of the study findings to other contexts. Hence, replication of this study in other learning contexts would be desirable. Second, analysis of trace data offers limited ability for interpreting the underlying reasons behind the observable behaviour. For instance, why students decided to adopt certain tactics and strategies in a certain way and what was the motivation that led their actions. A possible approach could be further investigation using self-reported instrument such as think-aloud protocols, interviews, or surveys (Winne, 2015) to complement trace data collected from digital learning environment. Third, this study relied on the trace data of students' interactions with online preparatory learning activities. Although this data allowed for examining actual behaviour in an authentic online settings, we could not capture

activities that occurred offline (e.g., downloading the learning material) nor in-class activities, such activities which take place in a physical context. Finally, we did not have access to the demographic information nor information on prior education due to the limited data access granted in the institutional ethics approval. Access to such data would allow for better estimation of the actual impact of feedback interventions on student learning.

In this study, considering the focus on time management and the way how we identified the coding of time management of individual actions (time of action relative to the time when a certain task was scheduled in the course design—see paragraph 2, Section 3.1), the use of timestamps available in the trace data assured validity. The server that recorded the time offered correct time that was in sync with the university network time. Given that the LMS produced all the timestamps and the coding was done fully automatically (Section 3.1), the reliability is assured as our approach would replicate in any other setting where similar data were used.

The validity of time management strategies and tactics through Messick's (1995) unified theory of construct validity. The content validity is assured through our choices from the coding of data (ahead, preparing, catching up, and revisiting). Also, our interpretation of the tactics/strategies with respect to the relevant theory (Section 5) offers additional support for content validity. External validity is assured the association with the student grades (RQ2). Structural validity is assured through our choices in the methods used for clustering. The consequential validity was demonstrated through the fact that the time management tactics and strategies can be targeted with external interventions. Our findings (RQ3) indicating that the intervention aiming to promote improved time management was indeed associated with the changes in the time management strategies. Considering the exploratory nature of our study, this dimension (structure) will warrant further testing in the future studies. We also acknowledge that generalizability needs to be tested in the future work. The proposed methodology for detection of time management tactics and strategies used established techniques to inform choices (e.g., the number of clusters was selected based on dendrograms). This reinforces some reassurance about the reliability of the proposed approach.

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CONFLICT OF INTERESTS

The authors have no conflict of interest to declare.

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2.3 Summary

The analytical methods proposed in this chapter have proven successful for mining time management patterns from students' learning sessions based on the modes of study (i.e., indicators of students' time management behaviour). This implies that the proposed methods enabled us to (i) detect meaningful patterns in the students' learning behaviour, which are indicative of the time management tactics that the students applied while interacting with online learning activities; (ii) identify several strategy groups that were distinguished by the enactment of tactics, which correspond to those reported in previous research (Fincham et al., 2019; Matcha, Gašević, Ahmad Uzir, Jovanović, & Pardo, 2019) and summarised in (Kovanović, Gašević, Joksimović, Hatala, & Adesope, 2015); and (iii) examine an association between the time management strategies adopted by the students and their course performance.

To answer research question one (RQ1), the study reveals that time management tactics vary in terms of their length and the composition of modes of study. For instance, Tactic 1 (*Mixed and Short*) comprises the shortest learning sequences among all clusters. Sequences in this cluster included all kinds of modes of study (i.e., ahead, preparing, revisiting, and catching-up). Tactic 2 (*Revisiting*) clearly concentrates on revisiting learning. Sequences in this cluster show a high probability of revisiting events performed by the students for the entire course. Tactic 3 (*Short Preparing*) predominantly focuses on short sequences of preparations for learning activities. Tactic 4 (*Long Preparing*) is characterised by the longest sequences, mainly focusing on preparation work, thereby suggesting that students were consistently preparing prior to the weekly face-to-face sessions.

Furthermore, this study discovered that throughout the course, the students employed distinct patterns of tactics while regulating their learning processes within online spaces. In particular, three different strategy groups were detected, namely, *Comprehensive*, *Selective*, and *Limited Activity*. The *Comprehensive* strategy group is the most active group in regulating their use of time management tactics. It shows high adoption of Tactic 1 (*Mixed and Short*) consistently paired with Tactic 3 (*Short Preparing*), as well as the deliberate use of Tactic 2 (*Revisiting*) throughout the course. The *Selective* strategy group applies relatively similar tactics as the *Comprehensive* strategy group. However, this strategy group is distinguished by the low use of Tactic 1 (*Mixed and Short*), while Tactic 4 (*Long Preparing*) is barely present. Whereas, the *Limited Activity* strategy group includes students who mainly focus on Tactic 1 (*Mixed and Short*) for the entire duration of the course but not as intensively as in the previous two groups. Meanwhile, all the other tactics were almost absent.

To address the research question two (RQ2) of the thesis, our findings show that students with higher academic performance are characterised by consistent efforts and diverse time management tactics throughout the entire course (*Comprehensive*) compared to mid-performing (*Selective*) and poorly performing students (*Limited Activity*). Besides, we found that more active and directive time management strategies promoted effective self-regulation and positive association with academic performance.

2. DETECTION OF TIME MANAGEMENT TACTICS AND STRATEGIES

To sum up, time management tactics and strategies can be considered as a sequence of events that unfold over time. Thus, understanding the temporal and sequential dimensions of learning events can shed light on how tactics and strategies have developed and modified, as well as enable the detection of situations where transitory state changes occur. In Chapter [three](#), we examine tactics and strategies based on their temporal and sequential characteristics of learning sequences.

3

Temporal Representation of Learners' Decision

It is often said that a wrong decision taken at the right time is better than a right decision taken at the wrong time.

— Pearl Zhu, *Decision Master: The Art and Science of Decision Making*

3.1 Introduction

LEARNING is a process that develops over time (Knight & Friend Wise, 2017). As learning analytics research aims to enhance the understanding of learning and support the processes of learning, the study of the temporal nature of learning has emerged as a central interest in the field of learning analytics. In the literature, the temporal dimension relates to the passage of time (i.e., how long and how often learners engage with learning activities), whereas the sequence relates to the order in which learning tasks take place (Chen et al., 2018). Although both temporal and sequential considerations are important in understanding learning (Chen et al., 2016; Malmberg, Järvelä, & Järvenoja, 2017; Saqr, Nouri, & Fors, 2019), the precise identification, measurement, and analysis of the temporal representations of learning remain as a challenge (Chen et al., 2018; Knight & Friend Wise, 2017). Thus, we posit that temporal analyses could be scrutinised with more fine-grained levels of analysis by looking at the decision learners made regarding what, how, and how long to study while working towards the learning goals (Kornell & Bjork, 2007). Therefore, this chapter investigates the temporal characteristics of different strategy groups by using process mining methods. This investigation allows us to discover process sequences in event traces in an inductive way by visualising them in process models. It also enables us to interpret the identified strategy groups based on their academic achievement in the course.

3.1.1 Chapter overview

In the preceding chapter (Chapter two), we demonstrate that analytical methods such as sequential analysis and unsupervised clustering method are proven to be beneficial for detecting time management tactics and strategies. However, one of the challenges is that unsupervised machine learning

algorithms often generate inconsistent cluster solutions (Studer, 2013) due to the degree of subjectivity in the interpretation of the cluster results (Kovanović et al., 2015). To address this limitation, we introduce a novel method for identifying patterns in student learning behaviour on the basis of learning sessions by using a combination of process mining and unsupervised clustering method. As such, this method allows for the automated detection of time management tactics. Furthermore, we adopt the same method using hierarchical clustering analysis (as described in Chapter two) to identify strategy groups that are characterised by sets of tactics that learners adopt while interacting with online learning activities.








As the focus of this chapter is on the analysis of temporal sequences of the learning process of the identified strategy groups, we further complement the proposed method with another process mining method, called “bupaR” R-package (Janssenswillen et al., 2019). The unique features incorporated in bupaR ensure that the time frame is sufficiently important to provide insight into the learning process and has a great potential to inform and enhance the understanding of how complex learning decisions are carried out. This process mining method allows for examining the tactics used across identified strategy groups, i.e., frequency and time dimensions through a visual representation of learning process models to bring insights into the temporal learning processes in order to get a better understanding of the underlying educational processes (Etinger, Orehovački, & Babić, 2018). We argue that this new method has a strong potential to inform relatively precise temporal dimensions of students' learning and enhance our understanding of how learners make complex decisions about their learning that can significantly be related to their academic achievement. Thus, the main contributions of the work presented in this chapter are the development of a: (i) new method for automated detection of time management tactics, and (ii) novel method that provides interpretable temporal representations of students' interactions with online courses.

3.2 Publication: Discovering Time Management Strategies in Learning Processes Using Process Mining Techniques

The following section includes the verbatim copy of the following publication:

Ahmad Uzir, N., Gašević, D., Matcha, W., Jovanović, J., Pardo, A., Lim, L.-A., & Gentili, S. (2019). Discovering Time Management Strategies in Learning Processes Using Process Mining Techniques. In *European conference on technology enhanced learning* (pp. 555–569). doi:<https://doi.org/10.1007/978-3-030-29736-7>{_}41

Discovering Time Management Strategies in Learning Processes Using Process Mining Techniques

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Abstract. This paper reports the findings of a study that proposed a novel learning analytic methodology that combines process mining with cluster analysis to study time management in the context of blended and online learning. The study was conducted with first-year students ($N = 241$) who were enrolled in blended learning of a health science course. The study identified four distinct time management tactics and three strategies. The tactics and strategies were interpreted according to the established theoretical framework of self-regulated learning in terms of student decisions about what to study, how long to study, and how to study. The study also identified significant differences in academic performance among students who followed different time management strategies.

Keywords: Blended learning · Learning analytics · Self-Regulated Learning · Time management strategies

1 Introduction

In higher education, blended learning is a well-recognized learning mode that combines online and face-to-face interaction among teachers and learners. It offers learners flexibility to control their own learning experiences and opportunity to extend their learning time from in-class instruction to out-of-class study time. However, flexibility comes with a great responsibility for learners to define learning tasks and set goals; plan and manage resources, time, and environment; and apply effective learning tactics and strategies with the aim of achieving desired academic outcomes [1].

It has been well-established that self-regulation is linked to a significant improvement in learners' time management, which, in turn, can contribute to learners' success in blended learning [2]. However, only a few empirical studies have examined the link between self-regulated learning (SRL) and actual time management practices in blended learning settings. To bridge this gap, the current study aims to provide evidence and solid understanding of how learners enact specific time management tactics and strategies while progressing in a blended course.

The paper proposes a learning analytic methodology to analyse time management within blended and online learning. The application of the proposed methodology identified four distinct tactics and three strategies of time management in a blended course in health sciences; the use of different strategies was associated with achievement. The results were interrogated against an established theoretical model of SRL to understand how student make decisions about what to study, how long to study, and how to study.

2 Background

2.1 Time Management Strategies and Self-regulated Learning

Time management is commonly linked to self-regulated learning, since it is closely related to learners' decision about what to study, how long to study, and how to study [3–5] with instructors' minimal intervention. In line with the self-regulation viewpoint, time management has been recognized as learners' effort to effectively use their time while progressing toward set learning goals. To define time management tactics and strategies, we borrow from the literature on study tactics and study strategies. In the literature, study tactics are described as cognitive routines that include several actions done in a sequence for performing specified tasks, while study strategies are made-up from a set of enacted tactics by means of selecting, combining, or redesigning these cognitive routines, directed by a learning goal [6–8]. Time management tactics and strategies refer to how timely students manage their study tactics and strategies.

Most models of SRL emphasize three kinds of strategies focused on planning, monitoring, and regulating [9]. In the context of this study, planning involves preparation at the cognitive level; for instance, learners decide to access certain course material in advance, before it was scheduled (*ahead*) or complete a learning task just in time before the relevant face-to-face session (*preparing*) rather than delay task engagement till later in the course (*catching-up*). Meanwhile, monitoring allows learners to evaluate the differences between their current condition (e.g., learning progress) and standards (e.g., predefined learning goals), which, in turn, activates control processes to reduce discrepancies (e.g., engaging more intensively in a certain topic) [10]. Finally, regulation strategies refer to deliberate acts of learners evaluating their comprehension in a specific learning context, such as re-studying learning materials after they have completed it as a part of preparation (*revisiting*). Obviously, all kinds of SRL strategies are inextricably associated with time management, as all include a temporal aspect and a need to plan and manage one's time to put the strategies in practice.

Students' decisions about learning are not random choices; they are driven by learning goals [4]. The current study builds on the work presented in [5] to unveil the students' decision made on their time management strategies, what tactics to use (e.g., how to modify their tactics to support their learning goal), frequency of tactics use (e.g., deciding how long to persist to master a concept) and timing of tactic use (e.g., how to space their learning).

2.2 Temporal Analysis of SRL

Research on SRL has emphasized the use of trace data as artifacts of students' learning [4] recorded over a given period of time in an authentic educational setting. Trace data captures fine-grained learning events and dynamics of learning sessions [11]. As such, trace data are used to unveil latent behavior of learners, indicative of how learners regulate their effort to achieve their learning goals. The SRL literature also stressed the importance of temporal and sequential dimensions of learning [12–16] with the objective of uncovering how patterns and processes of SRL unfold over time [14]. According to Chen et al. [17], the temporal dimension relates to the passage of time (e.g., how long and how often learners engage), whereas the sequential relates to the order in which learning tasks take place. Both dimensions are closely related to the research on time management. Thus, a combined temporal and sequential analysis promises to provide new perspectives into time management and ways to improve SRL as a whole.

Process mining has been used by several scholars in the field of learning sciences to investigate regulatory patterns of groups and individual learners [22]. For instance, Sonnenberg and Bannert [18] used process mining techniques to analyze coded think aloud data about SRL processes of students who studied with hypermedia. Similarly, Bannert et al. [16] employed process mining to detect differences in frequencies of SRL events between most and least successful groups of students with respect to post-test scores. Process mining models of the two groups detected a substantial temporal difference between the groups and more regulation activities in the group of high performing students. A novel approach that combines process mining and clustering to detect learning tactics and strategies from trace data has recently been proposed [19]. This approach was applied for the analysis of trace data about students' online activities in a flipped classroom. The findings showed five learning tactics that were combined in three different learning strategies. The identified learning strategies could explain (a) how the students enacted the learning tactics over course timeline and (b) academic performance in the course. The learning strategies were well aligned with approaches to learning [20], with high engagement students following a deep learning approach and having high academic performance, while low engagement students employed a surface approach to learning and had relatively low performance.

In line with the previous works, the current study aimed to explore meaningful time management tactics and strategies by combining process mining and clustering techniques to shed some light on this notable resource of learning within online spaces. Specifically, the study addressed the following three research questions:

- (1) What time management tactics and strategies can be detected from the students' interactions with online learning activities within a blended learning course?
- (2) How do students in different strategy groups enact time management tactics throughout the course timeline?
- (3) To what extent do the way students enact the tactics improve their self-regulated learning and course performance?

3 Methodology

3.1 Study Context

This study was conducted in a first year undergraduate course at an Australian university. The trace data were collected from 241 students enrolled in a Health Science course that ran for 13 weeks (1 semester). The course adopted a blended learning model which required students to complete online learning exercises provided via the university's LMS (Moodle) prior to face-to-face classroom activities. Two components of the online learning task were available to the students to prepare for the class in each week: tutorials and pre-laboratory exercises. Although the tutorials and pre-laboratory exercises were not mandatory to complete during the preparatory stage, they were beneficial for developing a strong foundation in the topics taught in the course. In the face-to-face setting, students were required to attend two weekly sessions: a 3 h lecture and a 1 h tutorial. The students were also required to attend 7 practical sessions (3 h each) and 3 laboratory sessions (2 h each).

3.2 Data Sources

Digital Traces. This study relied on digital traces from students' interactions with the online course activities in the period from February to June 2017, covering 13 weeks of the course. In total, there were 5,993 online learning sessions performed by the students throughout the entire course. The data were derived from LMS records which comprised every event's timestamp, unique user ID, event context, event name, IP address, and a description of the learning action. Time management was analysed by looking at times when the students performed online activities (out-of-class study), as evidenced in the trace data (timestamps) and validated against the course schedule provided by the course instructor. Note that the students were recommended to study one topic per week and complete pre-laboratory exercises during the assigned week. Each learning action was labelled with an appropriate *mode of study* based on its timing with respect to the week's topic as: (i) *preparing* - if the learning action was related to the topic the students were supposed to study in the given week, (ii) *ahead* - if the learning action was advance of the schedule, (iii) *revisiting* - if the learning action was related to a behind-the-schedule topic that the student had already studied at some earlier point in time, and (iv) *catching-up* - if the student had never accessed activities related to the behind-the-schedule topic. Successive learning actions between any two consecutive

events that were within 30 min of one another were grouped into a learning session [21]. Learning sessions served as the unit of analysis when identifying patterns indicative of students' time management tactics.

Academic Performance. The second data source was derived from the overall course score in the 0–100 range. The assessments contributing to the final course mark included 2 quizzes (contributing 20%), practical marks (25%), and the final exam (55%). Quiz 1 and Quiz 2 were administered in Week 7 and Week 13, respectively. Both quizzes were conducted in a conventional setting.

3.3 Data Analysis

Time Management Tactics. Initially, time management tactics were detected from sequences of study modes. In particular, First Order Markov Model (FOMM), implemented in the pMineR R package [22], was used to compute and visualize the process model from learning sessions. By inspecting the overall process model, potential time management tactics were inferred based on the density of connections among events (i.e., modes of study). To move from observations to automated detection of tactics, we used the matrix of transition probabilities between events, produced by the FOMM, as the input to the Expectation Maximization (EM) algorithm [19] to identify clusters of sequences. The identified clusters reflect patterns in the sequences of study modes and can be considered manifestation of students' time management tactics.

Time Management Strategy Groups. Time management strategies were inferred from the way a student employed time management tactics; i.e., strategies were characterized by one or more tactics [23]. Agglomerative Hierarchical Clustering based on Ward's algorithm [24] was used to identify time management strategies by grouping students with similar usage patterns of time management tactics. To identify such student groups, we represented each student as a vector of the following variables: (a) counts of instances of the identified time management tactics followed by the student (one variable per time management tactic); and (b) the total number of instances of time management tactics. The distance between students, required for the Ward algorithm, was computed as the Euclidean distance of the corresponding vectors. The optimal number of clusters was determined by inspecting dendrograms.

Time Management Tactics Use Across Strategy Group. To further explore the temporal data, we used another process mining technique implemented in the bupaR R-package [25]. The unique features introduced in bupaR assure that the time frame is relevant enough to bring insight into the learning process and has a great potential to inform and enhance understanding of how students make complex learning decisions. In our analysis, we considered event logs that recorded each student's active learning process from the beginning (Week 1) to the end (Week 13) of the course. Each event belonged to a case. A case, in general, is an instance of the process; in this study, a case is an individual student enrolled in the course. In addition, each event relates to a coarser concept of activity. In this study, activities are the tactics adopted by a student

while progressing in their learning. For this analysis, we combined the identified time management tactics with online learning resources (e.g., tutorials and pre-lab exercise) to provide meaningful representations of time management (e.g., *ahead_tutorial* and *prepare_tutorial*). When an activity is performed, an activity instance (occurrence) is recorded. For a given case (*user_id*), we would obtain, from the event logs, a set of execution traces. We denote the traces as a sequence of activities ordered by their time of occurrences in the course timeline (see Table 1).

Table 1. An example of a sequence of activities (trace) for each student obtained from event logs

user_id	trace_length	start_timestamp	complete_timestamp	trace
8	1	2017-06-08 09:56:00	2017-06-08 09:56:00	Prepare_Tutorial
14	2	2017-03-28 08:21:00	2017-04-28 15:37:00	Prepare_Tutorial,Catch.up_Prelab
212	2	2017-03-08 09:09:00	2017-04-06 22:55:00	Ahead_Tutorial,Prepare_Tutorial
12	3	2017-02-28 08:41:00	2017-03-17 08:19:00	Ahead_Tutorial,Mixed_Tutorial,Prepare_Tutorial
19	3	2017-03-06 22:07:00	2017-03-27 22:39:00	Prepare_Tutorial,Mixed_Tutorial,Prepare_Tutorial
35	3	2017-03-22 01:26:00	2017-04-27 12:20:00	Catch.up_Tutorial,Catch.up_Tutorial,Ahead_Tutorial
41	3	2017-03-15 15:01:00	2017-06-08 11:39:00	Catch.up_Tutorial,Prepare_Tutorial,Prepare_Tutorial
52	4	2017-03-15 19:57:00	2017-06-10 07:15:00	Catch.up_Tutorial,Catch.up_Tutorial,Catch.up_Tutorial,Prepare_Tutorial
77	4	2017-03-14 09:16:00	2017-03-19 21:31:00	Prepare_Tutorial,Prepare_Tutorial,Catch.up_Tutorial,Prepare_Tutorial

Process models were then generated based on the identified traces. A process model consisted of a set of nodes and a set of arcs, where the nodes were the process activities and the arcs were the order of the activities. The discovered models were often “spaghetti-like” showing all details of a process. To make the models usable for interpretation, 80% of the most frequent activities were kept for each time management strategy group. This allowed us to study temporal characteristics of different strategy groups.

Association Between Strategy Group and Academic Performance. To examine if there was a significant difference between the identified strategy groups on academic performance, we used Kruskal Wallis tests followed by pairwise Mann Whitney U tests.

4 Results

4.1 Time Management Tactics

By examining density of connections among events of the overall process model resulting from FOMM, a solution of four clusters was identified. Figure 1 illustrates a temporal distribution plot of study modes in each cluster indicative of time management tactics. Each point on the X-axis corresponds to one event (mode of study), whereas the position on the Y-axis represents the probability of study modes.

The characteristics of the identified clusters could be described as follows: (i) Tactic 1 – *Mixed* (N = 1511, 25.21% of all sequences). This tactic was comprised of ahead, preparing, and revisiting modes of study. Sequences in this tactic were focused on revisiting learning materials in a future week after they has been completed in advance or during the week when those activities were scheduled, (ii) Tactic 2 – *Catching-up* (N = 128, 2.14%). It was the least used tactic and consisted predominantly of the catching-up behavior apart from revisiting and preparing modes, (iii) Tactic 3 – *Preparing* (N = 2441, 40.73%). This is the most widely applied tactic and had the highest frequency of preparation activities compared to the other tactics, and (iv) Tactic 4 – *Ahead* (N = 1913, 31.92%) consisted predominantly of ahead activities.

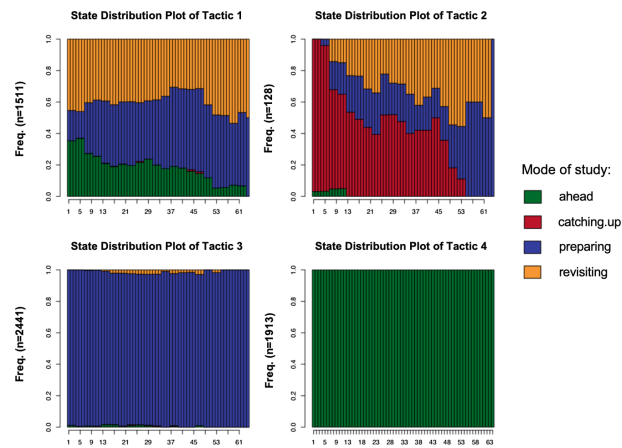


Fig. 1. Temporal distribution of study modes within the detected clusters (manifestations of the students' time management tactics).

4.2 Time Management Strategy Groups

By inspecting the dendrogram resulting from the applied agglomerative hierarchical clustering, a three cluster solution was chosen as the optimal one. To better understand the identified clusters as manifestations of the students' time management strategies, we examined, for each cluster (strategy), how the use of time management tactics changed throughout the course. Figure 2 shows, for each detected strategy, median number of different tactics applied in each week of the course.

Strategy 1 – Active (N = 74, 30.71% of all students) was the most active and dynamic group. This group was consistent in the use of the *Preparing* tactic throughout the course, but also applied different tactics (ahead, preparing and mixed) interchangeably along the course timeline. *Strategy 2 – Passive* (N = 101, 41.91%) had the highest number of students who adopted it. The students were averse towards spending time for studying online with low use of all tactics. Their activity level declined rapidly right after Week 2; in Week 4 they were back on track by adopting the *Preparing* tactic, but failed to maintain the momentum for the rest of the course. *Strategy 3 – Selective* (N = 66, 27.39%) included the students who were highly focused on the

Preparing tactic beginning from Week 3. Their effort dropped in Week 7, but they were able to get back on track and maintained the *Preparing* tactic until the end of the course.

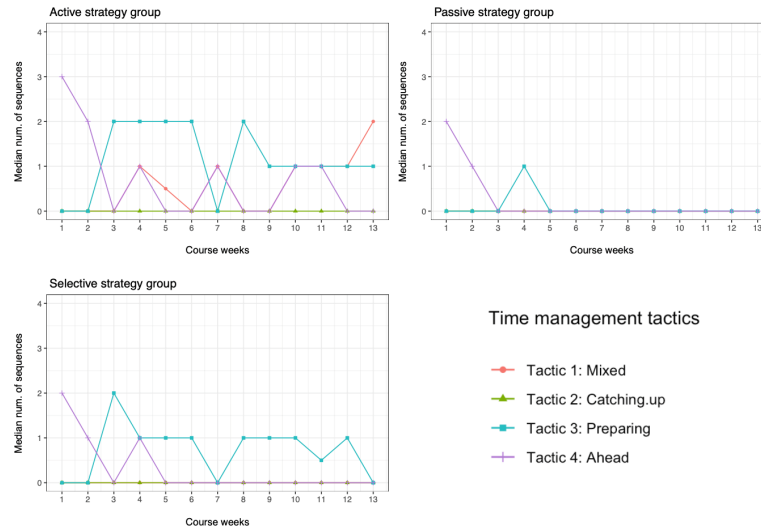


Fig. 2. The dynamics of time management tactics for each identified strategy group

4.3 Time Management Tactic Use Across Strategy Groups

Three process models were created to represent each identified strategy. Figure 3 illustrates the learning processes performed by the students (by enacting several tactics) in each strategy group. The course design permitted the students to decide which tactic to start with and they could change the tactics at any time. Clear differences in the temporal pattern can be identified between the groups, as explained below.

The total duration of time spent to complete the course (in days) was Mdn = 99.62, Q1 = 97.82, Q3 = 101.81 for the *Active* strategy group (Fig. 3(a)) had. This group was characterized by *Ahead_Tutorial* → *Prepare_Tutorial* → *Mixed_Tutorial* as a common activities sequence; that is, a path of transitions with high certainty in activity instances. The frequency of activity instances was relatively equally distributed among the tactics; i.e., all tactics are equally important. The students in this group tended to stay long in the same mode of study (loops around ahead, preparing, and revisiting). The transition often occurred between two tactics (based on the high frequency of activity instances); i.e., *prepare_tutorial* to *mixed_tutorial* (191 instances) and *mixed_tutorial* to *prepare_tutorial* (164 instances). The students in this group showed careful choices between cognitive, metacognitive, and regulation activities while progressing in their learning. This is evidenced by repeated efforts in preparing and reviewing course materials and the regularity in applying various tactics.

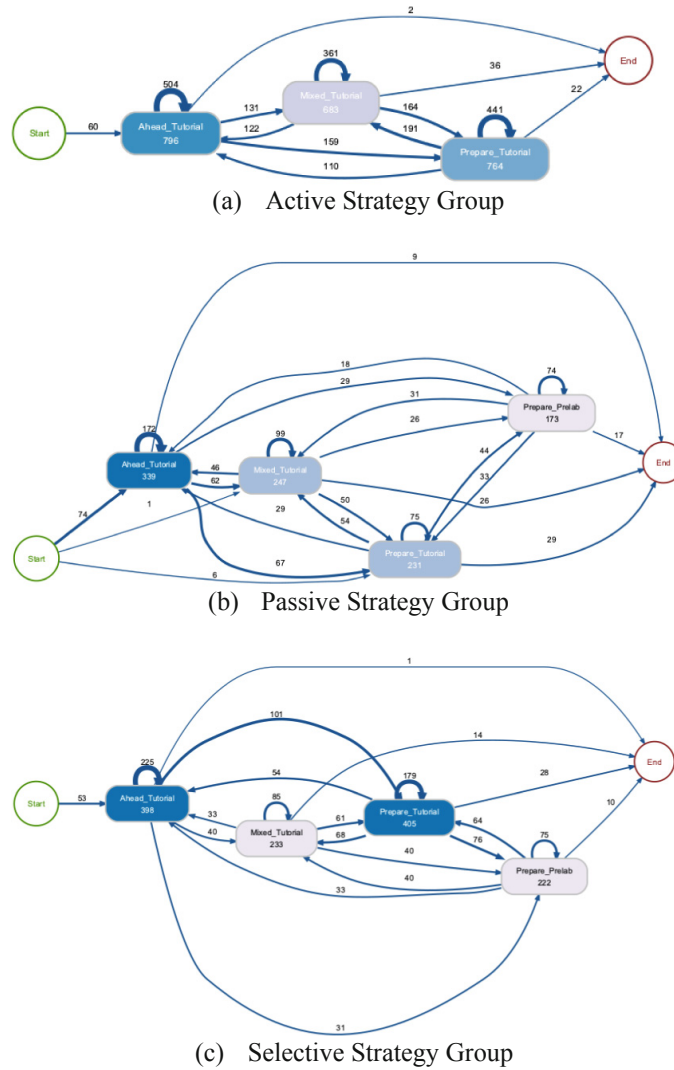


Fig. 3. Process models for the learning processes of the three identified strategy groups. The number in the box represents the absolute frequency of occurrences of events (activity instances), while the numbers associated with edges represent absolute frequency of transitions between consecutive activities. Darker node colour represents higher frequency of activities. (Color figure online)

The median time spent by the *Passive* group (Fig. 3(b)) to complete the course (in days) was 86.68 days (Q1 = 70.06, Q3 = 97.89). The most common path of transition displayed by this group was *Ahead_Tutorial* → *Mixed_Tutorial* → *Prepare_Tutorial* → *Prepare_Prelab*. In contrast to the *Active* group, this group demonstrated high transitions from *ahead_tutorial* to *prepare_tutorial* (67 instances) and *ahead_tutorial* to *mixed_tutorial* (62 instances), while, *prepare_tutorial* showed low connection with

mixed_tutorial (54 instances). The *Preparing* tactic was connected with both tutorial materials and pre-laboratory exercises and its usage frequency was relatively low. These results seem to suggest the *Passive* group adopted a surface approach to learning, with low frequencies in all learning tactics.

The median time spent by the *Selective* group (Fig. 3(c)) to complete the course was 98.04 days (Q1 = 92.48, Q3 = 99.90). *Prepare_Tutorial* → *Ahead_Tutorial* → *Mixed_Tutorial* → *Prepare_Prelab* was the most common sequence. Like the *Passive* group, this group was focused on preparing for both tutorials and laboratory exercises. Similarly, both groups showed relatively low frequency of re-studying (*mixed tactics*). In comparison to other groups, this group had frequent transitions from *ahead_tutorial* to *prepare_tutorial* (101 instances) and from *prepare_tutorial* to *prepare_prelab* (76 instances). That is, the group predominantly focused on planning (e.g., ahead and preparing), while less frequently on preparing and revising.

The graphs shown in Fig. 4 depict the discussed process models from the time perspective. The time periods associated with directed edges represent idle time; i.e., time period between two consecutive activities. The *Active* strategy group had the longest idle time between *ahead_tutorial* and *prepare_tutorial* (Mdn = 4.20 days). In comparison with other group, students in this group took less than 2 days to prepare and revisit the topics; i.e., from *prepare_tutorial* to *mixed_tutorial* (Mdn = 1.90) and from *mixed_tutorial* to *prepare_tutorial* (Mdn = 1.21). The *Passive* strategy group had the longest idle time is between *ahead_tutorial* and *prepare_prelab* (Mdn = 7.34) followed by *ahead_tutorial* to *mixed_tutorial* (Mdn = 5.80) and *ahead_tutorial* to *prepare_tutorial* (Mdn = 5.95). That is, this group took at least 5 days to shift from their first activity (*ahead_tutorial*) to other activities. This group took the longest time from *prepare_tutorial* to *mixed_tutorial* (Mdn = 5.83) and from *mixed_tutorial* to *prepare_tutorial* (Mdn = 4.40) comparing to the other two groups. Although the *Selective* strategy group predominantly focused on ahead and preparing tactics, it took them a long time (almost a week) to shift from *prepare_tutorial* to *ahead_tutorial* (Mdn = 6.14) and from *ahead_tutorial* to *prepare_tutorial* (Mdn = 6.11).

4.4 Association Between Strategy Groups and Academic Performance

The results of the Kruskal Wallis test showed a significant association between the identified strategy groups and the students' course performance (p-value < 0.001 for total score). The pairwise tests showed significant difference with effect sizes (r) ranging from small to medium (Table 2).

The *Active* group (Mdn = 78.01, Q1 = 72.57, Q3 = 84.05) was highest performing. The *Passive* group (Mdn = 74.29, Q1 = 59.57, Q3 = 81.28) was lowest performing. The *Selective* group (Mdn = 76.46, Q1 = 73.65, Q3 = 82.66) was mid-performing.

3. TEMPORAL REPRESENTATION OF LEARNERS' DECISION

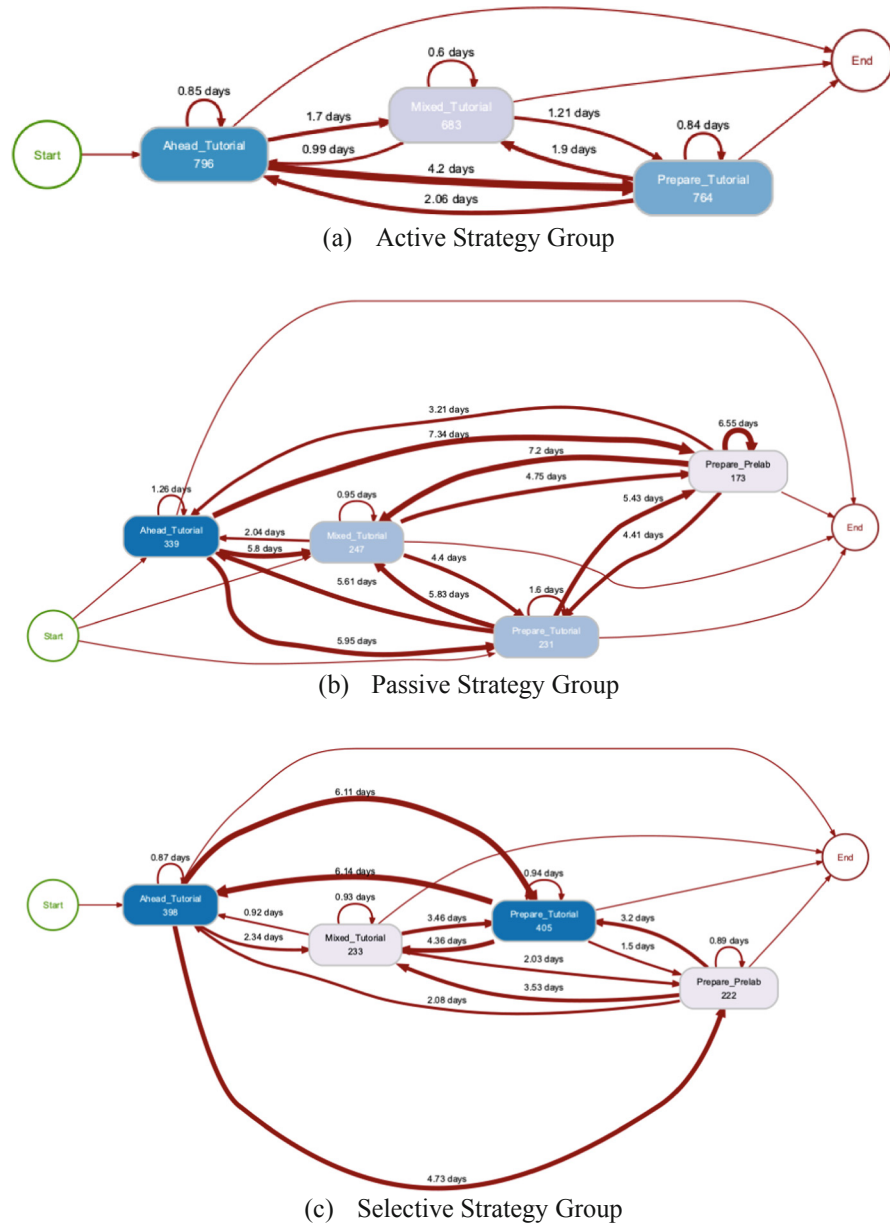


Fig. 4. Idle time (in days) between the end of the from-activity and the start of the to-activity across three identified strategy groups. Darker line color represents longer idle time. (Color figure online)

Table 2. Pairwise comparison of strategy groups with respect to the total course score.

Cluster 1	Cluster 2	Z	p	r
Passive	Selective	1.0226	<0.001	0.198
Active	Passive	-0.2921	<0.001	0.203
Selective	Active	-0.6678	<0.001	0.020

5 Discussion

We discuss the findings based on the framework proposed by Kornell and his colleagues [5] on SRL decisions of what to study, how long to study, and how to study. The results showed that the students employed a wide range of tactics and strategies to manage their learning. The study confirmed this proposition by identifying three strategy groups – *Active*, *Passive*, and *Selective*. The profiles of these groups reflect their time management strategies and academic achievement in the course. The *Active* group was the most active and dynamic; the students in it adopted diverse tactics and used them throughout the course. Due to the careful alignment of diverse tactics such as study in advance (*ahead tactics*), prepare learning prior to a face-to-face session (*preparing tactics*), re-studying right after a class and revision during the test weeks (*mixed tactics*), this strategy was recognized as the one of autonomous learners and associated with the highest achievement. In contrast, the *Passive* group, associated with the lowest achievement, used only a few tactics during their learning, and sometimes used tactics in a way not supporting their study. Unlike the *Active* group, the *Selective* and *Passive* groups highly focused on preparation with less revisiting efforts. A possible explanation may be that both groups believed that having already learned a topic, little would be gained from re-studying. However, such a strategy is far from optimal. To sum up, our results indicate that students who were identified as high performing – the *Active* group – put efforts to plan their study (cognitive), modified their learning accordingly (metacognitive), aligned their study tactics with the course structure and maintained their level of motivation (regulation strategies) throughout the course timeline. In line with the SRL theories, the *Active* group demonstrated productive self-regulation [4, 9, 26].

One of the major problems in regulation of learning lies in how much time to put into practice. The current study found that the high performing students (*Active*) were willing to invest more time to study compared to the low performing (*Passive*) and mid-performing students (*Selective*). This is evidenced by the frequency of activity instances that the high performing group allocated for each tactic (Fig. 3(a)) which was two times higher than that of the lowest performing group. The students in the high performing (*Active*) group also devoted to course completion on average 13 days more than the lowest performing (*Passive*) group. This may reflect the *perseverance of effort* exhibited by high performing students to sustain the time and efforts necessary for completing long-term tasks [27]. Furthermore, on average, the *Active* group spent more time revisiting (*mixed_tutorial*) weekly topics ($M = 5.45$, $SD = 10.42$) minutes. The *Passive* and *Selective* groups spent longer time on preparing for pre-laboratory exercises (*prepare_prelab*) ($M = 9.74$, $SD = 13.57$ and $M = 11.81$, $SD = 18.61$ min, respectively). This may be attributed to the students' *judgement of rate of learning* (jROL). Maybe the two groups perceived pre-laboratory exercises as a difficult task and, thus, maintained a high learning rate. Commonly, the students in all three strategy groups spent more time revisiting learning materials (*mixed_tutorial*) after the week to which the materials were assigned. This was almost twice the time they spent using those materials to prepare (*prepare_tutorial*) for the class. These findings suggest that,

all students used regulatory processes to some degree, but self-regulated learners were distinguished by their awareness of active decisions between regulatory processes and learning outcomes and their use of these strategies to achieve academic goals [28].

Furthermore, the use of time in learning is often linked to the *spacing effect* [29]. Spacing—defined as separating successive study sessions rather than massing such sessions—has positive effects on long-term memory [30]. The finding of this study indicated that, after preparatory work, the *Active* group took 2 days on average before immediately returning to the course material to review it, whereas the *Passive* and *Selective* groups waited approximately 6 and 4 days, respectively, before returning to the materials to re-study. A possible explanation may be that the *Active* groups established optimal metacognitive judgments that they could forget some items they had previously studied, so they kept coming back to the items immediately as a priority [26] thereby promoting better recall. In contrast, the *Passive* and *Selective* groups were less sensitive to change as they allowed for maladaptive delay between two tactics. Undoubtedly, long idle time did not benefit recall. Students could forget what they have learned before. In summary, the students in the highest performing group (*Active*) showed a clear endorsement of massing over spacing for predicted learning outcomes [31] contrary to consistent findings in the literature of a benefit for spacing [32].

6 Conclusions and Implications

The purpose of this study was to explore the differences in time management tactics and strategies from the perspective of self-regulated learning theories. We present the time management aspects based on study decisions students make on what to study (what tactic to use), how long to study (frequency of tactics used) and how to study (timing of tactic use). From a methodological point of view, we demonstrated how quantitative temporal data about students' online learning activities can be analysed by methods of process mining. Although used in SRL research, the application of this method, as done in the current study, for exploring students' time management tactics and strategies in the context of online and blended learning activities is original.

This study contributes to the literature on time management and SRL by providing empirical evidence on what, how, and how long students enacted their tactics across different strategy groups and academic achievement. Our research reinforced the importance of time management tactics in students' learning that improve their SRL and performance. From an instructor viewpoint, this study has a potential to inform instructors about what tactics students applied to learn, how students spaced out their learning, and how regularly students engaged in online preparatory work. This allows instructors to understand different characteristics of students to make necessary adjustment in their learning approach and feedback to the students. From a student viewpoint, this study can provide awareness and useful guidelines for the students to inform them about the effective tactics and strategies they could employ while studying online and the opportunities to improve their time-management skills as well as their academic success.

This study highly relied on the trace data of students' interactions with online preparatory learning activities. Although this data allowed for examining actual behavior in an authentic online settings, we could not capture activities that occurred offline (e.g., downloading the learning material) nor in-class activities; such activities which take place in a physical context could influence students' decision in learning.

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3.3 Summary

Placement of the Sonnenberg and Bannert (2015), temporality is central to the regulation of learning. Thus, the identification of temporal and sequential patterns in a learning process throughout the course duration can inform students' decisions of their learning process. In this chapter, we present a novel method for the analysis of time and ordering in students' learning processes indicative of learners' decisions on the enactment of time management tactics and strategies.

This study addresses the research question one (RQ1) by using FOMM combined with the EM algorithm. This analytical method can discern a variety of time management tactics that are distinguishable by modes of studies. Accordingly, our findings show that the students employed a wide range of tactics and strategies to manage their learning, and three strategy groups are identified – *Active*, *Passive*, and *Selective*. Meanwhile, to address the research question two (RQ2), we demonstrate that there is a significant association between the identified strategy groups and the course performance (p -value < 0.001 for total score) with effect sizes (r) ranging from small to medium.

To address the research question three (RQ3), we interpret the identified tactics and strategies according to the established theoretical framework of SRL, in relation to student decisions about what tactics to use (e.g., how to modify their tactics to support their learning goal), frequency of tactics use (e.g., deciding how long to persist to master a concept) and timing of tactic use (e.g., how to space their learning). Our results indicate that there are clear differences in the temporal patterns between identified strategy groups in terms of the frequency of transition between consecutive tactics and interval time between one tactic and another (measured by day(s)). We then discuss the time management aspects based on the student's perseverance of effort, judgement of rate of learning (jROL), and use of time in learning, which is linked to the spacing effect.

Although the work in the present chapter provides comprehensive methods in examining the temporal state of learning in terms of time management practices, there is a paucity of research in examining relationships between time management and learning strategies. Ideally, the interpretation of learning strategies should consider both time management and learning tactics to understand learning as a complex phenomenon. Accordingly, the investigation of mutual connections between time management and learning strategies in Chapter four aims to provide a comprehensive evaluation of students learning experiences.

4

Network Representation of Students' Learning

Time is the wisest of all things that are; for it brings everything to light.

— Thales, *Encyclopedia of Time*

4.1 Introduction

AN active learning environment introduced in a flipped classroom encompasses two components: pre-class preparation and in-class interaction (O'Flaherty & Phillips, 2015). Pre-class preparation focuses on the interaction with online content like lecture videos, reading materials, and online tests. In some cases, students' are required to complete an assessment to ensure that they have completed the pre-class preparation (He, Holton, Farkas, & Warschauer, 2016). In face-to-face sessions, students are involved in activities that require high-order thinking such as problem-solving, discussion, or collaboration with peers and teachers. The flipped classroom is a response to the idea that learning can occur anywhere with minimal instructional intervention. Therefore, it creates the impetus for strong self-regulated learning skills.

Much research in SRL suggests that time management and learning strategies can improve the quality of learning as represented by academic performance (Ahmad Uzir, Gašević, Matcha, Jovanović, & Pardo, 2020; Ahmad Uzir et al., 2019; Fincham et al., 2019; Matcha, Gašević, Ahmad Uzir, Jovanović, & Pardo, 2019; Matcha, Gašević, Ahmad Uzir, Jovanović, Pardo, et al., 2019). However, there is a limited understanding of links between learning strategies and time management, along with their combined effects on academic performance. Hence, the work presented in this chapter investigates mutual connections between time management and learning strategies and their combined connections with academic performance using epistemic network analysis. To examine the comparison between high and low performing groups in a methodologically rigorous manner, we use 2-sample t-test in order to better understand the difference between these two groups (high and low groups) with respect to the time management and learning strategies. In this regard, the study presented in this chapter provides some of the first insights into the interrelations

between three constructs – time management, learning strategies, and course topics by using trace data and learning analytics method.

4.1.1 Chapter overview

In this chapter, we propose a new analytics method to reveal the links between time management, learning strategies employed by students while interacting with online components of flipped classroom, and their academic performance by using a network analytics approach based on epistemic network analysis (ENA) (Shaffer, Collier, & Ruis, 2016). ENA is a network analysis method developed to analyse trace data of individual or collaborative learning (Arastoopour, Shaffer, Swiecki, Ruis, & Chesler, 2016; Csanadi et al., 2017; Shaffer et al., 2016, 2017; Shaffer & Ruis, 2017). ENA has the novelty to (i) model the whole networks of connections by illustrating the structure of connections and measure the strength of association among elements in a network (Shaffer et al., 2016), and (ii) quantitatively and qualitatively compare different epistemic network models (Shaffer & Ruis, 2017).

First, we use qualitative analysis methods to understand how time management and learning strategies changed over the course timeline. To achieve this, we create individual epistemic networks for each week in the course to visualise connections between weekly topics, time management, and learning strategies. In the generated epistemic networks, frequent co-occurrences between elements (i.e., weekly topics, time management, and learning strategies) are illustrated by darker and thicker lines. Through this study, we observe a strong engagement in online activities not only in pre-class preparation but also in revisiting activities (i.e., after class activities). This finding corroborates the philosophy of flipped classroom that aims for students to gain a knowledge foundation prior to face-to-face activities and to re-study after class to fully benefit from in-class sessions.

Second, to get a clear idea of how high and low performing groups differ in terms of their time management and learning strategies, we compare student groups based on their scores of both the midterm and final exams. In order to explore this, we create individual network models to present high and low performing groups (in both the midterm and final exams) by maintaining the nodes that relate to time management and learning strategies, while nodes representing the course topic are removed. This is due to our current focus on studying the association of academic performance with time management and learning strategies. To further explore the difference between these groups, other epistemic networks spaces are created using the “subtracting networks” function. This function allows for contrasting two network models by subtracting the weight of their nodes and connections from each other (Csanadi et al., 2017).

Finally, to increase the robustness of the findings, we offer quantitative measures with the aim to add precision to the qualitative descriptions for the comparison of learning processes between high and low performing groups. To do this, we create an additional epistemic network space using a means rotation function of ENA with respect to time management and learning strategies. This ENA

function allows for representing the maximum difference between two groups of networks. Then, we used t-tests to examine the presence of a significant difference in two dimensions, that are: (i) the mean rotation (x-axis) and (ii) singular value decomposition (y-axis) of the two groups over the 12 active weeks of the course. This t-test results clearly show the contrast between high and low performing groups, particularly at the beginning of the course and in the week of the midterm test. Consistent with existing SRL literature, all the students used regulatory processes to some degree, but self-regulated learners were distinguishable by their active decision on time management and effective learning strategies, which are also related to higher academic achievement.

4.2 **Publication: Epistemic Network Analytics to Unveil Links of Learning Strategies, Time Management, and Academic Performance in Flipped Classrooms**

The following section includes the verbatim copy of the following publication:

Ahmad Uzir, N., Matcha, W., Gašević, D., Eagan, B., Jovanović, J., Williamson Shaffer, D., & Pardo, A. (2020). Epistemic Network Analytics to Unveil Links of Learning Strategies, Time Management, and Academic Performance in Flipped Classrooms. *Manuscript submitted for publication to the IEEE Transactions on Learning Technologies*

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

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Abstract— Flipped classrooms have received much attention as an approach to promoting sustained active learning. However, less is known regarding how course design is associated with learning strategies used by learners in a flipped classroom or how students manage time vis-à-vis choices of learning strategies. This paper aims to address this research gap and to investigate mutual connections between learning strategies and time management and their combined connections with academic performance. The paper reports on a study that employed a network analytic approach based on epistemic network analysis to analyze the trace data collected in an undergraduate engineering course (N=290) with a flipped classroom design. The results suggest that many students effectively managed their time, though some of them did not use effective learning strategies. The main difference between high and low performing students were in the choices of learning strategies especially when revising previously studied content and in the ineffective time management of low performing students. The paper draws several implications for research and practice.

Index Terms— Learning analytics, learning strategies, self-regulated learning, time management.

I. INTRODUCTION

THE goal of contemporary education is to empower learners with opportunities for active learning rather than passive reception of knowledge from instructors with the aim to promote self-regulated and deep learning. In this context, flipped classroom – as a form of blended learning – has emerged as a strategy to improve traditional and often heavy lecture-based models [1]. This pedagogical model commonly encompasses two elements: pre-class and in-class learning activities [2]. Pre-class learning allows students to work on online (preparatory) activities to develop background knowledge and skills. In-class time with teaching staff and

peers is used to encourage active participation and application of what students learned during the online (preparatory) activities.

Despite some early promise reported in different studies [3], [4], there is often a concern that learners may not have sufficient skills to study on their own during preparatory activities [5]. Preparatory activities are typically offered in online formats, which require strong skills for self-regulation of learning [6], [7], [8]. In such online formats, students with low self-regulation skills are at higher risk of attrition [9]. To deal with weaknesses in self-regulated learning skills, the existing literature recommends theory-informed instructional designs that promote effective self-regulation; e.g., assignments should be developed to assist students in recognizing the importance of goal setting and reflection [6], [10].

Learning strategy is a key element of productive self-regulated learning [11], [12]. However, little is known about how effectively learners manage their time and select learning strategy in a flipped classroom, or how time management in use of learning strategies is associated with academic performance [3], [4], [13]. Existing studies that examined students' learning strategies in a flipped classroom have been aimed at identifying strategies from trace data and at gauging associations between the frequency of use of particular strategies and academic performance [4], [14]. However, there is a limited understanding of links between learning strategies and time management along with their combined effects on academic performance.

Learning strategies and time management are key components of self-regulated learning. The literature suggests that self-regulated learning is a dynamic process that involves the use of different tools to operate on information under given (internal and external) conditions [15], [12], [16], [17]. An effective self-regulation is a process that requires the use of learning strategies to operate on information at times

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empirically proven to maximize performance. Methods commonly used for (statistical) analysis cannot offer sufficient insights into the ways that processes represented by different learning and time management strategies are interlinked with each other and with course topics, how these links can qualitatively be interpreted, and whether there are (statistical) differences in such links among different groups of learners. This paper proposes a network analytic approach to address the above limitations in a study that looked at preparatory activities of undergraduate students in a computer engineering flipped classroom.

II. BACKGROUND

This section outlines relevant background literature on flipped classroom, learning strategy, time management, and network analytics of learning.

A. Flipped Classroom

The concept of flipped classroom has been gaining much attention recently due to its potential to facilitate active learning. It was initially inspired by the work of [18] who offered an approach to guiding students to understand learning content more effectively through the use of online resources to prepare for face-to-face classes. The preparatory activities were primarily focused on remembering, comprehending, and applying. Meanwhile, face-to-face time was typically used to encourage the development of higher-order thinking and promote active learning [19] through analysis, synthesis, and evaluation [5], [20].

Design for flipped learning makes use of combinations of conventional face-to-face and online delivery in order to optimize knowledge construction [21]. The role of the teacher is particularly important in a flipped classroom environment. Instead of the lecture-only teaching approach, the teacher acts as a designer of opportunities for independent (online) learning and as a facilitator of (collaborative) activities in face-to-face settings [1], [22]. Due to this changing landscape, the teacher acts as an operational agent to promote learning in preparatory activities and to encourage higher-order thinking skills among students during the face-to-face sessions. In order for a teacher to fulfil this responsibility, design for learning in flipped classrooms requires special attention. Arguably, as learning design becomes more complex, there is a growing need to provide guidance to both teachers and students in their use of resources, technologies, support mechanisms, and feedback provision [23], [24].

Preparatory activities, typically delivered online, play an important role in flipped classrooms. The purpose of preparatory activities is to enable students to develop background knowledge prior to face-to-face sessions that feature activities with peers and teachers. Weekly pre-class work needs to be carefully designed to stimulate learners' engagement, especially those learners who are new to flipped classrooms and have limited experience with online learning [6], [25]. Activities such as readings, videos, individual or group work (e.g., online discussions), summative or formative assessment, or a combination of these could be utilized for preparation [1], [26]. The role of both formative and summative assessment – both before and after face-to-face classes – is

particularly emphasized to maximize learning outcomes, while some authors highlight summative assessment as an effective strategy to promote learning in the preparatory period [27].

In spite of many studies reporting benefits of flipped classroom designs to enhance learning outcomes and motivation, [24], [28], [29], [30] the literature reports also some challenges that may negatively affect the learning experiences. Some of these have already been reported in the research on online learning such as a need to have adequate self-regulated learning skills, time management, use of effective learning strategies, and high responsibility for own learning [2], [31]. In this paper, we particularly focus on learning strategies and time management in the flipped classrooms.

B. Learning Strategy

1) Definition

The study presented in this paper is based on the suggestion by Rachal and colleagues [32] to define learning strategy as “methods and techniques used by students to improve learning” (p.192). In this regard, this study presents learning strategies as a sequence of actions that students performed to complete a learning task [15]. Building on the research on desirable difficulties [33], Dunlosky [34] classified learning strategies as effective (practice testing, distributed testing, interleaved practice, elaborative interrogation, and self-explanation) and less effective learning strategies (rereading and highlighting, summarization, keyword mnemonic, and imagery). Dunlosky also stressed that less useful learning strategies (e.g., reading and rereading) were most frequently used by students [34] which often lead to the poorer academic performance [35]. Thus, decisions that students make about regulating their learning strategies (i.e., effective or less effective) has tremendous impact on their performance [36], [37].

Previous research has demonstrated that the relationship between learning strategies and academic performance is mediated by self-regulation [38]. Self-regulation involves the students' decision on how and when to apply effective learning strategies in completing learning task while directed by a learning goal [12]. According to Winne and Hadwin's model of self-regulated learning (SRL) [12], students critically evaluate the effectiveness of study techniques used in the preceding sessions (metacognitive monitoring) to adapt to changing circumstances and future improvement [39]. Based on the prevailing evidence, productive self-regulated learners showed relatively strong endorsement of the effective learning strategies (i.e., practice testing, distributed practice and interleaved practice) and have higher academic results, while low self-regulated students more inclined to use less effective learning strategies (i.e., reading, re-reading) which negatively affected their academic performance.

With regard to this foundation, the present study uses the Winne's theory of SRL [12] and Dunlosky's work [34] on learning strategies for the interpretation of the study findings. The proposed methodology is judged based on its capacity to identify learning strategies that are meaningful from the perspective of the underlying theory.

2) Contextual Factors

Contextual factors need to be considered for a comprehensive understanding of learning strategies. These

factors can be conceptualized as what Winne and Hadwin [12] refer to as internal and external conditions. Internal conditions include motivation, beliefs, prior knowledge, and knowledge of learning strategies and tactics. External conditions are typically characterized by instructional conditions, social context, time, and resources available. Existing research on automatically extracted strategies has primarily been focused on the links with internal conditions. Associations have been found with self-reported measures of deep approaches to learning [40], [41], achievement goal-orientation, and students' instructional conceptions [42]. For example, in the Gašević et al. [40] study, students who made use of effective learning strategies had significantly higher values of self-reported measures of approaches to learning than their counterparts who made use of ineffective learning strategies.

Research on learning strategies can offer only a limited insight if external conditions are not accounted for [43], [44]. The interpretation of learning strategies requires a consideration of the sequencing of tasks and topics included in a course curriculum [23]. This is especially important in flipped classrooms where timely completion of pre-class tasks and topics is essential for effective engagement in in-class activities. The timing of task completion is also indicative of the use of some of the most effective learning strategies such as spaced practice [34]. While the use of formative assessment opportunities is important, it is even more important to return back to those assessments while revising content of the topics studied in the previous weeks. Whereas time management of learning strategies is obviously an important topic, it has not received the needed attention of the research community. Therefore, this research is set out to address research gap and provide a more comprehensive insight into learning strategies by taking into consideration topics of study and time of activity completion.

3) Data Analytics and Learning Strategies

Whereas learning strategies were conventionally studied using different self-reported instruments, contemporary literature suggests the use of trace data to overcome inaccuracies and biases learners are typically susceptible to [45], [11], [46]. For example, recent research on learning strategies used in preparatory tasks in flipped classrooms and blended learning made extensive use of trace data [4], [14], [47]. Promising results in the identification of learning strategies have been achieved with methods based on graph theory [15], [48], [49], [50] sequence mining [4], [51], process mining [52], [53], and different clustering methods [14], [41], [54]. For example, Jovanovic and her colleagues [4] made use of sequence mining and unsupervised machine learning to identify four general strategies computer engineering learners used when working on preparatory learning tasks in a flipped classroom. Each of these strategies was interpreted according to the categorization of effective and ineffective study strategies proposed in [34]. Strategies focusing on the content only (video or textual) were found ineffective and those that promote memory practice (assessments) proved effective. The students who made use of the entire range of strategies had highest performance.

Learning strategies automatically detected from learning trace data differ from those posited in the established theoretical

models. Such models include, for example, practice testing, distributed practice, interleaved practice, and rereading, among others [34]. This difference stems from the fact that learning strategies that were detected from trace data are context dependent [55]. Trace data can only capture information from the use of tools that directly support completion of learning tasks. However, trace data are still able to capture time-stamped information about actual learning events. By combining the knowledge of task design, relevant research on learning strategies (e.g., as documented by Dunlosky [34]), and theory of self-regulated learning [11], [12], the conceptual validity of automatically detected strategies is addressed. Such theoretical models as the one proposal by Dunlosky [34] define relevant cognitive and metacognitive mechanisms can be used to interpret and corroborate findings.

C. Time Management

The time management is considered a key enabler for effective learning progress, regardless of the learning environment. In their model of learning, Winne & Hadwin [12] suggest that time is one of the external conditions that learners need to take into account when making decisions about their learning – e.g., set their learning goals, plan their learning, and monitor their own progression against the goals they previously set. There is a body of evidence suggesting that learning strategies and time management have a strong association towards higher academic achievement [56], [57]. Mclean et al. [13] posit – based on the results of a study with medical students – that flexibility in deciding when to complete pre-class activities in a flipped classroom can be a “double-edged sword”. For those students who have good time management skills, it can be quite beneficial; however, for those with poor time management skills, it could be problematic and promotes procrastination. A recent literature review suggests that time management has an ambiguous connection with student performance in undergraduate education [58]. Thus, the aim of the present work is to contribute to better understanding of time management by examining it in relation to learning strategies and sequencing of course topics in flipped classrooms.

Given the undesirable consequences of poor time management in flipped classrooms, research on procrastination have recently received considerable attention. There is an extensive body of research that explores the effects of procrastination in traditional learning environments [59]. Procrastination can be define as “self-regulated failure” [59]. Michinov et al. [60] report that there is a negative correlation between the level of procrastination and learning performance in online learning settings. Michinov and colleagues [60] suggest that those with a high level of procrastination tend to participate less in online discussions and had lower performance. Procrastination is also reported as one of the main reasons students dropped out or fail in online courses [57], [60]. Students tend to delay their work until the deadline, which often leads to cramming and unsatisfactory learning products [61]. This is in turn associated with poor learning outcomes (*ibid.*). However, few studies have investigated associations of procrastination with learning strategies and learning outcomes in flipped classroom settings, due to the recency of this instructional model.

D. Network Analytics of Learning

Network analytic approaches have already been established in the study of self-regulated learning [15], [48], [49], [50]. Networks are typically built by creating nodes based on occurrences (i.e., events) of relevant learning processes (e.g., micro-level self-regulated learning processes such as goal setting or planning) and interventions (e.g., software features developed to promote goal setting). Links between nodes are usually established based on temporal sequencing of events represented by the nodes. Finally, graph theoretical statistics – well-known in social network analysis [62] – are often used to gauge mutual importance of each of the self-regulation processes and interventions. Although they can produce valuable insights, these analytical methods do not allow for quantitative and qualitative comparisons of learning processes of individuals and groups. Therefore, we propose the use of epistemic network analysis (ENA) [63] as it allows for individual and group comparisons required for addressing the gaps in the literature identified in the paper.

ENA is a network analytic technique developed to analyse log data and other traces of individual and collaborative learning [64], [65], [66], [67], [63]. ENA is created to support the learning science theory of epistemic frames [68], [69], [70], which looks at expertise in complex domains not as a set of isolated processes, skills, and knowledge, but as a network of connections among knowledge, skills, values, and decision-making processes. ENA focuses on categories of action, communication, cognition, and other relevant features of individual and group learning [71]. These categories are then used to create nodes in an epistemic network. Connections among nodes are established based on occurrence of the codes within a relevant unit of analysis (e.g., the same event captured in trace data). The weights of the links among nodes are a central point of interest in ENA as these weights capture the pattern of the observed events.

ENA uses computational and statistical techniques to compare the salient properties of networks, including networks generated by different individuals or groups and at different points in time. ENA calculates properties relevant to the content of the network and traces of learning processes. ENA has been used to identify critical patterns of interaction in expert and novice teams [63], [64], [65] successful and unsuccessful teams and individuals [66], [67], and assessment of engineering design thinking [72], [73], [74], [65], [75].

E. Research Questions

In summary, the reviewed literature reveals missing links between flipped classroom learning design, student choices of learning strategies [4], [44], time management, and learning performance [13], [44]. The following two research questions are formulated to guide this study:

RQ1: How do students select and modify their learning strategies and manage time while completing online 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?

III. METHODOLOGY

A. Context

The study was conducted in an undergraduate flipped classroom course offered at an Australian research-intensive university. The study collected trace data from 290 first year engineering students (18.5% female) in a 13-weeks long course on Computer Systems. Most of the students had limited or no experience with 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 ii) face-to-face classroom activities which were designed to promote active learning [4], [76].

TABLE I
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 (multiple choice question - 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

This study focused on the pre-class preparation activities that were run from week 2 to week 12 (with exception of week 6 when the midterm examination was scheduled) and included:

Videos with multiple-choice questions (MCQs). The students were provided with short videos to introduce and explain the key concepts. The videos were followed by a set of MCQs as a form of formative assessment introduced into the course design to promote a simple recall of the relevant explained concept. The students were immediately informed whether their answers to MCQs were correct or not. If the answer was incorrect, they could request to see the solution or try again.

Web pages with embedded MCQs. The students were provided with readings (as Web pages) with embedded MCQs. This activity had similar purpose and characteristics for the use of MCQs as those related to the videos, that is, MCQs were part of 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 towards the final course marks. In particular, there were 10 exercise sequences (weeks 2-5 and 7-12) and each one contributed one percentage point towards the final score. These problem-solving exercises served as summative assessments. To do this, students only had a single attempt to complete each of the problem-solving assessments. After the completion of those assessments and receiving the marks, students could continue accessing and repeating those

4. NETWORK REPRESENTATION OF STUDENTS' LEARNING



Fig. 1. The flow of the data preparation and extraction of learning strategy and time management by using sequence mining and clustering.

problem-solving exercises as many times as wanted, but, at that point, the completion of those summative assessments had no impact on students' marks and it was completely voluntarily (i.e., those are summative assessments in the revision mode and play the role of formative assessments).

The students were provided with a dashboard as a real-time feedback that allowed for performance monitoring – details can be found in [77]. The dashboard presented the level of a student's engagement with the resources. They could monitor their performance based on the success in solving MCQs and the percentage of completed problem solving sequences. The students could also compare their performance with the class overall scores. The data in the dashboard were updated every 15 minutes and were reset each week to show the values for the current week. The course had two examinations – a midterm exam (20 points) and a final exam (40 points) that happened in weeks 6 and 13 of the course. Face-to-face sessions during any given week of the course consisted of a 2-hour lecture, a 2-hour tutorial, and 3-hour hand-on laboratory session. In face-to-face lectures, four to six active problem-solving exercises were covered. They were related to the videos and problems discussed in the preparation stage. The exercises were preceded by a brief explanation and then solved in small groups (3-4 students). The solutions to the exercises were then discussed by the lecturer. In tutorial sessions, a similar approach was adopted although the problems were higher in complexity and the solutions were produced working in pairs. The tutors would explain the rationale behind the exercises and solutions.

TABLE 2

WEEKLY TOPIC COVERED 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
Week 11 - 12	T_HLP	High Level Programming Construct
Week 13		Final Examination

B. Data

The trace data were extracted via the click-streams that recorded students' interaction with online learning resources during the pre-class activities for week 2-13 (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 of event id, anonymized student id, type of learning action, course topics and timestamp. Each action that students performed were assigned with a specific action code (e.g., MCQ_CO, MCQ_IN) and description. Meanwhile, a sequence of actions that a student performed to complete a

task is considered as learning strategies [15]. The types of learning actions that were detected in the data are presented in Table 1, whereas course topics are shown in Table 2.

1) Identification of Learning Strategies

Fig. 1 illustrates the flow of the data preparation and extraction of learning strategy and time management. Learning strategies (steps 1 and 2 in Fig. 1) were extracted by following the methodology proposed by Jovanovic and her colleagues [4] including the reuse of the analysis scripts written in the R language. The methodology included a mix of data pre-processing, exploratory sequence analysis, and clustering.

The strategies along with their interpretation can be found in Table 3. It is important to note that a study session was unit of analysis in the detection of learning strategies in the Jovanovic et al. study [4]; that is, each study session is labelled with one of the four learning strategies. Further details about the methodology and the identified learning strategies are provided by Jovanovic et al.

TABLE 3
LEARNING STRATEGIES IDENTIFIED BY THE LEARNING ANALYTICS METHOD PROPOSED BY JOVANOVIC ET AL. [4]

Learning Strategies	Description
S_formative_assess	Sequences in this learning strategy showed the dominance of formative assessment, and almost no summative assessment. Access to the course reading materials was minimally present and mostly at the start of learning sessions. Metacognitive activities (i.e., access to the dashboard) mostly occurred towards the end of learning sessions.
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_forms_assess	Sequences in this learning strategy had a large presence of video watching. Formative assessment activities were also present, but they were gradually superseded by summative assessment activities towards the end of the sessions. The presence of metacognitive activities at the beginning of the sessions in this strategy was also observed.
S_readings	Sequences in this learning strategy would be mostly characterized by access to the class reading materials and a small amount of formative assessment activities. These sequences tended to be short and to end with watching the course videos.

2) Identification of Time Management Modes

Time management was automatically analyzed by looking at times when the students completed some of the pre-class activities as evidenced in the trace data and validated against the course schedule provided by the course instructor (refer to Fig. 1).

Each week, students were required to study one topic. The algorithm was defined to detect if the students completed the requested activities in weeks as scheduled (preparing), or if they were ahead of schedule (ahead), or if they were accessing activities related to the topics that were scheduled for the previous weeks. In the last case, we further distinguished between the following two modes: if students visited an activity

that they had completed earlier, the “revisiting” mode was assigned. The “catching up” mode was assigned to the activities that were behind the scheduled topic and students had never accessed them before. Accordingly, each event in the trace data was coded according to the four codes representing time management modes of study summarized in Table 4.

TABLE 4
INDICATORS OF THE STUDENTS' TIME MANAGEMENT ARE LABELED AS MODES OF STUDY

Mode of Study	Description
M_preparing	Students completed learning actions prior to their weekly face-to-face sessions and in the week when the course topic associated with the learning action were scheduled.
M_revisiting	Students returned to course topic in a future week after they had completed them as part of the preparation, catching up, or study ahead of time.
M_ahead	Students completed some of the course topic ahead of the weeks in which the course topic were scheduled.
M_catching.up	Students completed the course topic after the schedule time (catching-up), but without completing them in the scheduled week as that was the case for the revisiting activities.

C. Data Analysis

Individual students were the unit of analysis to produce an epistemic network of each participant. Epistemic networks were created for each learner by establishing links between the four learning strategies (Table 3), four time management modes (Table 4), and course topics (Table 2). That is, nodes in the networks were the codes shown in Tables 2-4. The links were based on the co-occurrence of these three dimensions in the dataset. Following this logic, the links could only happen between the elements of the three dimensions but could not exist between elements of the same dimension (e.g., two learning strategies could not be linked). Specifically, the processing of each event (i.e., row) in the trace data as shown in Fig. 1 resulted in creation of the three links, namely links between:

- a learning strategy and a topic
- a time management mode of study and a topic, and
- a learning strategy and a time management mode.

For example, the first row in the two spreadsheets shown in Fig. 1 would result in the following links: i) DRM – S_formative_assess; ii) DRM – M_catching-up; and iii) S_formative_assess – M_catching.up.

To address research question 1, for each study participant, we created three epistemic networks with N nodes: 1) N=18, nodes include 10 course topics, four learning strategies, and four time-management modes of study; 2) N=8, with nodes based on four learning strategies, and four time-management modes of study; and 3) N=14, based on 10 course topics and four time management modes of study. Following the regular ENA procedure, each network was represented with an NxN adjacency matrix that described the connections between the nodes. These were then accumulated for each participant into a cumulative adjacency matrix. The cumulative adjacency matrix for each participant was represented as a point in a high-dimensional space by taking each cell in the matrix as a dimension in the space. We used singular value decomposition (svd) to project the points into a lower dimensional space of orthogonal dimensions that maximized variance accounted for

in the data. We used the first six dimensions (svdi=1..6) as descriptors for study participants in the ENA space, based on the amount of variance explained by the addition of subsequent dimensions.

Shaffer et al. [71] suggest it is up to the researcher to assess which two dimensions to use in presenting an ENA space. We used the first two dimensions – svd1 and svd2 – to produce two-dimensional epistemic network graphs for each participant. After positioning nodes of the epistemic networks, for each participant, we calculated the position of centroid c_i of his or her resulting network graph. Next, we optimized the positions of the nodes so as to minimize $\sum i(p_i - c_i)$. The positions of the nodes in the svd1 x svd2 space were then used to interpret the significance of the spatial location of participants' networks—that is, in this study we examine how students modify their learning strategies according to the course topics, the positions of the course topics were used to explain the dimensions of the ENA space (refer to Fig. 3-5).

In the resulting ENA graphs, frequently co-occurring nodes were projected close to one another and the line that connected them was darker and thicker. The projection of the nodes was fixed for the same view of the data set. Therefore, we could examine differences between two or more students' network in the same condition. The superimposed and subtracted functions in ENA allowed us to observe mutually strong connections and differences in network structures of the (groups of) study participants, as it was needed to compare the high and low performing students to address research question 2.

In the previous ENA space, we used a singular value decomposition (svd) to represent maximum variance in the network models. To further investigate the difference between the high and low performing groups, we made use of the ENA feature to produce a rotated space, refer to as mean rotation (mr1). Mean rotation computes a dimensional reduction from a matrix of points such that the first dimension of the projected space passes through the means of two groups in the original space. Subsequent dimensions of the projected space are computed using ENA singular value decomposition (ena.svd). The singular value decomposition provides a rotation of the original high-dimensional space, such that the rotated space reduces the number of dimensions to show the greatest variance in the data. This feature allows for representing the maximum difference between two groups of networks [78]. We used the first and the second dimensions of the rotated space (using mr1 and svd2) to show the connection between time management and learning strategies. To examine if there was a significant association between the mean positions of individual week for each high and low performing group, we used sample t-test.

Note also that the ENA diagrams shown in the figures in the rest of the paper do not show labels of all the course topics in order to maximize the readability and reduce the clutter. The removal of the topic labels was done for all those topics that had a low number or no links with the codes representing learning strategy and time management mode of study for a period under consideration (e.g., week, half of a course, or entire course).

IV. RESULTS

A. RQ1: Strategy Selection and Time Management

The epistemic network shown in Fig. 2 visualizes the connection between weekly topics, learning strategies, and time management modes of study that students adopted in the flipped learning course.

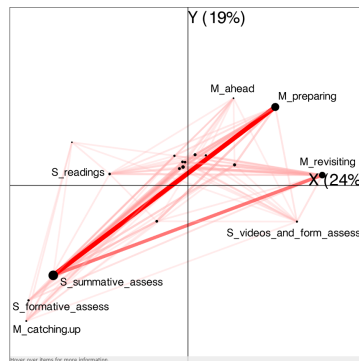


Fig. 2. The overall mean epistemic network of weekly topics, time management mode of study, and learning strategy for the 12 weeks included in the study.

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 in this 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 of *S_summative_assess*, *S_formative_assess*, and *M_catching_up*.

It is important to note that the work on the summative assessment is graded, if *S_summative_assess* nodes linked with *M_preparing*, *M_ahead*, and *M_catching_up* in the ENA, whereas *S_summative_assess* is considered as formative assessment (non-graded item), if the links between *S_summative_assess* and *M_revisiting* were added in the ENA. Apparently, this could offer a partial explanation for the highest co-occurrence of summative assessment (*S_summative_assess*) during preparation activities (*M_preparing*) followed by the link between *M_revisiting* and *S_summative_assess*. Interestingly, among four learning strategies offered, *S_summative_assess* shows a higher density connection compared to *S_formative_assess*, *S_reading*, and *S_video_and_form_assess*. That is, the high number of links of *S_summative_assess* with other nodes in the network indicates the highest co-occurrence of summative strategy exercises during preparation and revision activities.

The approach to learning in Weeks 10 and 12 (Fig. 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 contact and with little revision work done after

4. NETWORK REPRESENTATION OF STUDENTS' LEARNING

that. The topics of Weeks 10 and 12 (T_ADM and T_HLP) seemed to be found by the students as highly important given they kept intensively preparing for them and revisiting them later on, as shown by the networks in Fig. 3 (b-c), Fig. 4, and Fig. 5 (b).

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. Initially, in Week 2, students mainly focused on *M_preparing* and *S_summative_assess* 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) (Fig. 3 (a)).

practice opportunities to prepare for the examinations. The use of summative assessment was also combined with some reading activities. However, as completing the summative activities in the examination weeks could not contribute to the student final marks (their deadlines passed in the previous weeks), the summative assessments played the role of formative assessments.

The epistemic networks also revealed that the *M_preparing* (T_HLP; T_COD; T_CD_L and T_SDL) and *M_revisiting* (T_COD; T_DRM and T_SDL) time management modes of study had dominant links with other nodes in the network in contrast to the other two modes of study – *M_catching_up* and *M_ahead*.

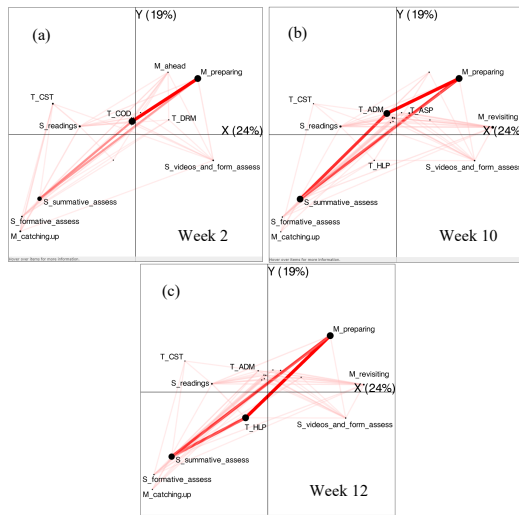


Fig. 3. Epistemic networks for week 2, week 10, and week 12

Starting in Week 3, the pattern changed as shown in Fig. 4. The model highlights the 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 revised the same topic in the subsequent week (Week 4). Apart from that, links of weekly topics and time management models with other three learning strategies (video watching, reading, and formative assessment) were low. As is evident in the epistemic networks (Fig. 4), these scenarios were consistent in most of the subsequent weeks that featured some preparation activities (i.e., Week 4, 5, 7, 8, 9 and 11).

Rather different patterns in learning approaches were observed in epistemic networks for Week 6 and Week 13 (Fig. 5 (a) 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 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 summative assessment as

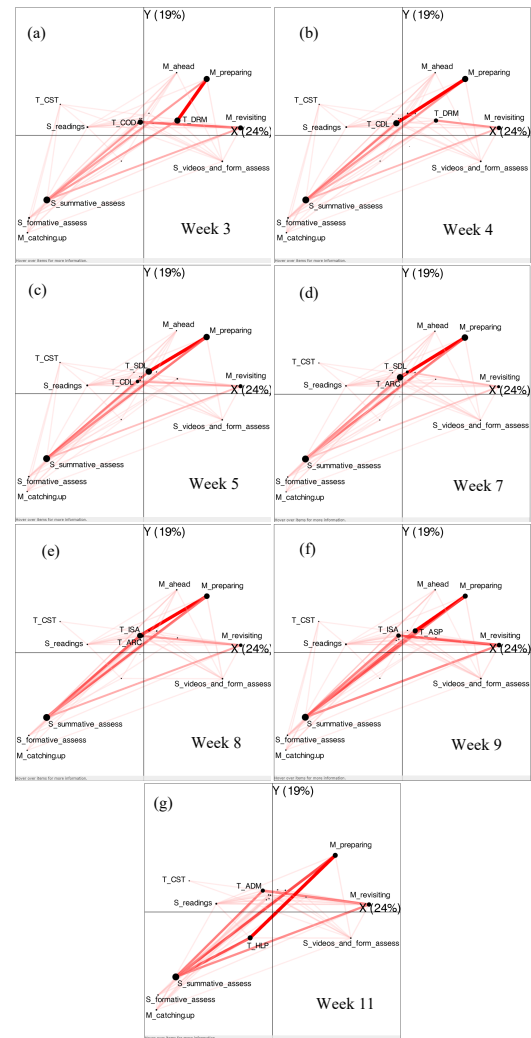


Fig. 4. Epistemic networks for week 3, 4, 5, 7, 8, 9, and 11

4. NETWORK REPRESENTATION OF STUDENTS' LEARNING

Cohen's $d = -0.388$; and Y dimension $t=1.577$, p -value = 0.123, Cohen's $d = 0.412$). Even though the differences in learning strategies selection between low and high performing students based on their midterm performance were detected in the network model, the differences were not statistically significant.

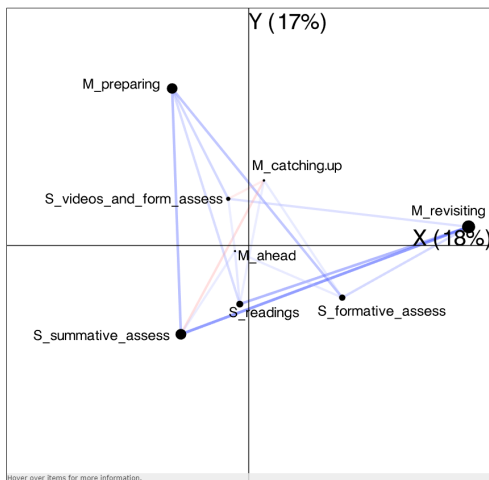


Fig. 8. Subtracted epistemic network between the low (red) and high (blue) performing students for the midterm exam.

2) Final Exam Performance

Fig. 9 plots the centroids of individual students where the red nodes represent low performance and blue ones high performance students based on their final exam score. The squares represent the mean centroids of the two networks and the rectangles around them confidence intervals.

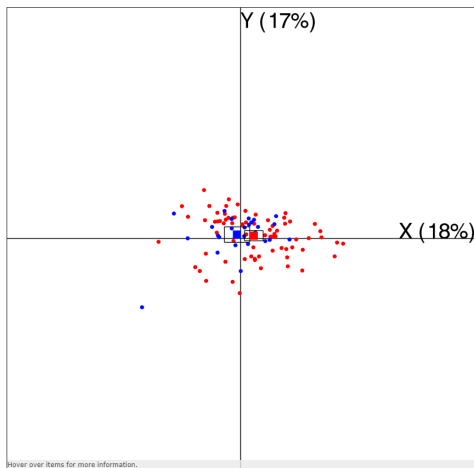


Fig. 9. Centroids of the high (blue) and low (red) performing students on the final examination.

To explore the differences between the two performance groups, their mean epistemic networks were further studied and are shown in Fig. 10.

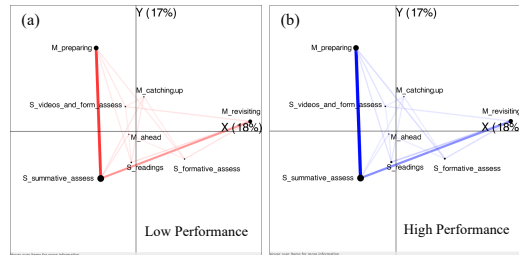


Fig. 10. Mean epistemic networks for low (a) and high performing students (b) on the final examination.

Similar to case of 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 subtracted equiloat. The subtracted network is in Fig. 11.

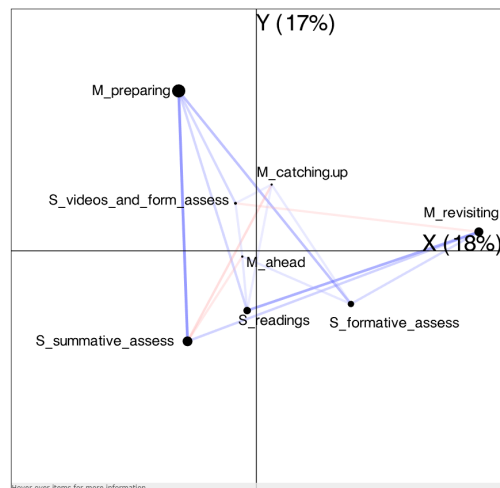


Fig. 11. Subtracted epistemic network between the low (red) and high (blue) performing students for the final exam.

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 performance students also demonstrated dominant links related to watching videos while revising. T-

tests showed significant differences between the two networks in Fig. 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 $d=-0.056$).

As the choices in 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 Fig. 12.

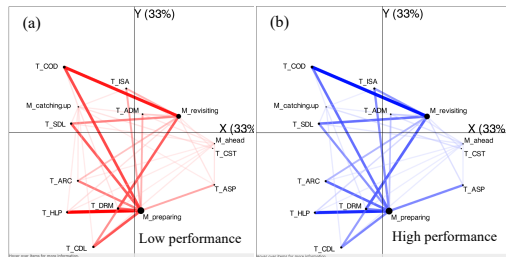


Fig. 12. Mean networks for time management mode of study and topic for low (a) and high (b) performing students.

The figure shows the networks that are presented in a different epistemic network space to highlight time management in connection to the topics as studied by the students included in the study.

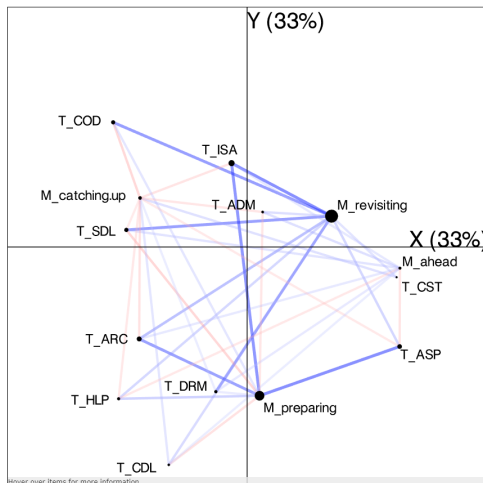


Fig. 13. Subtracted network for time management mode of study and topic between low (red) and high (blue) performing students.

Fig. 13 shows the ENA space comparing the mode of study and the topic of high and low performance students. The network reveals that low performing group (red lines) completed ahead of time more activities (M_ahead) related to only two topics (ASP and HLP) in comparison of their high performing peers who did so for a few other topics. The low performing students did not tend to complete on time the

relevant activities for most of other topics except for CST, DRM and CDL. Note that these topics (CST, DRM, and CDL) were introduced in weeks 1, 3 and 4, respectively. It should also be noted that CST was not an actual course topic; it rather represented the course introduction, description of available resources, and expectations. The high performing students exhibited less catching up behaviour, especially towards the end of the course. They did not have any catching up behaviour in relation to topics ARC, ASP, HLP that belonged to weeks 7, 9, and 11-12, respectively.

3) Mean Comparison

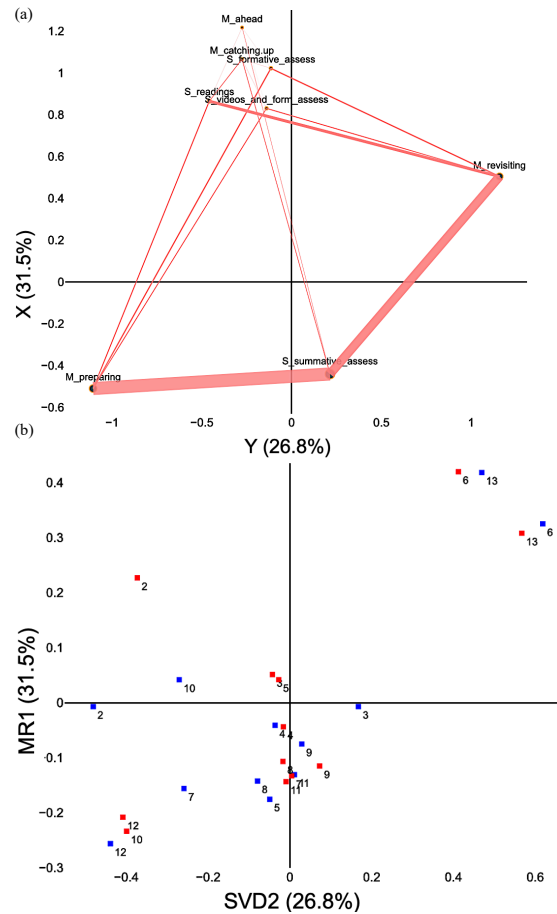


Fig. 14. (a) The network model generated using the mean rotated function of ENA, (b) position of the mean plots (shown as squares) of high (blue) and low (red) performing groups based to 12 active weeks (week 2 – week 13).

To further explore the difference between the high and low performing groups, we created an additional ENA space using a means rotation function of ENA. Fig. 14 (a) shows the network model generated using mean rotation, where the

network for each unit of analysis is represented as a point, and the distances between units are a measure of the difference between the connections in the two 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. Fig. 14 (b) uses the same ENA space as the one used in Fig. 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 90th percentile, whereas the low performing group counted 31 students ($N_{below25th} = 31$) with below 25th percentile for both midterm and final exam.

In order to better understand the difference between the two groups with respect to the time management and learning strategies, we used sample t-tests to examine the presence of a significant difference in the mean rotation (mr1) and singular value decomposition (svd2) of the two groups over the 12 active weeks of the course (refer to Table 5). Table 5 shows a significant difference in Week 2 ($p = 0.0282$; $r = 0.4370$), Week 3 ($p = 0.0386$; $r = 0.3500$) and Week 7 ($p = 0.0056$; $r = 0.4240$) along the x-axis which is interpreted as a medium difference between the mean of the high and low performing group based on the values of the r effect sizes [79]. Moreover, there was a significant shift along the y-axis in the network connections present in Week 5 ($p = 0.0454$; $r = 0.3430$) and Week 10 ($p = 0.0381$; $r = 0.5210$). The effect size of 0.34 is considered large according to [79]. Particularly, the critical difference between the high and low groups was in Week 6. The main contrast between groups was over the x-axis ($p = 0.0104$; $r = 0.2800$) and also shows a high difference across the y-axis ($p = 0.0481$; $r = 0.1460$), which implies a small effect size [79].

TABLE 5
COMPARISON OF THE MEAN PLOT OF HIGH AND LOW PERFORMING GROUPS BASED ON MEAN ROTATION (MR1) AND SINGULAR VALUE DECOMPOSITION (SVD2) OVER THE 12 ACTIVE WEEKS OF THE COURSE.

WEEK	MR1 (p-value)	r	SVD2 (p-value)	r
Week 2	0.0282*	0.4370	0.0927	0.0986
Week 3	0.0386*	0.3500	0.6571	0.0547
Week 4	0.8313	0.0075	0.9812	0.1870
Week 5	0.8290	0.0135	0.0454*	0.1120
Week 6	0.0104*	0.2800	0.0481*	0.1460
Week 7	0.0056*	0.4240	0.8370	0.2120
Week 8	0.5438	0.1650	0.7318	0.0525
Week 9	0.6518	0.1260	0.7157	0.3070
Week 10	0.0570	0.4630	0.0381*	0.5210
Week 11	0.8220	0.0338	0.8978	0.1020
Week 12	0.4749	0.0476	0.5264	0.2430
Week 13	0.2618	0.2510	0.3687	0.3430

Note: * indicated $p < 0.05$

V. DISCUSSION

A. Interpretation of the Results

The study found that students generally preferred assessment activities in each week except in the weeks scheduled for preparation for midterm and final exam. It is encouraging to note that not only did the study observe a strong engagement in pre-class preparatory activities, but it also revealed a strong tendency of learners to revisit the previously studied topics through assessment activities as shown in Section IV.A in response to research question 1. This finding is consistent with the philosophy of flipped classrooms that aims to provide students with opportunities to gain prior knowledge before face-to-face classes and to revise previously studied content and activities for the entire duration of a course [5], [80], [81].

The study (see Section IV.A) revealed that students in a flipped classroom can have a strong tendency towards engaging into effective study strategies. However, further studies are required in order to confirm the finding of this study. The incorporation of summative assessments into the activities of each week stimulated the students to prepare prior the face-to-face sessions. The students also returned back to those summative assessment as part of their revising strategy, even though the assessments did not have any summative function in the following weeks. This pattern is indicative of the use of one of most effective study strategy - self-testing [34]. Attempts to recall some information, commonly known as retrieval practice, enhances learning and slows the rate of forgetting [82], [83]. Therefore, the results of this study point to the need to incorporate retrieval practice through self-testing into course designs to both improve comprehension of meaning [84] and increase the accuracy of metacognitive judgments learners make about what they know. As summative assessment became formative while revising, the findings of the study are consistent with previous studies that recommended complementing summative and formative assessments to enhance the overall learning experiences [1], [85]. This finding also corroborates the suggestion by Bernard et al. [6] to create assignments that will promote the use of effective learning strategies.

The study showed that high performing students made better choices of learning strategy than their low performing colleagues. The high performing students stressed the use of retrieval practice through their engagement with assessment activities while revising as shown in Section IV.B in response to research question 2. They also made use of the whole range of the four learning strategies as defined in Table 3; the strategies were used both for preparation and revision. The low performing students made suboptimal choices of learning strategies while revising (i.e., video watching with some formative assessment). The significant difference was revealed when students were divided into high and low performing groups based on the final exam scores (see Section IV.B.2). The difference was along the dimension that showed the use of revising time management mode and assessment focused strategies.

Not only did the use of ENA enable us to identify and show qualitative but it also enabled us to unveil the quantitative differences in the studied groups. That is, differences between low and high performing students were not qualitative only as

some literature [86] may suggest but they were also quantitative [87] (see Section IV.B.3). The difference was corroborated with the sample t-test results (see Table 5) that clearly show the contrast between the high and low performing student groups over the weeks 2, 3, 5, 6, 7 and 10. Particularly, the learning behavior of the two groups differed at: (i) the beginning of the first-half of the course (Week 2 and 3), (ii) in a week before midterm test week (Week 5), (iii) in a week during midterm test were conducted (Week 6), (iv) at the beginning of the second-half (Week 7), and (v) in the mid of the second-half of the course (Week 10).

Drawing upon our theoretical background rooted in the self-regulated learning literature, the quantitative difference can suggest high performing students were aware and sufficiently skillful with the use of study time and effective learning strategies. That is, the high performing students likely had higher self-regulation skills [88]. The existing literature reports that individuals with strong self-regulated learning skills tend to manage their learning by preparing course materials prior to a face-to-face session (preparing) and re-studying during the test weeks (revisiting) [38], [89], by directing their efforts towards practice testing or self-testing (i.e., assessments etc.) as one of the most effective strategies to improve students' learning [34]. In line with the previous works, the current study demonstrates that the high performing students tended to begin the course on-time (e.g., Week 2 and 3), by using one of the effective study strategy, that is summative assessment prior to face-to-face sessions. They kept this learning behaviour in the beginning of the second half of the course (Week 7) as well as put extra efforts during the test weeks (Week 6 and 13) by revising the learning content.

In contrast, the study uncovered that low performing students were characterized by the catching up behavior and inconsistent time management patterns. That is, the low performing students likely had lower self-regulation skills as they exhibited catching up behaviour in the use of less effective learning strategies (e.g., reading, video watching) in the beginning of first-half of the course (e.g., Week 2 and 3) (see Fig. 14). Still, they maintained the same learning strategies in the week before midterm test were conducted (Week 5). Yet, they attempted to modify their study behaviour by using more effective learning strategies: summative assessment combined with revisiting activities during midterm test week (Week 6) and at the beginning of the second-half of the course (Week 7). However, procrastination and delayed revision till later in the course did not appear to profoundly influence success in learning. Therefore, the current study suggests that exercising effective learning strategies alone is often not enough. Rather, the choices that students make regarding time management and learning strategy are significantly associated with their performance.

The results also revealed that the high performing students showed a limited number of instances of the catching up behaviour. Meanwhile, the low performance of the students with high catching up behaviour is consistent with the findings of the studies that reported negative associations of procrastination with academic performance [59], [90]. The association of inconsistent time management with low academic performance observed in the current study is connected to the work by Bos & Brand-Gruwel [91] who found

that highly inconsistent learning patterns were related to poor academic performance.

This study supports the suggestions that time management is a critical characteristic of effective self-regulated learners [12]. Although time management is linked to procrastination, not every form of procrastination is unproductive. Since the low performing students exhibited a higher frequency of catching up behaviour that had a detrimental association with their performance, their time management behaviour can be considered a passive procrastination as posited by Kim, Fernandez, & Terrier [92]. Passive procrastination is linked to suboptimal performance as also shown by other authors [61]. Conversely, according to Kim et al. [92], a deliberate act of delay, also known as active procrastination, could contribute as a success factor. Future research should seek to collect other and richer forms of data than those collected in this study to be able to determine accurately occurrences of the two types of procrastination and determine whether, when, and how procrastination can have positive effects on performance and learning [93].

B. Implications

The results of this study have implications for the development of instruction, early warning systems, and provision of personalized feedback. The results related to time management strategies of low performing students indicated that an early detection mechanism to identify those with catching up behaviours in early stages of the course can be beneficial. Moreover, the qualitative differences in the choices of study strategies between low and high performing students, especially those used for revising, can serve as a strong foundation for preparing personalized feedback to students. Therefore, a suggestion for practice is that the choices of time management and learning strategies should be discussed during the introductory classes to communicate their critical role for success in flipped classrooms. Given that patterns of time management and learning strategies can be unobtrusively collected through trace data and processed with analytic methods, such patterns can be used for the provision of personalized feedback. Analytics based feedback has shown promising results to promote learning success, satisfaction, and improvement of learning strategy [94], [95]. We agree with Marzouk and her colleagues [96] that personalized feedback should still leave sufficient room for autonomy to help students exercise their agency in the choices of time management and learning strategies. The use of non-controlling language [97] combined with the rationale for a particular study approach [98], [96] is a promising approach to feedback formulation.

The network analytic approach based on ENA used in this paper offers a promising methodological and practical implications. Methodologically, studies that aim to understand links among (meta)cognitive processes and their links with course design and academic performance can benefit from this approach. The use of ENA allows for qualitative and quantitative comparisons of individuals and groups that can be situated in design contexts on the levels of individual topics. ENA can also complement other methods applied for the study of learning processes such as sequence and process mining. This study gives an example how learning strategies extracted with sequence mining can be further analyzed with ENA to

study connections with other relevant constructs. Practically, the connections between nodes and their weights can be used as a foundation for an automated system for personalized feedback provisioning on the level of learning strategies, time management, and course topics. For example, students who show no or limited links between revising and relevant study strategies (e.g., indicative of retrieval practice) for some course topics could receive a personalized feedback on process and self-regulation levels [99] with actionable recommendations [95]. The main value of the proposed network analytic approach lies in its potential to analyse interrelations between three constructs – learning strategies, time management, and course topics – in the same latent variable space. The benefit of such latent variable space is that we can track student progression on the combined use of time management and learning strategies and in connection to specific course topics.

C. Limitations

Some limitations of this study must be highlighted. This research studied learning strategy, time management, and academic performance by using trace data collected during preparatory activities in a flipped classroom. Many factors could have had an impact on each of these three dimensions as it can be concluded from our main theoretical source [12]. The attendance of face-to-face classroom, personal learning goals, participation in the activities during conventional classroom sessions, and face-to-face participation in small group discussions were not considered. Further research should focus on the combination of both offline and online course activities to account for the complete cycle of study activities in a flipped classroom when studying time management.

Moreover, individual differences – e.g., prior knowledge, motivation, and approaches to learning – might have an important impact on the each of the three dimensions studied in this paper [4], [40], [91]. Next, it should be noted that this study was exploratory and correlational in nature. Therefore, any causal inferences are unwarranted. Future studies should also look at the links between the three dimensions in other courses with different (flipped) designs and especially those that are in different subject domains to test generalizability of the study results.

VI. CONCLUSIONS

The paper presented a novel network analytic approach to the study of the associations between learning strategies and time management patterns automatically detected from trace data about online activities taken by students in flipped classrooms. The study offers multifold contributions for researchers, instructors, and learners.

From a research perspective, this study contributes to the literature by offering a network analytic approach to investigate mutual connections between learning strategies and time management, as well as their connections with academic performance, through the use of epistemic network analysis. In particular, the proposed methodology uses computational and statistical techniques to allow for both quantitative and qualitative comparisons of learning processes of individuals and groups. The proposed methodology also allows for tracking progression of learning processes of individuals and groups in

a latent variable space that has parallel to those used in summative assessment. This could help both researchers and practitioners improve the interpretation of their results related to learning strategies and time management practice.

From an instructor perspective, this study makes a step forward to translate learning strategies and time management into actionable feedback. Our findings highlight effective learning strategies and time management practice as a vital element for self-regulation of learning as well as a strong predictor of academic success. By having a solid understanding of how students enacted specific time management and learning strategies while progressing in learning, an instructor would be in a better position to generate feedback to guide learners towards the achievement of their learning goals [100]. Better incorporation of learning strategies and time management into provision of feedback affords a potential for the student to exercise metacognitive control and monitoring that adapts engagement in mid task [101].

From a learner perspective, this study could offer practical guidelines for making necessary adjustments of their learning strategies and timing of engagement in pre-class preparatory activities. Our findings suggest that assessment activities (summative assessment) before face-to-face sessions coupled with revision practices (formative assessment) after class tend to lead to the best learning outcomes. The findings also stress that both the chosen learning strategy (e.g., summative assessment, formative assessment) and the timing of engagement (e.g., preparing, revisiting) are equally important determinants of learning success.

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4.3 Summary

The work presented in this chapter offers the first insights into the mutual connections between time management and learning strategies, as well as their association with academic performance. The proposed method is chosen based on its capacity to: (i) allow for an integrated analysis of both time management and learning tactics as components of learning strategies (Ahmad Uzir, Gašević, Jovanović, et al., 2020), and (ii) identify time management and learning strategies that are meaningful from the perspective of Winne and Hadwin (1998)'s theory of SRL and Dunlosky (2013)'s learning strategies principle.

Our results indicate that the choices of time management and learning strategies play an important role in students' learning and, ultimately, academic achievement. In response to research question three (RQ3), the study found that the students typically preferred assessment activities (i.e., summative assessments) in their preparatory tasks prior to face-to-face sessions in each week. The students also returned back to those assessment activities as part of their revising strategy in the following weeks. This pattern indicates that the students have a strong tendency towards engaging in effective learning strategies – self-testing or testing practice (Dunlosky, 2013) to strengthen their understanding from week to week. These results corroborate the idea that all students acquire certain levels of regulation skills while progressing in their learning (Zimmerman, 2001). However, high and low achieving students can be distinguished by the quality of time management and learning strategies taken by them.

Given our concerns about the differences between high and low performing students in terms of their learning and time management practices, we extend the use of ENA to compare high and low performing groups. In doing so, we demonstrated that high performing students were sufficiently skilful with the use of study time, in which they prepared their learning by studying course materials prior to the face-to-face session (preparing) and revisited the course topics after in-class sessions were scheduled (revisiting). In addition, this group exhibited a frequent use of the learning strategies regarded in the literature as effective, such as self-testing or practice testing (i.e., assessments and problem-solving) (Dunlosky, 2013; Dunlosky et al., 2013). Conversely, this study revealed that students in low performing groups were characterised by catching up behaviour and less effective learning strategies while progressing in their learning, such as reading and video watching.

The difference was then corroborated with the sample t-test results that clearly showed the contrast between the high and low performing student groups. Particularly, the learning behaviour of the two groups differed at (i) the beginning of the first half of the course (Week 2 and 3), (ii) in a week before the midterm test week (Week 5), (iii) during the week when the midterm test took place (Week 6), (iv) at the beginning of the second half of the course (Week 7), and (v) in the middle of the second half of the course (Week 10). In particular, this study demonstrates that the high performing students preferred to gain timely access to the course content (e.g., Week 2 and 3) by using one of the effective study strategies, which is a summative assessment. They kept this

4. NETWORK REPRESENTATION OF STUDENTS' LEARNING

learning behaviour at the beginning of the second half of the course (Week 7), as well as put extra effort during the test weeks (Week 6 and 13) by revising the learning content. In contrast, the low performing group made suboptimal choices of learning strategies (e.g., reading, video watching) at the beginning of the course (e.g., Week 2 and 3). Despite their attempt to use more effective learning strategies (i.e., summative assessment) during midterm test week (Week 6) and at second-half of the course (Week 7), but procrastination and delayed revision till later in the course did not appear to profoundly influence success in learning.

In light of the potential and capacity of ENA in bringing insights into mutual connections between time management and learning strategies demonstrated in this chapter, we use the same method in the work presented in Chapter [five](#) to (i) further analyse the connection between time management and learning tactics and their combination as a manifestation of learning strategies, and (ii) examine the temporal dimensions of learning in order to provide an interpretable explanation across different learning strategies.

5

Analytics of Time Management and Learning Strategies

The time for action is now. It's never too late to do something.

— Antoine de Saint-Exupery, *World's Greatest Motivational Quotes*

5.1 Introduction

OVER the years, learning analytics has demonstrated significant value in discovering and providing measurable insights into students' learning experiences. In essence, learning analytics helps to address some of the problems that traditional measures have struggled to resolve. Ultimately, learning analytics does not have an agenda to replace conventional methods. However, it aims to complement them for bridging the gap in improving the quality of measurement aspects relating to student learning, especially in digital education (Gašević et al., 2017).

In response to Hadwin et al. (2007)'s recommendation, recent development in learning analytics has shown the adoption of a wide range of sophisticated analytics that are based on methods used for the identification and measurement of learning processes, learning activities and learning outcomes across groups of students. Rather than relying on counts of the clicks, learning analytics research has evolved by making use of multiple learning analytics-based methods to enhance the precision of measurement and enrich insights into SRL (Matcha, Gašević, Ahmad Uzir, Jovanović, & Pardo, 2019; Saint, Gašević, Matcha, Ahmad Uzir, & Pardo, 2020). As examples, we demonstrate new learning analytics methods in Chapter three and Chapter four that can be used to enhance our understanding of SRL in a complex learning environment, focusing on time management and learning strategies.

Recent years have witnessed an increasing interest in capturing and examine student data, both of the time management and learning behaviour to provide insights into patterns of SRL. It is widely accepted that time management (Ahmad Uzir, Gašević, Matcha, Jovanović, & Pardo, 2020; Ahmad Uzir et al., 2019), and learning strategies (Matcha, Gašević, Ahmad Uzir, Jovanović, & Pardo, 2019; Matcha, Gašević, Ahmad Uzir, Jovanović, Pardo, et al., 2019) play critical roles in promoting effective self-regulation and academic success. However, existing studies that have pieced them together

is scarce (de Barba et al., 2020). This chapter aims to address this gap in the literature by proposing a method that enables an integrated analysis of both time management and learning tactics.

5.1.1 Chapter overview

The work presented in this chapter extends the studies in Chapter [three](#) and Chapter [four](#) by proposing a novel method that aims to incorporate both time management tactics and learning tactics as dimensions of learning strategies. Rather than detecting time management tactics alone, this study uses a learning analytics method (First Order Markov Model and expectation-maximization algorithm) proposed in Chapter [three](#) to detect both time management tactics and learning tactics. Then, we employ the network analysis method proposed in Chapter [four](#) combined with a hierarchical clustering method to integrate the detected time management and learning tactics for identifying the strategy groups.

The significant methodological contributions of this chapter are twofold: First, we present a new method that uses epistemic network analysis (Shaffer, 2018) and agglomerative hierarchical clustering based on Ward's algorithm (Gabadinho et al., 2011) to extract patterns of how the students used the time management tactics and learning tactics and explore how their interconnections shape learning strategies. Second, we present a learning analytics method that uses network analysis and process mining methods to articulate patterns of temporality. In particular, we use (i) rENA R-package (Shaffer, 2018) to compute and visualise the network model representing the combination of time management and learning tactics that correspond to each strategy group; then, we use (ii) a process mining method implemented in the bupaR R-package (Janssenswillen et al., 2019) to visual the learning process that derived from students' learning traces across identified strategy groups.

In essence, we posit that the combined methods (i.e., network analysis and process mining) can provide a richer insight into temporal patterns of student's activities than any one single method. Also, the proposed method allows for a close inspection of the role of time management and learning tactics in learning strategies according to relevant principles documented in educational psychology (Dunlosky, 2013) and model of SRL (Winne & Hadwin, 1998) as theoretical foundations to support the interpretation of the research findings.

5.2 Publication: Analytics of Time Management and Learning Strategies for Effective Online Learning in Blended Environments

The following section includes the verbatim copy of the following publication:

Ahmad Uzir, N., Gašević, D., Jovanović, J., Matcha, W., Lim, L.-A., & Fudge, A. (2020). Analytics of Time Management and Learning Strategies for Effective Online Learning in Blended Environments. *Proceedings of the 10th International Conference on Learning*

Analytics of Time Management and Learning Strategies for Effective Online Learning in Blended Environments

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ABSTRACT

This paper reports on the findings of a study that proposed a novel learning analytics methodology that combines three complementary techniques – agglomerative hierarchical clustering, epistemic network analysis, and process mining. The methodology allows for identification and interpretation of self-regulated learning in terms of the use of learning strategies. The main advantage of the new technique over the existing ones is that it combines the time management and learning tactic dimensions of learning strategies, which are typically studied in isolation. The new technique allows for novel insights into learning strategies by studying the frequency and strength of connections between, and ordering and time of execution of time management and learning tactics. The technique was validated in a study that was conducted on the trace data of first-year undergraduate students who were enrolled into two consecutive offerings ($N_{2017} = 250$ and $N_{2018} = 232$) of a course at an Australian university. The application of the proposed technique identified four strategy groups derived from three distinct time management tactics and five learning tactics. The tactics and strategies identified with the technique were correlated with academic performance and were interpreted according to the established theories and practices of self-regulated learning.

CCS CONCEPTS

• **Applied computing** → **Learning management systems**; *E-learning*.

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Blended learning, Learning analytics, Learning strategies, Time management strategies, Self-regulated learning

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1 INTRODUCTION

Blended learning increases flexibility for learners to study at their own pace, while offering opportunities to promote active learning in the classroom. Due to the heavy online component, blended learning requires strong skills for self-regulated learning (SRL) considering that learners need to engage with online resources and to study autonomously [1]. SRL assumes the use of effective learning strategies. In this context, learning strategies can be defined as “methods and techniques used by students to improve learning” [28, p. 192]. Learning strategies are made up based on the application of tactics or a pattern of how each learner uses certain tactics [9]. Tactics are defined as a sequence of actions that a learner performs in relation to a given task within a learning session [15].

The literature [10, 12] demonstrates the importance of the effective use of learning strategies to enhance learners’ (a) understanding of complex subjects and (b) academic achievement. In particular, learning strategies can be categorized [10, 12] as *effective* (e.g., practice testing, distributed testing, interleaved practice, elaborative interrogation, and self-explanation) and *less effective* (e.g., re-reading and highlighting, summarization, keyword mnemonic, and imagery). Dunlosky [10] also highlights that learners are more likely to exert less useful learning strategies, that is, reading and re-reading.

Learners may rely on ineffective learning strategies for many reasons. Examples of such reasons would be setting lower performance goals that they are easily able to achieve; failing to plan study, and

hence cramming the night before exam, and poor use of tactics because of sub-optimal decision making. In essence, the choices that learners made are not random [34]; they are highly dependent on their awareness of the regulation processes and their ability to effectively regulate their strategies towards set learning goals [33]. According to Winne and Hadwin's [35] model of self-regulated learning (SRL), learners make decisions about their learning in four basic cycles – by making a clear definition of the task at hand, setting up realistic goals, careful choices of tactics and strategies to conduct learning, and evaluating the effectiveness of learning strategies based on internal (e.g., prior knowledge and experiences) and external conditions (e.g., feedback from instructors) to adapt to changing circumstances and future improvement [33].

Notwithstanding the importance of appropriate use of tactics and strategies for academic success, comparatively little is known about the effectiveness of time management and study tactics and strategies chosen by learners during online learning. Hence, the present study offers an empirically validated methodological approach to the detection of learning patterns from trace data recorded by digital learning platforms that reflect learners' (a) time management and learning strategies and (b) are associated with academic achievement in blended and online learning. The application of the proposed methodology identified four distinct strategies that reflect the relationship among three time management and five learning tactics. In line with previous studies (e.g., [4, 10]), the study found that effective regulation of strategies led to higher academic achievement and vice versa. The results were interrogated against the Winne and Hadwin [35] model of SRL to provide further insight into the application of effective learning practices to support robust online learning.

The current study extended existing research on automatic detection of learning strategies and tactics by (i) providing a novel method for integrating time management and learning tactic components of learning strategies, which are usually studied in isolation from each other in the literature [3, 13, 23, 27], thereby providing a holistic view of self-regulation of learning strategies in blended and online learning; and (ii) offers a new methodological combination of unsupervised machine learning with network and process analytic techniques to offer deeper insights into relevant dimensions (i.e., time, ordering, frequency, and strength of connections) for understanding self-regulation of time management and learning tactics.

2 BACKGROUND

2.1 Learning in Blended Environments

Blended learning involves online and face-to-face components reiterated on a weekly basis throughout a course. In the online component, learners are provided with digital materials to develop basic knowledge of the current topical unit at their own pace. The face-to-face component involves active learning and higher-order thinking guided by an instructor, giving learners an opportunity to practice and apply the knowledge they gained during the online preparatory work [17]. As learning is taking place in profoundly diverse and rich environments, course grades are often based on the completion of various learning activities (e.g., assessments, assignments, and quizzes), each with specific time-related requirements (e.g., priorities, deadlines, and timeliness). To succeed in a blended

learning setting, learners need to deliberately allocate time to both online and face-to-face components, since the time devoted to both in-class and out-of-class activities have proven to be predictive of academic success [8, 22].

The extant empirical research on blended learning has demonstrated that both time management [2, 3] and learning strategies [13, 26, 27] are positively associated with course performance. For instance, Ahmad Uzir et al. [3] examined the relationship between learners' enactment of time management strategies, self-regulation, and course performance. Their finding suggests that the relationship between learners' time management strategies and academic achievement is mediated by self-regulation. In particular, learners capable of effective SRL made better decisions on three time-related constructs – what to study, how to study, and how long to study [20] – and had higher course performance. High performers adopted diverse tactics and modified these according to the course requirements. For instance, they actively prepared by studying prior to face-to-face sessions and returned to the course materials to re-study right after the class and during the test weeks. Given these findings, learners' choice of time management strategies can be considered a manifestation of a learner's self-regulation processes.

Grounding their work in theories of SRL, Matcha et al. [27] investigated the association of learning strategies and academic performance. The study found that the students' learning strategies were significantly associated with their course performance. This finding is consistent with the results of other recent studies of learning strategies in blended learning settings [13, 14, 19]. Matcha and colleagues [27] also reported that learners in higher performing groups tended to adopt various learning tactics such as re-watching videos or re-reading course materials, and frequently turned to self-testing exercises; these behaviours were far less present among low and mid-performing groups. This suggests that high performing groups comprised autonomous learners who were aware of possible learning actions and were able to make good decisions on how, when, and where to apply learning tactics and strategies. Simply put, those learners demonstrated the ability to plan, monitor, evaluate, and modify their learning effectively.

To sum up, the empirical evidence indicates that, in the blended learning context, learners' time management and management of learning strategies are tightly related to their ability to self-regulate learning. Hence, examining both time management and learning tactics and strategies through the perspective of self-regulated learning (SRL) theory could potentially be a promising approach for advancing our understanding of the choices learners make when managing their learning in a blended learning setting. Thus, obtained insights could inform instructional interventions that aid learners' successfully progress through the course.

2.2 Analytic Methods for Detection of Tactics and Strategies

Research into identification of tactics and strategies in blended and online learning highly relies on digital trace data. Trace data are recognized as latent artifacts of learners' actual behaviour in an authentic online setting [34]. Therefore, incorporation of trace data into appropriate analytics methods could afford opportunities to observe cognition that learners create as they engage in online platforms [36]. Research into learning strategies has demonstrated

that sequential analytical methods [13, 19] and process mining methods [26, 27] are successful in detecting learning tactics and strategies within trace data.

Meanwhile, time management tactics and strategies can also be inferred by applying data analytic methods to trace data. Specifically, time management tactics can be defined as “a sequence of time-related decisions and enactment of learning actions during a learning session to meet the requirements of specified tasks, whereas strategies represent sets of enacted time management tactics made up by selecting, combining, or redesigning those tactics as directed by a learning goal” [2, p.4]. In particular, Ahmad Uzir et al. [2] has empirically demonstrated that sequential analytics methods, applied on trace data, allow for examining how students modify their time management tactics over time. In a recent study, Ahmad Uzir et al. [3] explored time management tactics using process mining techniques as proposed by Matcha et al. [27]. Similar analytics-based methods have also been successfully used to detect learning tactics [13, 19, 27]. These analytical methods allow for detection of tactics across study sessions as compared to traditional methods (i.e., self-report surveys and interviews).

Once tactics are framed, strategies can be more easily identified. In particular, strategies encompass one or more tactics that learners employ across the course timeline [9]. With respect to the adopted methodological approaches, several studies [13, 19, 21, 27] shared a common approach to identifying strategy-based student groups, namely using a hierarchical clustering method. Meanwhile, [24] used a K-means cluster analysis to reveal learner strategies. Alternatively, the present study applied a new approach that combined a network analysis technique and a hierarchical clustering method to identify and examine strategy groups, starting from the identified tactics – both time management and learning tactics. The rationale for using network analysis method was to analyse the connections between time management tactics and learning tactics in each learning sessions before the co-occurrence of the two kinds of tactics was used as an input to carry out strategy detection through the clustering process.

Specifically, this paper reports on the results of an empirical study that aimed to address the following research questions:
 RQ1: To what extent can a combination of data analytic methods provide a holistic view to theoretically meaningful learning strategies composed of time management and learning tactics?
 RQ2: To what extent a combination of network and process analytics techniques, proposed in this study, can be used to explain the critical dimensions (i.e., time, ordering, frequency, and strength of connections in tactic use) of learning strategies extracted from trace data?

3 METHODOLOGY

3.1 Study Context

This study was situated in a first-year undergraduate Foundation Studies course at an Australian university. The trace data were collected from two consecutive student cohorts, enrolled in years 2017 and 2018. The number of students enrolled in 2017 and 2018 were 250 (124 females, 107 males, 19 others) and 232 (131 females, 79 males, 22 others) respectively. The course lasted 13 weeks and included 12 course topics. One course topic was covered in each

course week except week 13 when students were required to prepare a research paper.

In this course, students were recommended to i) complete online learning activities provided, via the institutional learning management system (LMS), on a weekly basis, prior to the face-to-face classroom sessions, and, ii) participate in active face-to-face learning sessions with the instructor that took the form of collaborative problem-solving tasks. Particularly, this study focused on the online learning activities that were designed to prepare students for the face-to-face sessions. Four online learning resources were available: reading materials (e.g., lecture slides and e-books), quizzes, assignments and discussion boards. Meanwhile, in the face-to-face setting, the students were required to attend 2 hours weekly tutorial session and a 1 hour lecture.

3.2 Data Sources

3.2.1 Digital Traces. The digital traces originate from the students' interactions with the online course activities in the period from July to November of 2017 and 2018, covering, in each year, 13 active weeks of the course. In total, there were 8,061 online learning sessions throughout the entire course. The data were derived from LMS records which comprised timestamp of each event, anonymous user IDs, course module IDs, and a description of the learning action.

3.2.2 Course Performance. The second data source was the students' assessment grades that were used to derive the overall course score in the 0-100 range. The grade components contributing to the final course mark included five assessments. Three assessments were conducted in Week 3 (Assessment 1 – Quiz) (contributing 15%), Week 6 (Assessment 2 – Annotated Bibliography) (20%), and Week 9 (Assessment 3 – Argumentative Paragraphs) (20%), respectively. From Assessment 2 onwards, the assessments were progressive, so that the completion of Assessment 2 and 3 would inform Assessment 4 (Research Paper – 35%) (Week 14) score. All the assessments were conducted through the online platform. Lastly, Assessment 5 (contributing 10%) score was based on the students' participation (including in-person tutorial attendance and online participation) throughout the semester.

3.3 Data Analysis

Figure 1 illustrates the analytic-based methods used in the study. The methodology relies on linear pipeline that consists of three phases (refer to subsection 3.3.1 - 3.3.3):

3.3.1 Labelling the Study Mode. Time management was analysed by examining the times (timestamps) when students performed online activities (out-of-class study) validated against the course timetable provided by the course instructor. The students were recommended to study one topic per week and to complete an assessment during the assigned weeks (Week 3, 6 and 9 respectively). We associated each learning event with an appropriate *mode of study* based on its timing with respect to the weekly topic as suggested in [2]: i) *preparing* – if a learning action was related for the first time to the topic the students were supposed to study in a given week, ii) *ahead* – if the learning action was in advance of the schedule, iii) *revisiting* – if the learning action was related to a behind-the-schedule topic that the student had already studied at

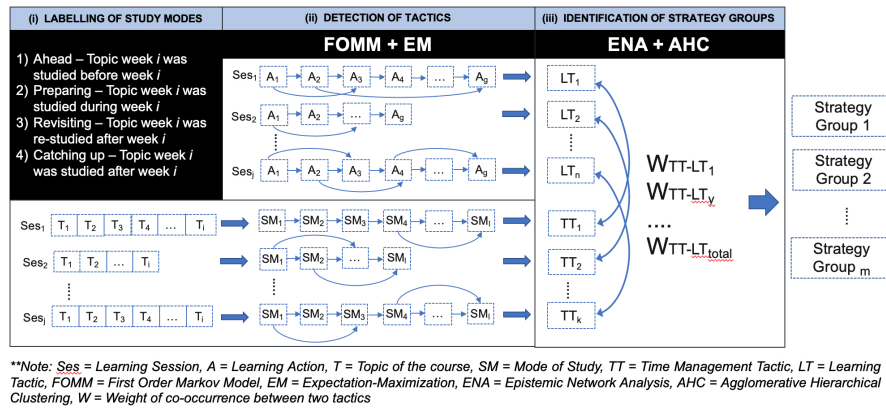


Figure 1: The pipeline of the analytic-based methods used in the study.

some earlier point in time, and iv) *catching-up* – if the student had never accessed activities related to the behind-the-schedule topic.

Meanwhile, learning actions were analysed by combining the students' action (e.g., view, attempt, and update) with a learning module (e.g., assignment, quiz, resource, and forum) to provide meaningful representations of the students' learning action (e.g., resource_view and quiz_attempt). Successive learning actions between any two consecutive events that were within 30 minutes of one another were grouped into a learning session [19]. Learning sessions served as the unit of analysis when identifying patterns indicative of the students' time management and learning tactics. To gain an insight into the general patterns of learning events, 'outliers' were excluded: overly short sessions (one action in a session) and overly long sessions (>95th percentile of events per session).

3.3.2 Detection of Time Management and Learning Tactics. A process mining technique (First Order Markov Model - FOMM) paired with a clustering method (Expectation Maximization) was used to detect: i) patterns in sequences of the students' modes of study (i.e., ahead, preparing, revisiting, and catching-up), as a manifestation of students' time management tactics, and ii) patterns in sequences of students' learning actions (e.g., Quiz_Attempt, Discussion_Post, and Course_View) as a manifestation of their learning tactics. In both cases, FOMM implemented in the pMineR R package, was used to compute and visualize process models derived from learning sessions. By inspecting the overall process models, potential time management and learning tactics were inferred based on the density of connections among learning events. To move from observations to automated detection of tactics, we used the matrix of transition probabilities between events, produced by the FOMM, as the input to the Expectation Maximization (EM) algorithm to identify clusters of sequences.

3.3.3 Identification of Strategy Group. Strategies were characterized from the way a student incorporated time management tactics and learning tactics throughout the course timeline. The rENA R package for Epistemic Network Analysis (ENA) [30] was used to compute the co-occurrence of time management tactics and learning tactics (as identified with the procedure in Section 3.3.2) in

each learning session. By generating a network using ENA, a matrix of co-occurrences of the two kinds of tactics was created. To identify student groups, we represented each student as a vector of the following variables: a) counts of co-occurrences of distinct time management and learning tactics, and b) the total counts of co-occurrences of time management and learning tactics. Then, vectors based student representations were normalized and used as an input to the Agglomerative Hierarchical Clustering (AHC). The distance between students, required for the Ward algorithm [16], was computed as the Euclidean distance of the corresponding vectors. The optimal number of clusters was determined by inspecting dendrograms.

3.3.4 Time Management and Learning Tactics Used Across Strategy Groups. To explore the identified strategy groups, we used ENA to compute and visualize the network model representing the combination of time management and learning tactics that corresponded to each strategy group. The X-axis of an ENA network model is the dimension that accounts for the highest percent of the explained variance, and the Y-axis is a dimension orthogonal to the first that explains the next highest percentage of variance (these percentages are shown on each axis). The node size in a network model represents the frequency with which tactics occurred in the student group. The thickness of the lines between the nodes indicates the strength of the connections, where thicker lines correspond to stronger relationships (i.e., by more frequent co-occurrence).

To further explore the strategies, we used another process mining technique implemented in the bupaR R-package [18], which allows for easier understanding of the complexity of a learning process. In our analysis, we considered event logs that recorded each student's active learning process from the beginning (Week 1) to the end (Week 13) of the course. Each event belonged to a case. A case, in this study, is an instance of the process which corresponds to an individual student enrolled in the course. In addition, each event is an instance of activity. In this study, activities are the combinations of time management tactics and learning tactics adopted by a student while progressing in their learning. When an activity is performed, an activity instance (event) is recorded. For a

given case (user_id), we would obtain, from the event logs, a set of execution traces. We denote the traces as a sequence of activities ordered by their time of occurrences in the course timeline. Process models were then generated based on the collected traces. A process model consisted of a set of nodes and a set of arcs, where the nodes were the process activities and the arcs indicated the order of the activities. The discovered models were often “spaghetti-like” showing all details of a process. To make the models usable for interpretation, 60% of the most frequent activities were kept for each strategy group. This allowed us to study processes typical of different strategy groups.

3.3.5 *Association between strategy group and course performance.* To examine if there was a significant association between the identified strategy groups on the students’ course performance, we used Kruskal-Wallis tests followed by pairwise Mann Whitney U tests.

4 RESULTS

4.1 Time Management and Learning Tactics

Resulting from running the FOMM and EM algorithms, a solution of: i) three time management clusters, and ii) five learning clusters were identified.

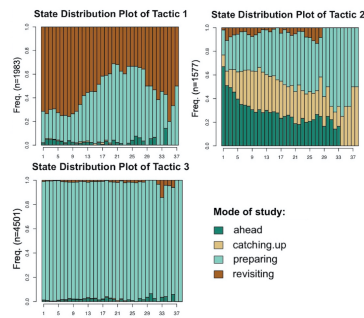


Figure 2: Distribution plot of study modes within the detected clusters (manifestations of the students’ time management tactics).

Figure 2 depicts a distribution plot of study modes in each cluster indicative of time management tactics. Each point on the X-axis corresponds to a mode of study within a learning session, whereas the position on the Y-axis represents the probability of study modes. In particular, the three detected time management tactics are:

- Time Tactic 1 – *Prepare and Revisit* ($n=1,983$, 24.60% of all sequences). This tactic comprised a relatively equal proportion of actions in the preparing and revisiting modes. These seem to be sessions where students would first do some reviewing of the previously studied materials, then do some preparation activities for the week’s face-to-face session, and finish the session by a mix of revisiting and preparing actions.
- Time Tactic 2 – *Mixed* ($n=1,577$, 19.56%) was the smallest cluster. This tactics consisted of all modes of study (i.e., ahead, preparing, and catching up), though the revisiting mode was barely present.

- Time Tactic 3 – *Prepare* ($n=4,501$, 55.84%) was the most dominant cluster with a clear focus on the preparing mode, thereby suggesting that students were consistently preparing prior to the weekly face-to-face sessions.

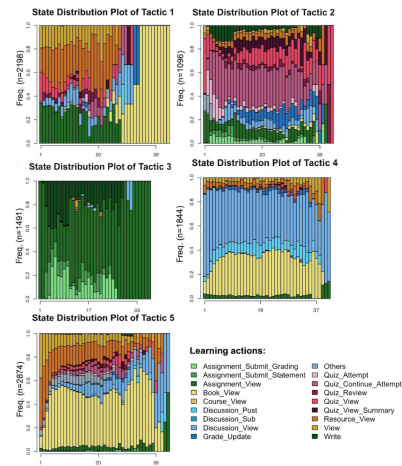


Figure 3: Distribution plot of learning actions within the detected clusters (manifestations of the students’ learning tactics).

Figure 3 illustrates a distribution plot of learning actions in the clusters indicative of learning tactics. Each point on the X-axis corresponds to a learning action within a learning session, whereas the position on the Y-axis represents the probability of learning actions. The characteristics of the identified learning tactics could be described as follows:

- Learn Tactic 1 – *Information View Oriented* ($n=2,198$, 23.13% of all sequences). This grouping comprises learning sequences that were related to viewing information such as Book_View, Quiz_View, and Assignment_View.
- Learn Tactic 2 – *Assessment Oriented* ($n=1,096$, 11.53%) was the smallest cluster with a clear focus on actions related to quizzes (i.e., Quiz_Attempt and Quiz_Continue_Attempt), thus indicating that students were mainly assessment oriented.
- Learn Tactic 3 – *Assignment Oriented* ($n=1,491$, 15.69%) learning actions predominantly focused on the assignment, like Assignment_Submit, Assignment_View, and Assignment_Wri
- Learn Tactic 4 – *Reading and Discussion Oriented* ($n=1,844$, 19.40%). This grouping had dominant learning actions related to discussion activities (i.e., Discussion_View, Discussion_Post) and reading of the e-book (i.e., Book_View).
- Learn Tactic 5 – *Book and Resource Oriented* ($n = 2,874$, 30.24%) was the largest cluster. In this group, learning sessions were predominantly focused on reading the e-book (required reading a chapter for a given week) and viewing learning resources.

4.2 Strategy Group

The dendrogram resulting from the Agglomerative hierarchical clustering, applied to detect student strategy groups, indicated a four cluster solution as the optimal one, and thus addressed our first research question (RQ1). To better understand the identified clusters, we examined, for each cluster (strategy), the connections between time management tactics and learning tactics by using ENA network model. The strategy groups (Figure 4 - 7) could be described as follows:

- Strategy 1 – *Reading* (n=191, 39.63% of all students) was adopted by the largest number of students. The students in this group were highly focused on preparing (*Time Tactic 3*) for face-to-face sessions by reading the e-book and viewing the learning resources (*Learn Tactic 5*). Apart from that, they were also preparing (*Time Tactic 3*) for the assignments (*Learn Tactic 3*), as well as preparing and revisiting (*Time Tactic 1*) the course information (*Learn Tactic 1*) related to the e-book, quizzes, and assignments. Meanwhile, connections among other tactics were very low.
- Strategy 2 – *Diverse* (n=67, 13.90%) was the most diverse group. As students in this group showed equally distributed and balanced actions between pairs of time management and learning tactics (e.g., Prepare + Assessment, Prepare + Assignment, and Mixed + View Information). Preparing (*Time Tactic 3*) the e-book and learning resources (*Learn Tactic 5*) exhibited the strongest connections in this group. In contrast, the reading and discussion orientation tactic (*Learn Tactic 4*) showed relatively low connections with all the time management tactics.
- Strategy 3 – *Selective* (n=157, 32.57%) included the students who were highly concentrated on preparing (*Time Tactic 3*) their learning by reading the e-book and viewing learning resources (*Learn Tactic 5*) along with preparing (*Time Tactic 3*) for the course assessments (*Learn Tactic 2*) (i.e., quizzes). Assuming that, their choice of study (i.e., reading e-book) was determined by what they perceive to be relatively useful for the course assessments.
- Strategy 4 – *Surface* (n=67, 13.90%) included the students who put their efforts predominantly in preparing (*Time Tactic 3*) for the course assessments (*Learn Tactic 2*). Meanwhile, they also performed some preparing activities (*Time Tactic 3*) using the e-book and learning resources (*Learn Tactic 5*) and often reviewing (*Time Tactic 1, Time Tactic 2*) the course information (*Learn Tactic 1*).

4.3 Time Management and Learning Tactics Used Across Strategy Groups

Four process models were created to analyze the learning process performed by the students in each strategy group, and thus, to address our second research question (RQ2). The differences among the strategy groups can be described as follows.

The majority of the students in the **Reading** (Figure 8 (a)) strategy group began their learning by preparing using the e-book and learning resources (*Prepare_Book.Resource*) (104 instances). This strategy group is characterized by *Prepare_Book.Resource* → *Prepare_Read.Discuss* → *Mixed_View.Info*

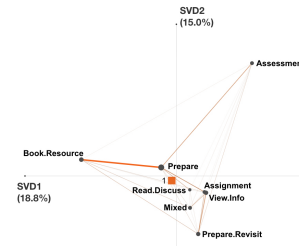


Figure 4: Network model for strategy group 1 (Reading)

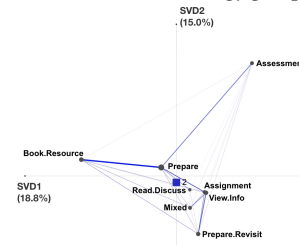


Figure 5: Network model for strategy group 2 (Diverse)

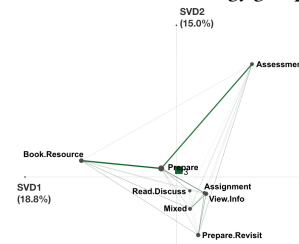


Figure 6: Network model for strategy group 3 (Selective)

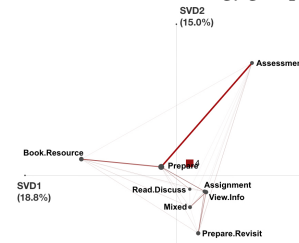


Figure 7: Network model for strategy group 4 (Surface)

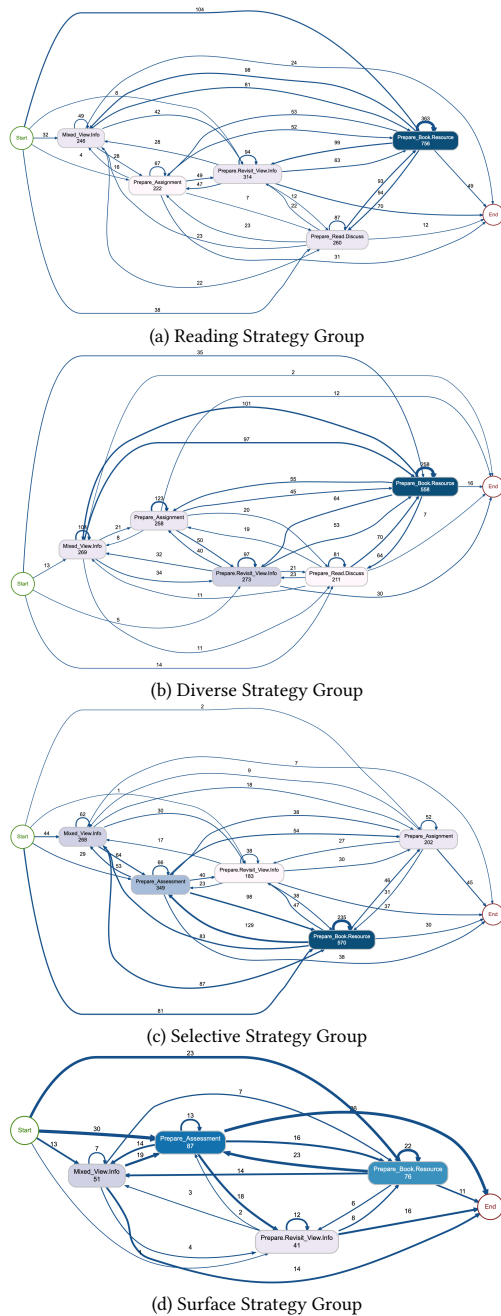


Figure 8: Process models for the learning processes of the four identified strategy groups. The numbers in the boxes represent the absolute frequency of occurrences of events (activity instances), while the numbers associated with edges represent absolute frequencies of transitions between consecutive activities. The darker node color represents the higher frequency of activities.

→ *Prepare_Assignment*, a path of transitions with a high frequency in activity instances. Regular transitions could be seen between two tactics: from *Prepare_Book.Resource* to *Prepare_Read.Discuss* (94 instances) and from *Prepare_Read.Discuss* to *Prepare_Book.Resource* (93 instances). Apart from that, students in this group were actively preparing and reviewing information that was related to the course (i.e., *Prepare.Revisit_View.Info* and *Mixed_View.Info*). This result seems to suggest that the students in the *Reading* strategy group were highly focused on preparing activities by reading the e-book and other learning course resources prior to getting involved in discussion activities.

The most common path of transitions exhibited by the *Diverse* (Figure 8 (b)) strategy group was *Prepare_Book.Resource* → *Prepare.Revisit_View.Info* → *Mixed_View.Info* → *Prepare_Assignment* → *Prepare_Read.Discuss*. The frequency of activity instances was relatively equally distributed among all tactics. As such, all tactics were equally important. In this group, transitions often occurred between the *Prepare_Book.Resource* and *Mixed_View.Info* (101 activity instances in one direction and 97 in the other), also between *Prepare_Book.Resource* and *Prepare_Read.Discuss*. Apart from reviewing the course information, this group also prepared for the assignments after reading the e-book (55 instances). In sum, this group showed careful learning actions in which they frequently returned to the course information as they progressed in their study.

Similar to the *Reading* strategy group, most of the students in the *Selective* (Figure 8 (c)) strategy group began their learning with *Prepare_Book.Resource* (81 instances). Meanwhile, the most common path of transitions in this group was *Prepare_Book.Resource* → *Prepare_Assessment* → *Mixed_View.Info* → *Prepare_Assignment* → *Prepare.Revisit_View.Info*. In contrast to the other groups, the *Selective* strategy group was highly focused on *Prepare_Book.Resource* and *Prepare_Assessment* as this group showed high frequency of activity instances related to those two tactics (129 instances in one direction and 98 instances in the other). Similar to the *Diverse* strategy group, this group was also regularly reviewing the course related information before and after turning to the preparation activities (*Prepare_Book.Resource*).

The most common sequence for the *Surface* (Figure 8 (d)) strategy group was *Prepare_Assessment* → *Prepare_Book.Resource* → *Mixed_View.Info* → *Prepare.Revisit_View.Info*. Compared to the other groups, the students in this group tended to begin their learning with *Prepare_Assessment* (30 instances) and ended their learning right after that (26 instances). On the other hand, we could observe that the transition began with *Prepare_Book.Resource* then shifted to *Prepare_Assessment* (23 instances). Connections with other tactics were relatively low. Apparently, students in this group predominantly focused on preparing for the course assessment (*Prepare_Assessment*).

The process model shown in Figure 9 depicts the discussed process models from the time perspective. The time periods associated with directed edges represent idle time, that is, time period between two consecutive activities. The *Reading* strategy group had the longest idle time between *Prepare_Read.Discuss* and *Prepare_Assignment* (Mdn = 22.46 days). Since students in this group were highly focused on reading and discussion activities to preparing their learning, they took at least one day (Mdn = 1.01 day) to shift from *Prepare_Book.Resource* to *Prepare_Read.Discuss*. However,

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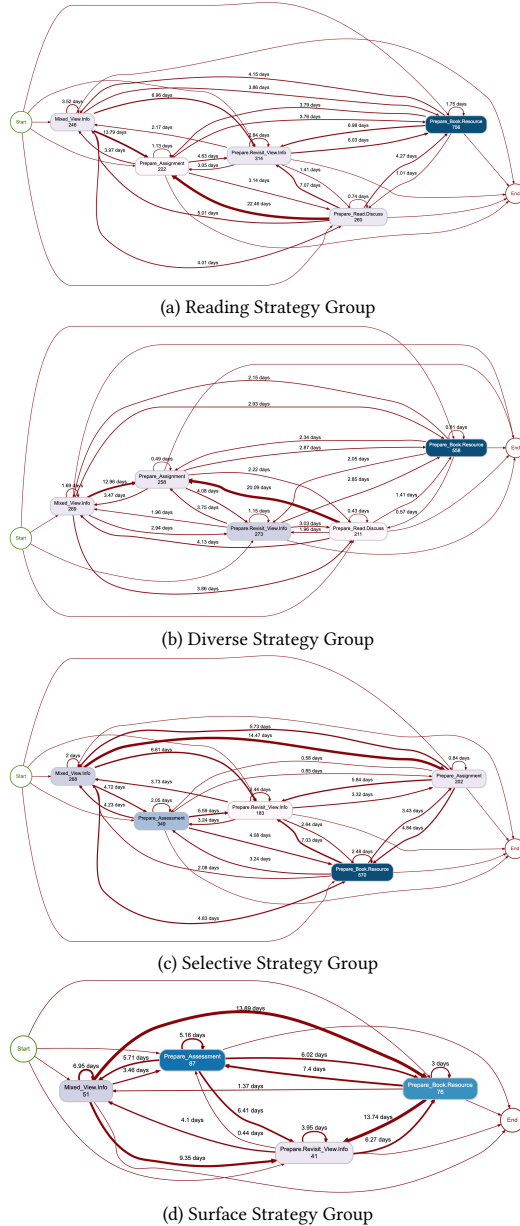


Figure 9: Idle time (in days) between the end of the from-activity and the start of the to-activity across four identified strategy groups. Darker line color represents longer idle time.

it took them quite some time to return to the *Prepare_Book.Resource* after the discussion took place (Mdn = 4.27 days). In addition, they spent less than 5 days to shift from *Prepare_Book.Resource* to *Prepare_Assignment* (Mdn = 3.79 days) and to *Mixed_View.Info* (Mdn = 4.15 days).

Meanwhile, the students in the *Diverse* strategy group took an average of 2 days to shift from the first tactic (*Prepare_Book.Resource*) to another tactics. For instance, from *Prepare_Book.Resource* to *Prepare.Revisit_View.Info* (Mdn = 2.05 days) and from *Prepare_Book.Resource* to *Mixed_View.Info* (Mdn = 2.15 days). This is to show that students in this group regularly returned to review the course information after preparing their learning using the e-book (*Prepare_Book.Resource*). The longest idle time they had (Mdn = 20.09 days) was between *Prepare_Read.Discuss* and *Prepare_Assignment*.

The *Selective* strategy group, which was highly focused on preparing for the course assessments (*Prepare_Assessment*) after preparing using the e-book and learning resources (*Prepare_Book.Resource*), took an average of four days to shift from/to *Prepare_Book.Resource* and *Prepare_Assessment*. The students in this group tended to shift to *Prepare_Assessment* (Mdn = 3.24 days) and *Prepare_Assignment* (Mdn = 3.43 days) activities after they had completed preparing with the course materials (*Prepare_Book.Resource*). The longest idle time they had was from *Mixed_View.Info* to *Prepare_Assignment* (Mdn = 14.47 days).

In contrast to the other strategy groups, the *Surface* strategy group spent an average of 6 days to shift from the first tactic (*Prepare_Assessment*) to another tactics (i.e., *Prepare_Book.Resource*, *Prepare.Revisit_View.Info*). This group had the longest idle time between *Mixed_View.Info* and *Prepare_Book.Resource* (Mdn = 13.89 days). Meanwhile, it took them, on average, a week to shift from *Prepare_Book.Resource* to *Prepare_Assessment* (Mdn = 7.40 days). This result seems to suggest that the students in this group preferred to end their learning session after they had completed a course assessment.

4.4 Association Between Strategy Group and Course Performance

The results of the Kruskal Wallis test showed a significant association between the identified strategy groups and the students' course performance (p-value < 0.0001 for total score). To further inspect these associations, pairwise tests were carried out (Table 1). All the pairs were significantly different with effect sizes (r) ranging from small to large.

In terms of the academic performance, the *Reading* strategy group (Mdn = 46.20, Q1 = 27.33, Q3 = 69.18) was the mid-lower performing group. The *Diverse* strategy group (Mdn = 78.78, Q1 = 71.11, Q3 = 83.18) was the highest performing group. The *Selective* strategy group (Mdn = 63.84, Q1 = 35.95, Q3 = 76.87) was the mid-higher performing group, and the *Surface* strategy group (Mdn = 20.50, Q1 = 14.68, Q3 = 29.57) was the lowest performing group.

5 DISCUSSION

This study aimed to propose a new analytic method that can identify learning strategy groups by investigating learners decisions while working towards the learning goals, that is, to evidence that learning

Table 1: Pairwise comparison of strategy group with respect to the total course score.

Cluster 1	Cluster 2	Z	p	r
Diverse	Surface	3.5253	<0.0001	0.595
Selective	Surface	2.4577	<0.0001	0.408
Diverse	Selective	1.0308	<0.0001	0.413
Surface	Reading	0.6366	<0.0001	0.320
Reading	Selective	-0.8605	<0.0001	0.170
Reading	Diverse	-2.6295	<0.0001	0.559

is always about making a right choice – on what to study, how long to study, and how to study [6, 7, 11, 20, 29]. Arguably, not all learners adopt effective learning practices and productive study decisions [6, 25, 32]. Hence, this study sought to examine learning practices observed in a blended learning setting based on Dunlosky et al.'s [6, 10, 12] works, as well as to examine learning strategies from the perspective of established SRL theory [35].

The results of this study showed that the *Prepare_Book.Resource* was the most common learning tactic. Almost all strategy groups (except the *Surface* group) used this tactic the most. Furthermore, the majority of the learners in these groups preferred to begin their learning by reading the e-book and other course content. Despite the popularity of this tactic, it has been criticised for its relative ineffectiveness [10, 20]. Admittedly, our findings endorsed this proposition by reflecting on the performance and the tactics employed by the *Reading* group (see Figure 8 (a)). This group (mid-lower performing group) was frequently reported to use re-reading tactics (i.e., from/to *Prepare_Book.Resource* and *Prepare_Read.Discuss*) to progress in their learning, which, might have been the cause of their low scores (Mdn = 46.20). On the other hand, the *Diverse* group (highest performing group) re-studied the materials using diverse tactics (i.e., *Prepare_Assignment*, *Prepare.Revisit_View.Info*, and *Mixed_View.Info*). The students in this group regulated their learning by directing their efforts towards reviewing the course-related information (planning) before starting with new learning activities or course assignments. A possible explanation for this behaviour might be that this group performed checks and balances on their study plan (cognitive), to align their diverse study tactics with the course requirements (regulation strategies), and choose those that would enhance their understanding, reduce mistakes, and maintain the motivation to achieve the learning goal. This also accords with the SRL viewpoint, which suggests improving task definition, goal setting and planning would have benefits in terms of the overall learning experience [35].

Practice testing or self-testing (i.e., assessments, quizzes etc.) has been recognized as one of the most effective strategies to improve students' learning [10]. However, our results indicate that without effective self-regulation, this strategy could be insufficient for learners. Evidence for this is present in the comparison of the *Selective* group (mid-higher performing group) and the *Surface* (lowest performing group) group that often used self-testing tactics (i.e., *Prepare_Assessment*) to study. The process model (Figure 8 (c)) revealed that students in the *Selective* group began their learning by reading the e-book and studying the course content (*Prepare_Book.Resource*). However, they complemented the less effective tactics with more-effective tactics (*Prepare_Assessment* and

Prepare_Assignment), which allowed them to achieve higher final scores (Mdn = 63.84) compared to the *Surface* group. Conversely, the *Surface* group was dominated by the learners who mainly concentrated on the self-testing tactic and seemed to disregard the other tactics. Although they practiced this tactic (deemed to be the most effective tactic), this group received the lowest grade. Such result can be partially attributed to the sub-optimal decisions that this group made when regulating their learning process [6, 25, 32]. To sum up, exercising effective learning practice is often not enough for improving learning. Productive self-regulations (i.e., planning, monitoring and regulating) should be considered, as well, to promote better learning experiences. It is also apparent from our findings that the choices that students make regarding time management and learning tactics are significantly associated with their performance.

Research by Dunlosky et al. [10, 12] reported two learning strategies as related to the spacing effect [5, 31]: distributed practice and interleaved practice. Distributed practice involves planning of learning practice by spreading study sessions over the study timeline, whereas, interleaved practice involves scheduling a mix of learning materials across the study session. Drawing on recent research [3], high performing learners are more likely to mass than to space learning, allowing for short intervals (on average of 2 days) between various tactics, that could promote better recall. The current study found that the best performing students (the *Diverse* strategy group) spent, on average, two days to shift from the first chosen tactic to another study tactic. For example, from *Prepare_Book.Resource* to *Prepare.Revisit_View.Info* (Mdn = 2.05 days), from *Prepare_Book.Resource* to *Mixed_View.Info* (Mdn = 2.15 days) and from *Prepare_Book.Resource* to *Prepare_Assignment* (Mdn = 2.34 days). As such, these results corroborate the idea of interleaved practice indicating that students plan their learning with various tactics across the course timeline. In contrast, the lowest performing group (the *Surface* strategy group) took more than three days to shift from reviewing course information to preparing for the course assessment (Mdn = 3.46 days) and delayed for more than a week to shift from preparing using the course content (*Prepare_Book.Resource*) to preparing for course assessments (*Prepare_Assessment*) (Mdn = 7.40 days). Apparently, this group allowed for extended delay between study tactics, which is far from optimal strategy, as suggested by [10, 12]. Taken together, the current study seems to further endorse the idea that massed practice (on average of 2 days) between diverse tactics (interleaved practice) could support better learning in the online component of a blended course, while maladaptive strategies are less applicable to support this [3].

6 CONCLUSIONS AND IMPLICATIONS

This study provides empirical evidence of, and contributes to, understanding of the diversity of strategies adopted by the learners while studying in an online learning environment. Our research reinforced the importance of various time management and learning tactics to promote effective learning strategies, to improve self-regulation and academic performance.

From the methodological perspective, we proposed a novel methodology with twofold aims: First, we combined two complementary analytical techniques: i) epistemic network analysis and ii) agglomerative hierarchical clustering to identify the strategy groups

by integrating two decisive learning constructs – time management and learning tactics – which has usually been done in isolation in the literature. The learning strategies found by using this new methodology were interpreted based on established self-regulation theory. Second, we further combined unsupervised machine learning with network and process analytic techniques to proposed a new approach that close inspection of the role of time management and learning tactics in learning strategies according to their principles documented in educational psychology [10, 12]. Additionally, this methodological approach allowed for a holistic analysis of the integral dimensions of learning strategies, i.e., connection, process, and time. Considering that this is a newly introduced methodology and applied to a dataset collected to a specific context, future replication studies are warranted.

From an educator's perspective, this study could inform productive educational practices to help learners to succeed in blended and online learning. It could support educators in encouraging the effective use of learning strategies by making necessary modification in their teaching approach and/or by devising actionable feedback interventions. From a learner's perspective, this study possibly can activate awareness and inform learners about effective learning strategies and motivate them to use them productively, so that they may then better decide how they could enhance their learning skills, and carry out the corresponding learning tactics autonomously to improve academic outcomes. In summary, success in online and blended courses is not only about how effective the strategies that learners need to put into practice are, but, how learners complement effective learning strategies with productive self-regulation (i.e., planning, monitoring and regulating) is equally important.

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5.3 Summary

In this chapter, we proposed a novel learning analytics method that combines three complementary methods, namely process mining, epistemic network analysis, and agglomerative hierarchical clustering. This proposed method particularly allows for: (i) integration of time management tactics and learning tactics, thereby providing a holistic view of SRL in terms of the use of learning strategies in an online learning environment; and (ii) deeper insights into relevant temporal dimensions (i.e., time, ordering, frequency, and strength of connections) that may enhance our understanding of students' learning patterns and processes that unfold over time.

In this study, we demonstrated that ENA could be combined with an unsupervised clustering method to present a holistic view of both time management and learning tactics, which lead to addressing the research questions four (RQ4). The application of the proposed method identified four different strategy groups deriving from three distinct time management tactics and five learning tactics. The identified strategy groups are: *Reading*, *Diverse*, *Selective* and *Surface*. To answer the research question two (RQ2), this study found that the identified strategy groups were significantly associated with course performance.

This result suggests that the profiles of these strategy groups reflect on students' enactment of time management tactics and learning tactics as well as their academic achievement in the course. Thus, we argued that not all students adopt effective learning practices and productive study decisions (Bjork, Dunlosky, & Kornell, 2013; Margaryan, Milligan, Littlejohn, Hendrix, & Graeb-Koenneker, 2009; Winne, 2005). A crucial distinction is articulated between their academic achievement in the course and the qualities (i.e., effective or less effective) of time management and learning tactics that students employed while working towards the learning goals. Hence, further analysis of the temporal features of learning is essential.

To this end, we used mixed methods of network and process analytics for unsupervised discovery and temporal analysis of students' learning patterns throughout a course. This analysis allows us to answer the research question three (RQ3). By doing this, we found that the *Diverse* strategy group, identified as the highest performing group, was characterised by active metacognitive control and monitoring. They were able to choose study tactics that could enhance their understanding and align those tactics with the course requirement to achieve learning goals. As examples, the students who used this strategy actively employed less effective learning tactics (i.e., reading) in their preparatory work. However, they complemented them with more effective tactics (i.e., assessment and assignment) during the revision activities.

On the other hand, the group of students with the lowest performance (i.e., *Surface* strategy group) predominantly adopted the testing practice tactic (i.e., assessment). However, the primary focus on assessment is found to be a superficial method of learning and does not promote the understanding of content (Entwistle, 1991). Thus, exercising effective learning tactics is often not enough for improving learning. In essence, success in online and blended courses is not only about

how effective the strategies that learners need to put into practice are but, how learners complement effective learning strategies (i.e., assessment and assignment) with productive self-regulation (i.e., planning, monitoring and regulating) is equally important.

Given that the proposed method in this chapter only applied to the blended learning context, the application of the proposed methods across different learning modalities (i.e., flipped classroom and MOOC) remains questionable. In an effort to evaluate the generalizability of our method, our final investigation in Chapter six seeks to address this concern by replicating the methods proposed in Chapter five across different learning settings (i.e., flipped classroom, blended learning, and MOOC).

6

Multivocal Analytics of Learning Strategies

It's really clear that the most precious resource we all have is time.

— Steve Jobs, *Business Insider*

6.1 Introduction

THIS chapter acknowledges the methodological contribution that has been made in the work of Chapter [five](#). The new method proposed in the preceding chapter (Chapter [five](#)) is relatively useful for (i) identification of learning strategies based on the combination of two kinds of detected tactics – time management and learning tactics; and (ii) holistic analysis of the integral dimensions of learning strategies (i.e., connection, process, and time). However, the study presented in Chapter [five](#) has several limitations. First, the dataset used in the study was collected from a specific learning context, that is, blended learning course. Second, considering that this is a new method, the replication of the use of the proposed method in different learning contexts is necessary to explore its generalizability. In this chapter, we argue that generalizability is of paramount importance for building robust methodological developments.

The work in this chapter builds on the notion of “productive multivocality” in order to further understanding of the relations between time management and learning tactics and strategies. Multivocal refers to the analytical “voices” (Balacheff & Lund, 2013) or collective discourse of researchers in the community about a specific learning context (Suthers, Lund, Rosé, & Teplov, 2013), which later becomes “productive” if progress is made towards refining analytic methods and understanding of the field as well as the data. This progress can then be generalised across different contexts (Balacheff & Lund, 2013). In sum, the key idea behind multivocality is an active pursuit of methodological clarity (Bergner, Gray, & Lang, 2018) to provide more general insights in and understanding of the processes and outcomes of learning and knowledge building (Law & Laferrière, 2013), which later can be generalised in other contexts (Dahlberg, 2017).

The overarching aim of the study included in this chapter is to explore whether the proposed method can be generalised across different learning contexts, each having a distinct delivery modal-

ity, i.e., flipped classroom, blended learning, and massive open online courses. Note that the three courses are in different subject areas, i.e., computer engineering, public health, and software engineering. Taken together, the main objectives of the study included in this chapter are to (i) validate the findings that were obtained from the synergies of multiple learning analytic methods, thus, can leverage the value of the learning analytics methods proposed in Chapter five to test its generalizability across different contexts; and (ii) test external validity by examining the association between student learning strategies, determined by the distinct patterns of time management and learning tactics, and academic performance across different learning modalities and diverse academic disciplines.

6.2 Publication: Theoretically Grounded Analytics of Learning Strategies: A Multivocal Approach

The following section includes the verbatim copy of the following publication:

Ahmad Uzir, N., Gašević, D., Matcha, W., Jovanović, J., Pardo, A., Lim, L.-A., Gentili, S., Pérez-Sanagustín, M., & Maldonado-Mahauad, J. (2020). Theoretically Grounded Analytics of Learning Strategies: A Multivocal Approach. *Manuscript submitted for publication to the IEEE Transactions on Learning Technologies*

Theoretically Grounded Analytics of Learning Strategies: A Multivocal Approach

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Abstract—‘Learning to learn’ is a skill commonly recognised in the literature and policy documents as critical for success in the digital age. This skill typically entails a rich repertoire of learning strategies that learners can use in different situations. The growing body of research in learning analytics offers a range of methods for analysis of learning strategies based on the use of digital trace data. Despite the significance of this research in offering robust interpretations of learning strategies in a specific learning context, the applicability of these methods across learning modalities and academic disciplines is still under-explored. The current study extends previously published work by examining the generalisability of a data analytic method that integrated unsupervised machine learning with network and process analytic methods. This data analytic method was proposed for detecting learning strategies as a composition of time management tactics and learning tactics. To test the generalisability of the proposed method, the study validated it on trace data from three academic courses that differed both in subject area (Computer Engineering, Health Science, and Software Engineering) and delivery modality (flipped classroom, blended learning, and massive open online course). The results of this study demonstrated that the proposed method was applicable in different learning modalities across diverse subject areas. The study also showed that learners’ enactment of time management tactics, learning tactics, and learning strategies was strongly associated with academic achievement. These findings contribute novel insights into learning strategies employed by learners in blended and online learning environments.

Index Terms—Learning analytics, learning strategies, multivocal analytics, self-regulated learning, time management tactics.

I. INTRODUCTION

THE use of technology to support teaching and learning has led to significant changes in higher education. Educational technologies have opened up opportunities for new pedagogies that facilitate knowledge building and sharing [1]. In contrast to traditional classrooms, a computer mediated setting offers (i) flexibility for learners to study at their own convenience, (ii) diverse learning resources, and (iii) extensive learning time, as learners can access virtual learning sites as long and as frequently as they need [2], [3], [4], [5], [6], [7], [8]. However, embracing computer mediated learning is riddled with challenges. Learners need to know how to manage their time throughout the designated learning periods in order to complete learning tasks and thus achieve the associated learning goals [9]. Furthermore, learners have to be able to select effective learning strategies and know when and how to apply them in order to succeed in a course [10].

Learners’ decisions regarding what, when, how, and how long to study ([11], [12], [13], [14], [15]) while working towards

learning goals have broad implications on the practice of self-regulated learning as a whole. Self-regulated learning (SRL) refers to the ability of learners to set their own goals, explore learning resources, manage time and environment, and apply effective learning tactics and strategies, in order to achieve desired learning outcomes [16], [17]. Existing research on digital trace data has demonstrated that learners’ decisions about the enactment of time management as well as learning tactics and strategies are strongly associated with academic achievements [18], [19], [20], [21], [22], [23], [24]. In this study context, time management tactic is defined as “a sequence of time-related decisions and enactment of learning actions during a learning session to meet the requirements of specified tasks”, whereas strategies represent “sets of enacted time management tactics made up by selecting, combining, or redesigning those tactics as directed by a learning goal.” [23, pg. 4]. Meanwhile, a learning tactic is defined as a sequence of actions that a learner performs in relation to a given task within a learning session [25], whereas learning strategies are composed of tactics or a pattern of how each learner uses certain tactics [26] across the study sessions.

The literature has found strong associations of learning and time management strategies with academic achievement in different learning modalities. For instance, a positive associations between learning strategies and the course performance were found in two different learning modalities such as flipped classroom [20], [19], [18] and MOOC [21], [27]. Likewise, significant associations of time management strategies with course scores were also found in flipped classroom [23] and blended learning courses [22], [24]. These research results have also elevated the enthusiasm for research that looks at the relationships between two constructs of SRL – time management and learning strategies – at a much deeper level than currently reported in the literature [28]. A new method that allows for novel insights into learning strategies by studying not only the frequency, order, and timing of time management and learning tactics, but also the strength of their connections has been proposed in [24]. The method was validated in a study that used trace data of two cohorts of freshmen undergraduates enrolled in a blended learning course. However, the method has not been applied in other learning contexts, and thus its generalisability (i.e., applicability across learning modalities and academic disciplines) is still unexplored.

In order to bridge the gap, this paper builds on the notion of “productive multivocality” in order to further understanding of the relations between time management and learning tactics and strategies. Productive multivocality in learning analytics

aims to “bring the various ‘voices’ of multiple theoretical and methodological traditions into productive dialogue with each other” [29, pg. 577]. Multivocal refers to the analytical “voices” [30] or collective discourse of researchers in the community about a specific learning context [29], which later becomes “productive” if progress is made towards refining analytic methods and understanding of the field as well as the data. This progress can then be generalized across different contexts [30]. Starting from the assumption that theory and method are interlinked and influenced by each other [31], the work reported in this paper focuses on exploring the relations between several theories and methods in the study of SRL. The overarching aim of this paper is to provide initial insights into the ways that large amounts of data, obtained from various learning modalities and analyzed by a range of data analytic methods, can be connected by using a multivocal approach to enhance theoretical and methodological integration.

The current study extends existing research on the integration of time management and learning tactics by (i) exploring how connections between time management and learning tactics shape learning strategies, (ii) examining time management tactics and strategies from multiple perspectives using combination of unsupervised machine learning with network and process analytic methods, and (iii) bringing together the findings of individual methods through the practice established in productive multivocality.

II. BACKGROUND

A. Learning Modalities

Educational technologies allow learning to occur anywhere and not necessarily in classroom settings. Nevertheless, removing the constraints of a conventional lesson structure and promoting an independent learning mode can be a “double-edged sword” for learners. On the one hand, it offers immense opportunities to enrich traditional education by maximizing learning outside the classroom; but, it can also induce pedagogical challenges that may impede learning effectiveness. This study examines the affordances and challenges of three learning modalities that have partially or fully adopted web-based educational technologies: flipped classroom, blended learning, and massive online learning course.

Flipped classroom. Flipped classroom is a contemporary pedagogical approach that aims to support active learning strategies. Flipped classroom typically involves three explicit components that reiterate on a weekly basis throughout the course timeline. The first component is about preparatory work in unsupervised study environments and includes pre-class preparation tasks that are realised through various online modules such as lecture video recordings, reading materials, quizzes, and problem-solving activities. The pre-class activities are used to facilitate the development of lower level cognitive skills, that are knowledge (recognising or remembering facts and concepts), comprehension (demonstrating an understanding of facts and concepts), and application (using acquired knowledge in new situations) [32]. The second component involves in-class learning where face-to-face interactions and collaborations with peers guided by the instructor can facilitate higher order

thinking skills typically through active participation in the analysis, synthesis, and evaluation of activities carried out in the preparatory stage. Finally, post-class activities are typically offered in online formats, e.g., formative quizzes undertaken to fully benefit from in-class sessions [33], [34], [35], [7], [5].

Flipped classroom is closely related to **blended learning**. Although the terms blended learning and flipped classroom are often used interchangeably in the literature to describe a combination of face-to-face and online learning, in this study we make a distinction between the two in that the completion of pre-class activities are not mandatory in blended learning. Nevertheless, blended learning recommends learners to regulate their own learning to construct the required knowledge prior to weekly face-to-face sessions.

Another form of web-based education relevant to this work is **Massive Open Online Courses (MOOCs)**. MOOCs are offered via purely virtual learning platforms (e.g., Coursera, FutureLearn, and edX) that host online modules and learning resources such as lecture videos, lecture notes, quizzes, problem-solving exercises, discussion boards, and course assessments. These resources are readily available to learners in either a fully or a partially unsupervised manner. This makes the MOOC format a resourceful and powerful [36], yet demanding learning modality that requires learners to be highly autonomous and responsible for making their own learning decisions to achieve their learning objectives.

B. Time Management, Learning Strategies, and Self-Regulated Learning

Given the diversity and flexibility offered by the three aforementioned learning modalities (i.e., flipped classroom, blended learning, MOOC), there are high demands on students to be independent and autonomous, so to engage in an active, timely, and regular manner with online learning activities. To put it simply, students need to self-regulate their learning. Self-regulation is related to the use of cognitive and metacognitive strategies that can help students to achieve their learning goals. The quality of strategy selection and use is substantially associated with academic performance [10], [37], [38].

Time Management. From the SRL standpoint, time management can be described as the ability of learners to schedule, plan, and manage their own study time by setting realistic targets, allocating sufficient study time and carrying out effective time management strategies [39]. Consistent with the propositions of the SRL literature, previous studies affirmed that productive self-regulated learners have a strong sense of control over their time as well as willingness to invest more time in studying [28] particularly by (i) gaining early access to the course materials (ahead), (ii) studying learning materials prior to face-to-face sessions (preparing), and (iii) returning to course materials to re-study after in-class activities or during the examination weeks (revisiting) [23], [22]. Productive self-regulated learners can proactively administer their learning process, thus lowering the risk of delay in their study. Conversely, learners with low self-regulation tend to rely on ineffective study planning and inappropriate time use, by delaying access to the course materials (catching up), allowing

maladaptive delays between learning activities, and cramming for exams [13], [38], [40], [41], [42]. These are also the most cited forms of ineffective time management, and are a major hindrance to learning success in any learning context [43], [44], [45], [46], [47].

Learning Strategies. Productive SRL is fundamentally about continuously improving one's study tactics and strategies [16], where learning strategy is related to practice that aims to promote effective learning experience driven by internal (i.e., prior knowledge and experience) and external conditions (i.e., task related instructions and feedback from instructor) to improve learning [10]. Dunlosky and colleagues [48], [49] prioritized practice testing, distributed practice, and interleaved practice as the most effective learning strategies, while re-reading, highlighting, and summarizing were listed as less effective learning strategies. Learners who have low levels of self-regulation often use less effective learning strategies, primarily reading and re-reading [24]. Reading and re-reading are regarded as popular, easy-to-use but passive choices of strategies, which could impede performance in a course [50]. Learners with productive self-regulation tend to employ diverse study tactics and effective learning strategies like taking practice tests (i.e., practice testing) and spreading out study activities over time (i.e., distributed practice and interleaved practice), thereby achieving higher academic outcomes [24]. Although previous research emphasized that both time management and learning tactics play important roles in the learning process, they usually focused on either time management tactics or learning tactics. That is, there is a lacuna in research that simultaneously studies the use of time and learning tactics. This might be due to the difficulty in capturing the dynamic changes of learning and time management tactics used. In light of this, this paper explores an innovative method combining unsupervised machine learning with network and process analytic techniques to understand connections between learning and time management tactics.

C. Analytical Methods for Detection of Tactics and Strategies

Several studies in online and blended learning environments [18], [19], [20], [21], [23], [22], [24], [27], [51] have offered compelling evidence that a combination of trace data and data analytic methods can serve as a reliable and useful approach to examining and understanding actual learning processes. This combination decreases the risk of bias and less discrepancy between perceptions and actual learning state as compared to conventional data collection methods such as self-report survey instruments and think aloud protocols [52].

Learning Tactics and Strategies. Research into analytical methods for the detection of learning strategies in trace data has demonstrated that the integration of different analytics methods such as clustering, sequence analysis, and/or process mining can be successfully used to detect learning tactics and strategies within trace data [18], [19], [20], [21]. For instance, Jovanovic and colleagues [18] examined learners' learning sessions as sequences of learning actions in a flipped classroom by using a sequence analysis technique. Then, the agglomerative hierarchical clustering method was used to (i) group similar learning sequences to detect patterns in the

learners' activities, and (ii) group learners based on the detected patterns that were considered manifestations of the students' learning strategies. Meanwhile, Fincham and colleagues [19] proposed a method that automatically detects learning tactics based on the percentages of the overall learning actions that a learner devoted to different kinds of preparatory (pre-class) learning activities in a flipped classroom. More precisely, these percentages were computed for each study session and served as the input for identifying study tactics as the states of a hidden Markov model. A sequence of such states was created for each learner according to the chronological order of the study sessions. Then, these sequences were clustered using agglomerative hierarchical clustering, based on Ward's method, to identify learner groups based on commonalities in the sequences of adopted learning tactics. Clustering results confirmed the presence of distinct patterns in learning activities, which were indicative of the learners' learning strategies.

Along the same line of research, Matcha et al. [20] proposed a method that combines process mining and clustering to detect learning tactics and strategies in trace data. Trace data about learners' preparatory learning activities in a flipped classroom were first represented as sequences of learning actions and organised into study sessions. The resulting session-level sequences of actions were used as the input for building a simple process model namely a first-order Markov model (FOMM). Thus, they obtained a transition matrix, as a mathematical representation of the FOMM, which served as the input for the clustering of the study sessions, via the expectation maximization algorithm, in order to identify study tactics. Finally, agglomerative hierarchical clustering of the detected tactics, based on Ward's algorithm, was applied to identify learning strategies. Matcha and colleagues [21] also examined different combinations of analytics methods across different learning modalities to compare three analytics methods, including process, sequence, and network analysis, for the detection of learning tactics and strategies. The analysis was performed on a dataset collected in a massive open online course on software engineering.

Time Management Tactics and Strategies. Borrowing the data analytic methods from research on the detection of learning strategies, studies of time management strategies have validated that both sequence analysis and process mining methods can be used to identify time management tactics based on study sessions that are captured through trace data. For example, Ahmad Uzir and colleagues [23] provide empirical evidence that a sequence analysis of trace data, similar to the one applied in [18], allows for examining sequences of time-related learners' decision. To achieve this, trace data about study activities in a flipped classroom were initially coded for the timeliness of activity completion (i.e., ahead, preparing, revisiting, or catching up). Such data were then analysed using sequence analysis methods to detect time management tactics; this was followed by agglomerative hierarchical clustering based on Ward's algorithm to identify time management strategies. Likewise, in another study, Ahmad Uzir et al. [22] made use of trace data from a blended course and process mining technique, as proposed by [20], to detect time management tactics across study sessions. Then, agglomerative hierarchical clustering was

Table I: Analytical methods used for detection of tactics and strategies in prior studies.

Study	Detection of Tactics		Detection of Strategies Learning Modalities	
	Time Management	Learning		
Jovanovic et al. [18]	-	Sequential Analysis	AHC	FC
Kizilcec et al. [51]	-	Sequential Analysis	PM + AHC	MOOC
Fincham et al. [19]	-	HMM + EM	AHC	FC
Cicchinelli et al. [53]	-	-	AHC	FC
Maldonado-Mahauad et al. [27]	-	Sequential Analysis	PM + AHC	MOOC
Matcha et al. [20]	-	FOMM + EM	AHC	FC
Matcha et al. [21]	-	FOMM + EM	AHC	MOOC
Ahmad Uzir et al. [23]	Sequential Analysis	-	AHC	FC
Ahmad Uzir et al. [22]	FOMM + EM	-	AHC	BL
Ahmad Uzir et al. [24]	FOMM + EM	FOMM + EM	ENA + AHC	BL
Ahmad Uzir et al. (Current)	FOMM + EM	FOMM + EM	ENA + AHC	FC, BL & MOOC

Note: HMM = Hidden Markov Model, PM = Process Mining, FOMM = First Order Markov Model, AHC = Agglomerative Hierarchical Clustering, EM = Expectation Maximization, ENA = Epistemic Network Analysis, FC = Flipped Classroom, BL = Blended Learning, MOOC = Massive Open Online Course.

applied to identify the clusters of tactics indicative of time management strategies.

Table I summarizes data analytic methods used in prior research on the detection of tactics and strategies in blended and online courses. Notably, most of this research, both on time management [23], [22] and learning strategies [18], [51], [19], [53], [27], [20], [21] share a common approach to identifying strategy groups, namely the application of the agglomerative hierarchical clustering method. To strengthen the explanatory potential of these methodological approaches, a recent study [24] relied on a network analysis method to examine and explain the detected strategies based on both time management and learning tactics; previously, the two kinds of detected tactics (learning and time management) were separately investigated [28], [24]. This novel method analyzes the connections between time management tactics and learning tactics in each learning session. The co-occurrence of instances of these two types of tactics then served as inputs to identify strategies through a cluster analysis. However, this method of strategy detection was validated on one learning context only. Hence, we posit that assessing the use of the [24] method across different learning modalities (i.e., flipped classroom, blended learning and MOOC) in various academic disciplines would be beneficial for the validation of the method and the exploration of strategies employed in different contexts.

D. Research Questions

The goal of the present study is to provide evidence-based and theoretically-grounded inferences about learning strategies across different learning contexts. As such, the research questions are twofold:

Research Question 1 (RQ1): *To what extent can a combination of analytic methods, including process mining, epistemic network analysis and clustering technique, provide a holistic view of learning strategies in different learning contexts?*

Research Question 2 (RQ2): *Is there an association between student learning strategies and academic performance in different learning contexts?*

III. METHODOLOGY

A. Data Sources

The datasets used in this study include trace data about online learning activities of large cohorts of students in multiple disciplines. Specifically, the trace data were collected from three academic courses (Computer Engineering, Health Science, Introduction to Python) offered in three distinct learning modalities (i.e., flipped classroom, blended learning, and MOOC respectively) in the period between 2014 and 2017 (see Table II). In addition to trace data, this study also relied on student performance data in the 3 examined courses.

Dataset 1 — Trace data were obtained from three consecutive student cohorts enrolled in years 2014, 2015, and 2016 ($N_{2014} = 290$, $N_{2015} = 368$, and $N_{2016} = 476$) in a first-year Computer Engineering undergraduate course at an Australian university. The course duration was 13 weeks (one semester) during which 10 course topics were covered. One course topic was covered in each week except for weeks 6 and 13 when midterm and final exams were conducted. This course adopted a flipped classroom design that required students to (i) complete online learning activities that were provided, via the institutional LMS, on a weekly basis prior to the face-to-face classroom sessions and (ii) participate in face-to-face learning sessions organized as collaborative problem-solving tasks, moderated by the instructor. A set of online learning tasks were available from weeks 2 to 13 and consisted of (i) videos with embedded multiple-choice questions, (ii) reading materials with embedded multiple-choice questions, and (iii) problem solving tasks (exercises). Each set of weekly exercises accounted for 2% of the final score. Meanwhile, academic performance in this study was derived from the scores on the midterm test and the final exam. The midterm test accounted

Table II: Summary of the datasets used in the study

Dataset	Course	Learning Modalities	Years	Course Durations	Instructional Materials
Dataset 1	Computer Engineering	Flipped Classroom	2014 – 2016	13 Weeks	Lecture videos with multiple choice questions, reading materials with embedded multiple-choice questions and exercises
Dataset 2	Health Science	Blended Learning	2016 – 2017	13 Weeks	Reading materials, pre-laboratory external tools (SCORM), discussion board and assignments
Dataset 3	Introduction to Python	MOOC	2017	7 Weeks	Lecture videos, reading materials, discussion forum and examinations

for 20% whereas the final exam accounted for 40% of the final course marks. Both were conducted in a conventional setting.

Dataset 2 — The second dataset was collected from 487 first-year undergraduate students who were enrolled in a Health Science course at an Australian university in years 2016 and 2017 ($N_{2016} = 255$, $N_{2017} = 232$). The course lasted 13 weeks (one semester) and covered 6 course topics. The course adopted a blended learning model with online learning exercises provided via the university’s LMS prior to face-to-face classroom activities. Two components of the online learning task were available to the students to prepare for the class in each week: (i) tutorials and (ii) pre-laboratory exercises. Although neither of the two online tasks were mandatory to complete during the preparatory stage, they were beneficial for developing a strong foundation for the topics taught in the course. In the face-to-face setting, students were required to attend two weekly sessions: a 3 hour-long lecture and an hour-long tutorial. The students were also required to attend 7 practical sessions (3 hours each) and 3 laboratory sessions (2 hours each). The second data source refers to the overall course score that was in the 0–100 range. The assessments contributing to the final course mark included 2 quizzes (contributing 20%), practical marks (obtained from the practical sessions) (25%), and the final exam (55%). Quizzes 1 and 2 were administered in week 7 and week 13, respectively. Both quizzes were conducted in a conventional setting.

Dataset 3 — The third dataset was obtained from 368 students who were enrolled in the Introduction to Python course offering by a Chilean university in 2017. The course was delivered virtually via the Coursera MOOC platform. Learning in the course was self-paced and no instructor intervention was present during the course. The course covered 6 course topics in 7 weeks (one semester). Students were recommended to engage with three ungraded online components: (i) short video lectures with embedded questions, (ii) reading materials, and (iii) discussion forum used to communicate with other students. There were also two graded online tasks, namely: (i) conceptual exercises (11 items) and (ii) practical exercises (13 items). A total of 22 of the best score items were calculated to the final mark. To pass in this course, the students needed to correctly answer at least 80% of the graded tasks.

B. Data Analysis

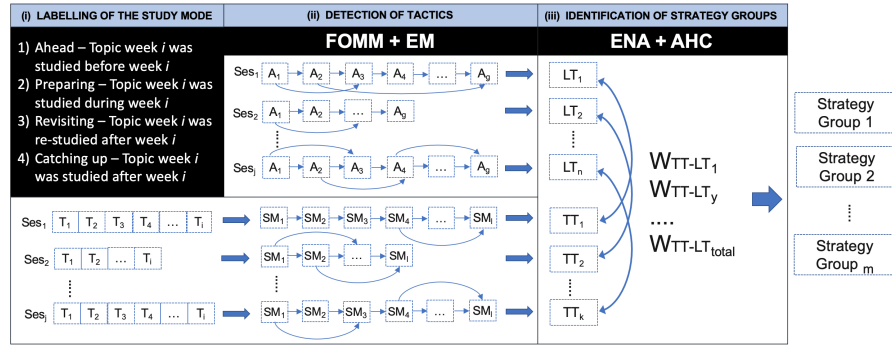
Initially, learning actions (e.g., viewing videos, taking quizzes, posting on the discussion board) of individual students were ordered chronologically. Thus ordered sequences of learning actions were used to create learning sessions by

assuming that 30 minutes of inactivity indicated the end of a session [18], [53]. Learning sessions were used as units of analysis with the aim of identifying session-level patterns indicative of the students’ time management and learning tactics. Learning sessions varied, both in terms of their length and composition of learning actions. To gain insights into the general patterns of learning actions within sessions, ‘outliers’ were excluded: overly short sessions (one learning action in a session) and overly long sessions ($>95^{\text{th}}$ percentile of learning actions per session). After the removal of outliers, Dataset 1 consisted of 65,710 learning sessions, ranging from 2 to 175 actions in length; Dataset 2 contained 25,648 learning sessions, ranging from 2 to 47 actions; whereas Dataset 3 consisted of 5,281 learning sessions that comprised of 2 to 359 learning actions.

To attain productive multivocality, the diversity of theoretical and methodological traditions is essential [29]. The key feature of the multivocal approach is its potential to triangulate multiple data analytic methods (i.e., process mining, network analysis and unsupervised machine learning), thus providing rich and valuable insights for validating results across different learning modalities (i.e., flipped classroom, blended learning and MOOC) and academic disciplines. We posit that this approach can offer robust interpretations of the complex nature of students’ learning processes in terms of time management and learning tactics and strategies through the juxtaposition of the perspectives of SRL theory [10] and educational psychology [48]. For clarity of presentation, we organized the data analytics methods used in this study into several sections. Data analytic methods introduced in the subsections III-B1 – III-B2 sought to address research question one (RQ1), while, methods described in subsection III-B3 were used to address research question two (RQ2).

1) *Detection of Tactics and Learning Strategies*: Figure 1 illustrates the data analytic methods used to address research question one (RQ1). The methodology relied on a linear pipeline that consisted of three phases: (i) labelling study modes (for time management analysis only), (ii) detecting tactics, and (iii) identifying strategy groups. In each step, different data analytic methods were used for the step-specific analysis, and the output of each phase served as the input to the next phase of the analysis.

i) **Labelling the study modes**. Time management was analysed by examining the times (i.e., time-stamped records) when students performed online activities (out-of-class study) against the course timetable provided by the course instructor. We associated each learning action with a *mode of study*



Note: *Ses* = Learning Session, *A* = Learning Action, *T* = Topic of the course, *SM* = Mode of Study, *TT* = Time Management Tactic, *LT* = Learning Tactic, *FOMM* = First Order Markov Model, *EM* = Expectation-Maximization, *ENA* = Epistemic Network Analysis, *AHC* = Agglomerative Hierarchical Clustering, *W* = Weight of co-occurrence between two kinds of tactics.

Figure 1: The pipeline of the analytic-based methods used in the study.

label based on its timing with respect to the weekly topic, as suggested in [23]: (i) *preparing* – if a learning action was related to the topic the students were supposed to study in the given week, (ii) *ahead* – if the learning action was in advance of the schedule (i.e., related to the topic scheduled for a later week of the course), (iii) *revisiting* – if the learning action was related to a behind-the-schedule topic that the student had already studied at some earlier point in time, and (iv) *catching-up* – if the student was performing an activity related to the behind-the-schedule topic for the first time.

ii) **Detection of tactics.** A process mining technique (First Order Markov Model - FOMM) paired with a clustering method (Expectation Maximization) was used to detect: (i) patterns in sequences of the students' modes of study (i.e., ahead, preparing, revisiting, and catching-up), as manifestations of students' time management tactics; and (ii) patterns in sequences of students' learning actions (e.g., playing videos, posting in discussion boards, and accessing content) as manifestations of their learning tactics. In both cases, FOMM, implemented in the pMineR R package [54], was used to compute and visualize process models derived from learning sessions. By inspecting the overall process models, potential time management and learning tactics were identified based on the density of connections among learning events. To move from observations to automated detection of time management and learning tactics, we used the matrices of transition probabilities between learning events (i.e., study modes and learning actions respectively), produced by the FOMMs, as the input to the Expectation Maximization (EM) algorithm to identify clusters of event sequences. Thus, identified clusters were interpreted, based on the underpinning learning theories (see Section II), as an expression of the students' time management and learning tactics.

iii) **Detection of strategy groups.** Strategies were characterized by the way a student incorporated time management tactics and learning tactics throughout the course timeline. The rENA R package for Epistemic Network Analysis (ENA) [55]

was used to compute the co-occurrence of time management tactics and learning tactics (as identified with the procedure in (ii)) in each learning session. The rationale for using the network analysis method was to allow for an integrated analysis of both time management and learning tactics as components of learning strategies [24]. Specifically, we represented each student as a vector of the following variables: (i) counts of co-occurrences of distinct combination of time management and learning tactics (for example, if there were 3 different time management tactics and 4 different learning tactics, we created 12 variables (counts)), and (ii) the total count of co-occurrences of a combination of time management and learning tactics. Then, these vector-based student representations were normalized and used as the input to Agglomerative Hierarchical Clustering (AHC). The distance between students, required for Ward's algorithm [56], was computed as the Euclidean distance of the corresponding vectors. The optimal number of clusters was determined by inspecting dendrograms.

2) **Time Management and Learning Tactics Used Across Strategy Groups:** To explore and visualize the frequency and strength of connections between time management and learning tactics, as well as their ordering and time of execution, we used network analysis and process mining techniques for each of the identified strategy groups across different learning modalities:

i) **Epistemic network analysis (ENA).** To understand strategy groups as patterns of interconnections of time management and learning tactics, we used ENA to compute and visualize a network model representing the combination of time management and learning tactics that corresponded to each strategy group. Each resulting epistemic network was plotted as a 2D graph using the dimensions defined by singular value decomposition (svd), with their respective percentages of explained variance shown on each axis. For example, in Figure 4, the x-axis and y-axis represent 16.6% and 14.3% of the variance in data, respectively. Each epistemic network comprises nodes representing individual tactics, green nodes being time management tactics and purple nodes denoting

learning tactics. The node size in the network represents the frequency in which tactics occurred in a strategy group. Meanwhile, the thickness of the lines between the nodes indicates the strength of the connections, where thicker lines correspond to stronger relationships (i.e., more frequent co-occurrence) [55], [57].

ii) **Process mining (bupaR)**. We used another process mining technique, implemented in the bupaR R-package [58], which allows for easier understanding of the complexity of a learning process. In particular, this process mining technique offered useful functions to compute and visualize the process (i.e., transition from one tactic to another), and time dimensions (i.e., interval time between the enactment of one tactic and another). In doing so, we were able to explore and gain insights into the temporal representations of learning in terms of the frequency of occurrences of tactics (activity instances), frequency of transitions between consecutive tactics, and idle time (in days) between the enactment of one tactic and another, across identified strategy groups. In our analysis, we considered event logs that recorded each student's active learning process from the beginning (e.g., Week 1) to the end of a course (e.g., Week 13). Each event belonged to a case. A case, in this study, was an instance of the process which corresponded to an individual student enrolled in the course. In addition, each event was an instance of activity. When an activity was performed, an activity instance (event) was recorded. In this study, activities were the combinations of time management tactics and learning tactics adopted by a student while progressing in their learning.

To put it simply, each student is represented as a case, each case comprises multiple events, each event denotes one unique activity carried out by the student, and each activity is a combination of tactics. For a given case (user_id), we would obtain, from the event logs, a set of execution traces. We denoted the traces as a sequence of activities ordered by their time of occurrence in the course timeline. Process models were then generated based on the collected traces. A process model consisted of a set of nodes and a set of arcs, where the nodes were the process activities and the arcs indicated the order of the activities. The discovered models were often "spaghetti-like, as described by [59], showing all details of a process. To make the models usable for interpretation, 60% of the most frequent activities were kept for each strategy group. This allowed us to study processes typical of different strategy groups.

3) *Association between strategy groups and course performance*: To address research question two (RQ2), we examined if there was a significant association between the identified strategy groups on the students' course performance by using Kruskal-Wallis tests followed by pairwise Mann Whitney U tests.

IV. RESULTS

A. RQ1: Detection of Time Management and Learning Tactics and Strategies

1) *Time Management Tactics and Learning Tactics*: The combination of FOMM and the EM algorithm detected time management and learning tactics. To facilitate their interpretation, we used:

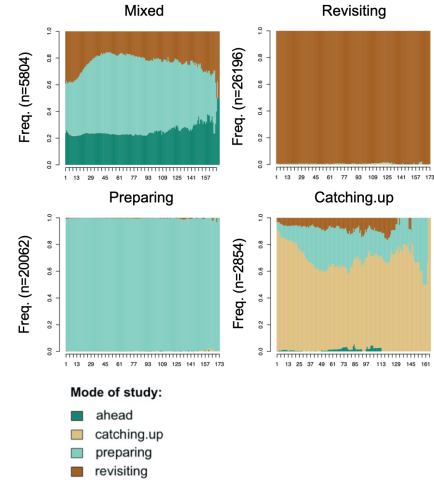


Figure 2: Distribution plots of study modes within the detected clusters (manifestations of the students' time management tactics) in the course that followed the flipped classroom pedagogical approach.

(i) distribution plots of study modes (i.e., ahead, preparing, revisiting, catching-up) in the clusters indicative of time management tactics.

(ii) distribution plots of learning actions (i.e., viewing video, reading lecture materials, answering test) in the clusters indicative of learning tactics.

Figure 2 shows temporal distribution plots for each of the four identified time management tactics in a flipped classroom-based course. Those tactics are: **Mixed**, **Preparing**, **Revisiting** and **Catching.up**. In addition, three time management tactics were identified from a blended learning-based course namely **Mixed**, **Ahead** and **Preparing**; four time management tactics were identified from the MOOC, namely, **Ahead**, **Preparing**, **Revisiting** and **Catching.up**. Note that due to space constraint, temporal distribution plots for a blended learning (Figure S1) and a MOOC (Figure S2) can be found in the supplementary document via: <https://bit.ly/2wT2jzy>. Accordingly, Table III summarizes the time management tactics detected from flipped classroom, blended learning and MOOC course.

In the remaining part of this section, we described the learning tactics that were identified from flipped classroom-based course, blended learning-based course and MOOC. **Flipped Classroom (Computer Engineering Course)**. Figure 3 shows five clusters indicative of learning tactics. The detected tactics can be described as follows:

- Learning Tactic 1 – **Diverse** (n=8,288, 12.61% of all sequences). This tactic consisted of a variety of learning actions, with a relatively equal proportions of actions related to exercises, MCQs, and course videos.
- Learning Tactic 2 – **Reading Oriented** (n=17,024, 25.91%) was the most frequently chosen tactic, which predominantly concentrated on the reading materials.
- Learning Tactic 3 – **Exercise Oriented** (n=16,287,

Table III: Time management tactics detected from Flipped Classroom, Blended Learning and MOOC course.

Time Tactics	Description	Learning Modalities and Courses		
		Flipped Classroom	Blended Learning	MOOC
		Computer Engineering Course	Health Science Course	Introduction to Python Course
Mixed	This tactic comprises ahead, preparing, and revisiting modes of study, while the catching up mode was barely present. Sessions in this tactic were focused on preparing learning materials in advance and during the week when those learning topics were scheduled, then followed by revisiting activities.	n=5,804 (10.57%)	n=3,181 (19.88%)	–
Ahead	This tactic contained sequences with the highest frequency of ahead activities. Sequences in this tactic suggest that students prepared the course materials by studying ahead of the weeks when those topics were scheduled.	–	n=6,054 (37.83%)	n=1,801 (34.14%)
Preparing	This tactic consisted of one dominant mode of study with a clear focus on the preparation activities, whereas other modes of study were almost absent. This tactic is indicative of the students' active preparation for the weekly face-to-face sessions.	n=20,062 (36.53%)	n=6,769 (42.30%)	n=1,025 (19.43%)
Revisiting	This tactic predominately focused on revisiting the course topics after initially studying them as part of the preparation.	n=26,196 (47.70%)	–	n=1,520 (28.82%)
Catching.up	This tactic consisted predominantly of the catching-up behavior.	n=2,854 (5.20%)	–	n=929 (17.61%)

Note: % indicates percentage of all sequences

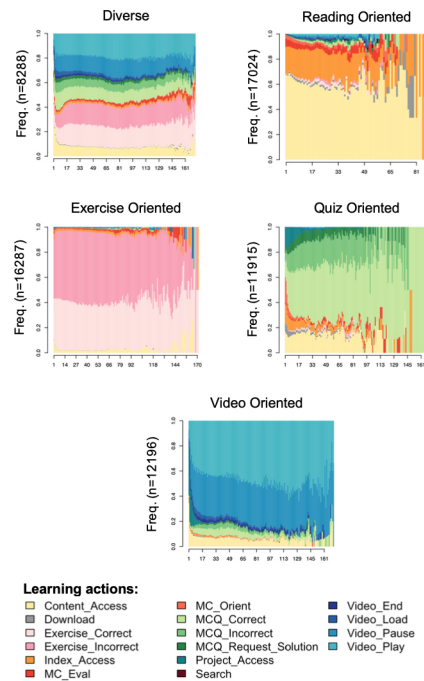


Figure 3: Distribution plots of learning actions within the detected clusters (manifestations of the students' learning tactics) in the flipped classroom course.

24.79%). The most dominant learning actions were problem-solving actions (i.e., Exercise_Correct and Exercise_Incorrect).

- Learning Tactic 4 – **Quiz Oriented** (n=11,915, 18.13%). This tactic comprises of reading learn-

ing materials (i.e., Content_Access) and MCQ-related actions (i.e., MCQ_Correct, MCQ_Incorrect and MCQ_Request_Solution).

- Learning Tactic 5 – **Video Oriented** (n=12,196, 18.56%). This tactic comprised predominantly video related actions (e.g., Video_Play and Video_Pause), while a mixture of MCQ-related actions (i.e., MCQ_Correct, MCQ_Incorrect and MCQ_Request_Solution) and content access had low presence.

Blended Learning (Health Science Course). The three identified learning tactics (Figure S3 in the supplementary document) could be described as follows:

- Learning Tactic 1 – **Reading Oriented** (n=11,112, 43.72% of all sequences) was the largest cluster and thus the most frequently chosen learning tactic. It was dominated by the activity of reading lecture materials, and to a lesser extent, by access to the course homepage with the general course information. Other types of learning actions were barely observed.
- Learning Tactic 2 – **Reading and Prelab Oriented** (n=5,124, 20.16%) was the least frequently adopted learning tactic. It is characterised by sequences of a variety of learning actions, among which the most prominent include access to the course homepage, retrieving the reading materials, and pre-laboratory preparation practice (i.e., Pre_Lab_Launch, Pre_Lab_Submit, Pre_Lab_View).
- Learning Tactic 3 – **Reading and Discussion Oriented** (n=9,182, 36.12%). The most frequently observed learning actions in this tactic were accessing the general course information and reading materials, as well as examining posts in the discussion forum (i.e., Discussion_View).

Massive Open Online (Introduction to Python Course). Figure S4 (refer to supplementary document) presents four learning tactics that were extracted from the learning sessions in the MOOC, including:

- Learning Tactic 1 – **Diverse Practice Oriented** (n=2,000, 37.87% of all sequences) was the most frequently adopted

tactic, with learning actions related to practical exercises being the most dominant. This is due to the design of the course that mainly focused on practicing the content covered in the MOOC. Other types of learning actions such as those related to quizzes, code execution, and video lectures were also observed.

- Learning Tactic 2 – **Lecture Oriented** (n=1,391, 26.34%). Sequences in this tactic consisted primarily of actions that were related to video watching and the embedded quizzes.
- Learning Tactic 3 – **Short Practice Oriented** (n=772, 14.62%) was the least frequently chosen tactic. It was characterized by exam-oriented activities (i.e., Exam_Start, Exam_Completed).
- Learning Tactic 4 – **Long Practice Oriented** (n=1,118, 21.17%). While similar to the *Short Practice Oriented* tactic in terms of the dominant types of learning actions (i.e., code execution and practical exercises), this tactic differed in the length of learning sessions: sessions were longer (Mdn = 31 actions per session) than those within the *Short Practice Oriented* tactic (Mdn = 8 actions per session). One explanation could be that this tactic corresponded to longer or more difficult exercises.

2) *Strategy Groups*: To better understand the strategy groups detected through Agglomerative hierarchical clustering (see Section III-B1), we examined the connections between time management tactics and learning tactics in each cluster (strategy group). This was done by creating an epistemic network for each group. The resulting network models led to the following characterisation of the strategy groups:

Flipped Classroom (Computer Engineering Course). Figure 4 presents the epistemic network models identified in the course based on the flipped classroom-based course, which can be described as follows:

- Strategy 1 – **Active** (n=402, 35.45% of all students). Students in this group adopted diverse learning tactics both in the preparation and revision activities. This group performed diverse preparing tasks by employing the *Exercise.Oriented*, *Diverse.Oriented* and *Video.Oriented* tactics, while for revisiting activities they highly concentrated on the *Reading.Oriented* tactic. On the other hand, *Mixed* and *Catching.up* tactics were only weakly related to the learning tactics.
- Strategy 2 – **Selective** (n=599, 52.82%) was adopted by the largest number of students. In contrast to the *Active* strategy group, this group comprised students who were selective in the choice of time management and learning tactics. As such, they were highly concentrated on preparing their learning by using the *Exercise.Oriented* tactic and they adopted the *Exercise.Oriented* and *Reading.Oriented* tactics while revisiting the course contents. Meanwhile, connections with other tactics were relatively very low.
- Strategy 3 – **Diverse** (n=133, 11.73%). Similar to the *Selective* strategy group, the *Diverse* strategy group included the students who were quite selective in terms of their choices of tactics; however, the students in this group were distinguished by enactment of diverse time management tactics such as *Preparing* and *Mixed*

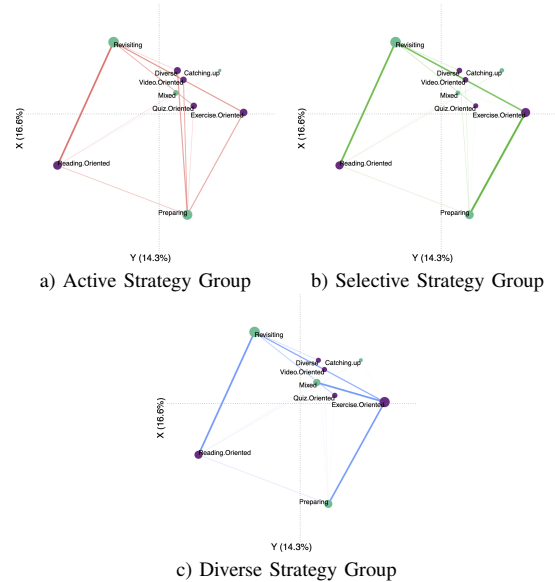


Figure 4: Epistemic network models identified in the course that followed the flipped classroom pedagogical approach. The green nodes represent time management tactics, while the purple nodes represent learning tactics.

on the *Exercise.Oriented* tactic, and *Revisiting* on the *Exercise.Oriented* and *Reading.Oriented* tactics.

Blended Learning (Health Science Course). Figure S5 (refer to supplementary document) show the patterns of interconnections of time management strategies and learning tactics indicative of students' learning strategies in blended learning course. The identified strategies can be characterized as follows:

- Strategy 1 – **Reading** (n=87, 17.90% of all students). Students in this group highly concentrated on the *Reading.Oriented* tactic, which they employed while preparing in advance (*Ahead*), in their preparatory work, prior to face-to-face sessions (*Preparing*), and when revisiting learning activities (*Revisiting*). Apart from reading the course materials, they also performed the pre-laboratory tasks (*Reading.Prelab.Oriented*) in the preparation stage.
- Strategy 2 – **Passive** (n=232, 47.74%) was the largest group. Like the *Reading* strategy group, students in this group managed their learning time by studying in advance, preparing lecture materials beforehand and revisiting course materials. However, they predominantly concentrated on the *Reading.Oriented* tactic, while other learning tactics were hardly observed.
- Strategy 3 – **Active** (n=119, 24.49%). Students in this group showed equally distributed and balanced actions between pairs of time management and learning tactics (e.g., *Ahead* + *Reading.Oriented*, *Preparing* + *Reading.Oriented* and *Preparing* + *Reading.Prelab.Oriented*) both on the preparation tasks (*Ahead*, *Preparing*) and

revision activities (*Revisiting*).

- Strategy 4 – **Selective** (n=48, 9.88%) included the least number of students. Compared to the three other strategy groups, the students in this group were highly selective in terms of their learning and time management tactics. They frequently used the *Reading.Oriented* tactic when studying in advance (*Ahead*) and prior to in-class sessions (*Preparing*). Links among others tactics was very low.

Massive Open Online Course (Introduction to Python Course). Figure S6 (refer to supplementary document) exhibits the epistemic network models identified in the MOOC. The results revealed clear differences in terms of the connections between time management and learning tactics across identified strategy groups, which may be described as follows:

- Strategy 1 – **Diverse** (n=202, 54.89% of all students) gathered the largest proportion of the students. They were highly focused on *Revisiting* tactic and *Short.Practice.Oriented* tactic. Furthermore, they performed *Diverse.Practice.Oriented* tactic (i.e., reading course materials, answering quizzes and viewing videos) prior to the scheduled week (*Ahead*) and revisited (*Revisiting*) them after the scheduled week (*Catching.up*).
- Strategy 2 – **Defer** (n=60, 16.30%) included the students who focused on the *Revisiting* tactic by practicing *Diverse.Practice.Oriented* tactic and *Short.Practice.Oriented* tactic. A general tendency of this group was to study the course topic after the scheduled week, and only occasionally accessed learning tasks prior to or during the scheduled week.
- Strategy 3 – **Selective** (n=53, 14.40%). The students in this group were highly selective in their choices of learning and time management tactics. They tended to perform *Diverse.Practice.Oriented* tactic in the weeks those activities were scheduled.
- Strategy 4 – **Advanced** (n=53, 14.40%). This group comprised students who preferred to study prior to the scheduled week (*Ahead*). They adopted diverse learning tactic especially on practice-related tasks (i.e., *Short.Practice.Oriented*, *Diverse.Practice.Oriented*) and to a small extent on *Lecture.Oriented* tactic.

B. Time Management and Learning Tactics Used Across Strategy Groups

This section presents process models that were created to examine learning processes performed by different strategy groups (through enactment of the adopted tactics). The graphical representation of the process models can be found in the supplementary document via: <https://bit.ly/2wT2jzy> (refer to Figures S7 - S12). Two dimensions of the temporal patterns presented in the process models include the process (i.e., transition from one tactic to another), and time (i.e., interval time between enactment of one tactic to another) across identified strategy groups are discussed in this section.

Flipped Classroom (Computer Engineering Course). Figure S7 (in supplementary document) presents process models for the three identified strategy groups in the flipped classroom. The most common sequence performed by the **Active** strategy group (Figure S7 (a)) was *Revisiting_Reading.Oriented*

→ *Revisiting_Exercise.Oriented* → *Preparing_Diverse* → *Preparing_Exercise.Oriented* → *Preparing_Video.Oriented*. The students in this group employed various learning tactics such as *Exercise.Oriented*, *Video.Oriented* and *Diverse* in their preparatory work. For the revision work, the students were highly concentrated on the *Reading.Oriented* and *Exercise.Oriented* tactics.

Meanwhile, the majority of the students in the **Selective** strategy group (Figure S7 (b)) began their learning by *Preparing_Exercise.Oriented* (314 instances). This group is characterized by *Preparing_Exercise.Oriented* → *Revisiting_Reading.Oriented* → *Revisiting_Exercise.Oriented* → *Revisiting_Video.Oriented* as a common learning sequence. Unlike the **Active** strategy group, the students in this group predominantly prepared for each week’s class by completing exercise-based tasks (*Preparing_Exercise.Oriented*). On the other hand, they adopted various tactics when revising previously studied topics, such as those focused on reading course materials, doing exercises, watching course videos, or completing quizzes.

Similar to the **Selective** strategy group, the majority of the students in the **Diverse** strategy group (Figure S7 (c)) tended to begin their learning by preparing through exercise oriented activities. The most common sequence of tactics displayed by this group was *Mixed_Exercise.Oriented* → *Revisiting_Reading.Oriented* → *Preparing_Exercise.Oriented* → *Revisiting_Exercise.Oriented*. That is, students in this group generally focused on problem-solving tasks prior to face-to-face sessions (i.e., *Mixed_Exercise.Oriented* and *Preparing_Exercise.Oriented*). This was followed by revisiting activities that combined the *Revisiting_Exercise.Oriented* tactic and the *Revisiting_Reading.Oriented* tactic, while revisiting through the quiz-focused tactic was far less prominent.

On the other hand, Figure S8 (in the supplementary document) depicts the process models from the time perspective. To further inspect the temporal aspect of learning process, in Table IV we present the most common transitions between a pair of tactics (including frequency of transitions and idle time between the tactics) across strategy groups identified from flipped classroom-based course.

In particular, the **Active** strategy group (Figure S8 (a)) had the longest idle times between *Preparing_Diverse* and

Table IV: Most frequent transitions and idle time between tactics across strategy groups in flipped classroom

Flipped Classroom (Computer Engineering Course)			
Strategy Group	Most Frequent Transitions Between Tactics	Freq.	Idle (days)
Active	<i>Revisiting_Exercise -> Revisiting_Reading</i>	999	0.57
	<i>Preparing_Video -> Preparing_Diverse</i>	807	0.05
	<i>Revisiting_Reading -> Revisiting_Exercise</i>	726	1.15
Selective	<i>Preparing_Exercise -> Revisiting_Exercise</i>	1398	4.72*
	<i>Revisiting_Exercise -> Revisiting_Reading</i>	1124	0.49
	<i>Revisiting_Exercise -> Preparing_Exercise</i>	1048	2.87
Diverse	<i>Mixed_Exercise -> Revisiting_Reading</i>	170	1.47
	<i>Preparing_Exercise -> Mixed_Exercise</i>	169	5.94
	<i>Preparing_Exercise -> Revisiting_Exercise</i>	166	5.96

Note: * indicates longest idle time (median days)

Revisiting_Exercise.Oriented (Mdn = 4.90 days). The students in this group shifted from preparing to revisiting activities and vice versa in less than 5 days, on average.

Similar to the *Active* strategy group, the students in the *Selective* strategy group (Figure S8 (b)) took less than 5 days to shift from preparation to revisiting activities. After completing revisiting activities, the students took, on average, less than 3 days to prepare for the following course topic.

In contrast to the other two groups, the *Diverse* strategy group (Figure S8 (c)) recorded the longest idle time that was between *Mixed_Exercise.Oriented* and *Preparing_Exercise.Oriented* (Mdn = 7.38 days). The students in this group took less than 6 days, on average, to shift from preparation to revisiting activities. Meanwhile, they took less than 5 days to shift from revisiting previous course topic to preparation for successive course topics.

Blended Learning (Health Science Course). The most common sequence of the *Reading* strategy group (Figure S9 (a)) was *Ahead_Reading.Oriented* → *Preparing_Reading.Oriented* → *Mixed_Reading.Oriented*. The process model indicates that students in the *Reading* strategy group were highly focused on reading course materials and on accessing the homepage with the general information about the course.

The *Passive* strategy group (Figure S9 (b)) followed similar sequences of tactics as those of the *Reading* strategy group (*Ahead_Reading.Oriented* → *Preparing_Reading.Oriented* → *Mixed_Reading.Oriented*), suggesting that these students focused on reading course materials in a manner similar to that of the *Reading* strategy group.

The *Active* strategy group (Figure S9 (c)) showed a different pattern of tactics. Their common path of transitions was *Ahead_Reading.Oriented* → *Preparing_Reading.Oriented* → *Preparing_Reading.Prelab.Oriented*. In contrast to the other strategy groups identified in this course, the *Active* group tended to prepare by not only reading the course materials, but also by completing the pre-laboratory tasks prior to the in-class sessions.

Meanwhile, the *Selective* strategy group (Figure S9 (d)) exhibited a relatively similar pattern of transitions to the one observed for the *Reading* and *Passive* strategy groups, in particular: *Ahead_Reading.Oriented* → *Preparing_Reading.Oriented* → *Mixed_Reading.Oriented*. As such, the students in this group mainly focused on the reading oriented tactic both in preparation (i.e., *Ahead_Reading.Oriented* and *Preparing_Reading.Oriented*) and revision activities (i.e., *Mixed_Reading.Oriented*).

Next, we examined the time aspect of the groups' temporal patterns. Table V illustrates the most frequent transitions between tactics and the time periods between those transitions. Accordingly, the *Reading* strategy group (Figure S10 (a)) had the longest idle time when transitioning from *Preparing_Reading.Oriented* to *Mixed_Reading.Oriented* (Mdn = 6.09 days). On average, it took members of this group less than 5 days to shift from one tactic to the next.

Meanwhile, the *Passive* strategy group (Figure S10 (b)) took a median of 6 days to shift from preparation activities prior to face-to-face sessions to the revision tasks. The longest idle time for this group was recorded for the transition from

Table V: Most frequent transitions and idle time between tactics across strategy groups in blended learning

Blended Learning (Health Science Course)			
Strategy Group	Most Frequent Transitions Between Tactics	Freq.	Idle (days)
Reading	<i>Ahead_Reading</i> → <i>Preparing_Reading</i>	233	4.91
	<i>Preparing_Reading</i> → <i>Ahead_Reading</i>	170	3.17
	<i>Preparing_Reading</i> → <i>Mixed_Reading</i>	139	6.09 [§]
Passive	<i>Ahead_Reading</i> → <i>Preparing_Reading</i>	431	4.99
	<i>Preparing_Reading</i> → <i>Ahead_Reading</i>	320	4.00
	<i>Preparing_Reading</i> → <i>Mixed_Reading</i>	263	5.73
Active	<i>Preparing_Reading</i> → <i>Preparing_Reading.Prelab</i>	291	2.09
	<i>Preparing_Reading.Prelab</i> → <i>Preparing_Reading</i>	254	3.75
	<i>Ahead_Reading</i> → <i>Preparing_Reading</i>	230	4.39 [§]
Selective	<i>Ahead_Reading</i> → <i>Preparing_Reading</i>	214	2.75 [§]
	<i>Preparing_Reading</i> → <i>Ahead_Reading</i>	170	1.59
	<i>Preparing_Reading</i> → <i>Mixed_Reading</i>	112	1.99

Note: * indicates longest idle time (median days)

Ahead_Reading.Oriented to *Mixed_Reading.Oriented* (Mdn = 5.78 days).

In contrast to the other groups, the students in the *Active* strategy group (Figure S10 (c)) mainly focused on preparation prior to face-to-face sessions. They took less than 3 days to shift from one tactic to another, except transition from *Ahead_Reading.Oriented* to *Preparing_Reading.Oriented* tactic that recorded the longest idle time (Mdn = 4.39 days).

The *Selective* strategy group (Figure S10 (d)) had the longest idle time between *Ahead_Reading.Oriented* and *Preparing_Reading.Oriented* (Mdn = 2.75 days). The students in this group made a 'pause' of less than 2 days before shifting to the revision tasks after completing the preparation tasks. In sum, the most common length of time spent on shifting from one tactic to another is average of 2 days.

Massive Open Online Course (Introduction to Python Course). The *Diverse* strategy group (Figure S11 (a)) tended to begin their study with a variety of learning tactics, rather than relying on one specific tactic. These students tended to access the course topics prior to the scheduled week by performing short practical exercises and by using learning tactics focused on quizzes, code execution, and viewing video lectures. They also adopted *Revisiting_Diverse.Practice.Oriented* and *Revisiting_Short.Practice.Oriented* for the revision activities. Sessions in this group often ended by using the *Revisiting_Short.Practice.Oriented* tactic.

Meanwhile, the *Defer* strategy group (Figure S11 (b)) was highly focused on *Revisiting_Short.Practice.Oriented* and *Revisiting_Diverse.Practice.Oriented* with high transitions between those tactics. Based on the process model, these students delayed somewhat their activities while studying in this course. They were inclined to access the course materials after the course topics had been scheduled (i.e., *Revisiting_Short.Practice.Oriented*, *Revisiting_Short.Practice.Oriented*).

The majority of students in the *Selective* strategy group (Figure S11 (c)) began their learning on schedule and they accessed the course topics during the week in which the topics were scheduled. The most commonly adopted learning tactic was the *Diverse.Practice.Oriented* tactic. Apart from that,

these students used the *Lecture.Practice.Oriented*, performed *Short.Practice.Oriented* and *Long.Practice.Oriented* tactics.

In contrast to the other groups, the *Advanced* strategy group (Figure S11 (d)) often accessed the course materials in the future week, prior to the week those topics were scheduled. The most frequently applied tactics were diverse practice-oriented and short practical exercise-oriented tactics.

We further investigated the students' learning processes by looking at the time perspectives presented by the process model. The *Diverse* strategy group (Figure S12 (a)) had the longest idle time between *Ahead_Short.Practice.Oriented* and *Revisiting_Diverse.Practice.Oriented* (Mdn = 16.48 days). The students in this group took more than 12 days to revisit the content previously studied by using the diverse and short practice tactics.

Although the *Defer* strategy group (Figure S12 (b)) somewhat delayed starting their learning sessions (i.e., *Catching.up* tactic), the students in this group showed quick transitions from one tactic to another. Overall, it took them less than 5 days (median) to shift from one tactic to another. This group had the longest idle time between *Catching.up_Lecture.Practice.Oriented* and *Revisiting_Short.Practice.Oriented* (Mdn = 15.38 days).

The *Selective* strategy group (Figure S12 (c)) is characterized by timely access to the course materials (i.e., *Preparing* tactic). Compared to the *Defer* strategy group, the students in this group made a relatively longer pause between preparation and revision activities.

In comparison to the other strategy groups, the *Advanced* strategy group (Figure S12 (d)) predominantly concentrated on the prior access to the course materials before those activities were scheduled (i.e., *Ahead_Diverse.Practice.Oriented* and *Ahead_Short.Practice.Oriented*). In addition, the students in this group spent less than 1 day, on average, to shift from one tactic to another.

Table VI: Most frequent transitions and idle time between tactics across strategy groups in MOOC

Massive Open Online Course (Introduction to Python Course)			
Strategy Group	Most Frequent Transitions Between Tactics	Freq.	Idle (days)
Diverse	<i>Revisiting_Short.Practice -> End</i>	63	-
	<i>Ahead_Short.Practice -></i>	59	0.38
	<i>Ahead_Diverse.Practice</i>		
	<i>Ahead_Diverse.Practice -> Ahead_Short.Practice</i>	55	0.87
Defer	<i>Revisiting_Short.Practice -> Revisiting_Diverse.Practice</i>	66	0.49
	<i>Revisiting_Diverse.Practice -> Revisiting_Short.Practice</i>	60	0.68
	<i>Catching.up_Lecture.Practice -> Catching.up_Diverse.Practice</i>	47	0.10
	<i>Preparing_Diverse.Practice -> Preparing_Short.Practice</i>	42	0.56
Selective	<i>Preparing_Short.Practice -> Preparing_Diverse.Practice</i>	42	0.32
	<i>Preparing_Lecture.Practice -> Preparing_Diverse.Practice</i>	32	0.08
	<i>Ahead_Diverse.Practice -> Ahead_Short.Practice</i>	116	0.66
	<i>Ahead_Short.Practice -> Ahead_Diverse.Practice</i>	116	0.40

C. RQ2: Associations between Learning Strategies and Academic Performance

The results of the Kruskal Wallis test showed significant associations between the identified strategy groups and the students' course performance (p-value < 0.0001 for total score). To further inspect these associations, pairwise tests were carried out (Table VII). All the pairs of identified strategy groups in the flipped classroom, blended learning and MOOC were significantly different with effect sizes (r) ranging from small to large [60]. The descriptive statistics of the strategy groups and course performance are provided in Table VIII.

V. DISCUSSION

To address research question 1 (RQ1), this study validates the use of the data analytic method introduced in [24] in three distinct learning modalities across various academic disciplines. The adopted method allowed the examination of learning strategies based on (i) the frequency of, (ii) the strength of connections between, (iii) the ordering, and (vi) the time of execution of the learners' time management and learning tactics. Accordingly, three strategy groups were identified from a flipped classroom-based course (*Active*, *Selective* and *Diverse*) and four strategy groups were identified from a blended learning-based course (*Active*, *Selective*, *Reading* and *Passive*) and a MOOC (*Advanced*, *Selective*, *Defer*, *Diverse*). To gain further insights into students' learning strategies (i.e., connection, process and time) and their association with course performance (research question 2), we grouped the identified strategy groups based on the academic achievement in the courses – highest, mid- and lowest – and discussed them from the perspective of SRL theory, specifically, Winne's work [61] and Dunlosky et al.'s [48] work on learning strategies.

Highest Achieving Groups. The results of this study found that the *Active* strategy groups identified in both the flipped classroom and blended learning courses and the *Advanced* strategy group from MOOC were recognized as the most active, dynamic and highest achieving groups in their contexts. In particular, the *Active* strategy groups (both from flipped classroom and blended learning) employed diverse time management and learning tactics, while progressing in their study. The students in these strategy groups frequently used reading, exercises and quiz oriented tactics in their preparatory works. Yet, they preferred to review the learning materials by re-reading and self-testing (i.e., *Exercise.Oriented* and *Quiz.Oriented*) (see Figures 8 (a) and S5 (c)). These results seem to suggest that, students in this group used well-balanced learning strategies by pairing less effective learning tactics (i.e., *Reading.Oriented* with effective ones (i.e., *Quiz.Oriented*, *Exercise.Oriented* and *Reading.Prelab.Oriented*) (see Figures S7 (a) and S9 (c)). This is consistent with Dunlosky et al.'s [48] recommendation to complement less effective learning tactics with more effective ones to increase students' understanding and performance. Moreover, the students in the *Active* strategy groups also demonstrated a careful alignment of diverse time management tactics by studying in advance (planning), preparing their learning prior to face-to-face sessions and revisiting course materials after the scheduled weeks (metacognitive monitoring),

which attribute to productive self-regulation [61], [53] and higher academic gains.

The results of the study revealed different learning strategies adopted by the highest achieving group in the MOOC (see Figure S6 (c)). The students in the *Advanced* strategy group preferred to study prior to the weeks when the course topics were scheduled, while other time management tactics (i.e., *Preparing*, *Revisiting* and *Catching.up*) were barely used by this group. Similar to the *Active* strategy groups, the *Advanced* strategy group chose to perform diverse learning tactics especially practice oriented tactics (i.e., *Short.Practice.Oriented* and *Diverse.Practice.Oriented*) followed by lecture oriented and long practice oriented tactics. The process model (Figure S11 (d)) revealed that the majority of the students in this strategy group tended to begin their study by gaining early access to the diverse practical tactics (i.e., exams and quizzes) and then shifted to short practice oriented tactics. Both tactics were reiterated throughout the course timeline. These results indicated that the *Advanced* strategy group exhibited a certain degree of awareness that helped them start their study early and procrastinate less. These findings indicate that successful MOOC learners regulated their learning by gaining early access (access course topics prior to scheduled week) to the practice testing or self-testing activities. This is in line with previous research that suggests planning and studying ahead (i.e., prepared learning by studying course content prior to scheduled face-to-face sessions) result in improvement of time management practices [62], [28].

Mid-High Achieving Groups. The *Selective* strategy groups identified in the three learning modalities fall into mid- and mid-high achievement groups. Similarly, the students in these strategy groups showed limited choice of learning tactics and were relatively selective in time management tactics. In the flipped classroom context, the students in this group were highly focused on the exercise oriented tactic, i.e., problem-solving exercises before they participated in in-class learning sessions. They were likely to use the same learning tactic (*Exercise.Oriented*), along with the reading oriented tactic while revisiting the previous studied content (see Figure 4 (b)). The process model (Figure S7 (b)) showed that learning

Table VII: Pairwise comparisons of the strategy groups with respect to the course scores

Learning Modalities	Cluster 1	Cluster 2	Z	p	r
Flipped Classroom	Active	Selective	1.812	<0.0001	0.264
	Selective	Diverse	-0.637	<0.0001	0.190
	Diverse	Active	-0.745	<0.0001	0.349
Blended Learning	Selective	Reading	1.270	<0.0001	0.180
	Selective	Passive	1.142	<0.0001	0.238
	Passive	Active	-0.207	<0.0001	0.188
	Reading	Passive	-0.262	<0.0001	0.070
	Active	Reading	-0.779	<0.0001	0.143
	Active	Selective	-1.272	<0.0001	0.055
MOOC	Selective	Diverse	1.991	<0.0001	0.296
	Selective	Defer	1.481	<0.0001	0.055
	Advanced	Defer	1.155	<0.0001	0.453
	Advanced	Selective	1.047	<0.0001	0.367
	Diverse	Advanced	0.242	<0.0001	0.608
	Defer	Diverse	-0.828	<0.0001	0.273

Table VIII: Descriptive statistics for the course performance of different strategy groups across the examined courses

Learning Modalities	Strategy Group	Grade	Scores		
			Median	Q1	Q3
Max. score: 60					
Flipped Classroom	Active	Highest	38.00	30.00	48.67
	Selective	Mid	30.00	24.00	40.00
	Diverse	Lowest	25.33	20.00	32.00
Max. score: 100					
Blended Learning	Active	Highest	72.80	56.64	78.82
	Selective	Mid-higher	72.47	62.48	81.63
	Reading	Mid-lower	65.88	53.90	75.44
	Passive	Lowest	64.77	50.37	76.18
Max. score: 100					
MOOC	Advanced	Highest	88.97	77.11	90.13
	Selective	Mid-higher	64.91	34.58	94.80
	Defer	Mid-lower	41.00	24.80	82.96
	Diverse	Lowest	24.23	8.90	58.48

Note: The identification of the Grade is based on the score median

often occurred as a 'mixture' of three tactics: begin with the preparing exercise oriented tactic followed by reviewing with the use of exercise oriented and reading oriented tactics. These results are consistent with previous research [24] that identified the *Selective* strategy group as a mid-performing group and highly focused on the exercise oriented and reading oriented tactics to progress in their learning. These findings also provide some evidence about the students' *judgement of learning* (JOL) [16], [63] since it seems that the students tended to choose to re-study those items that they perceived as knowing less [63].

In the blended learning setting, students in this category (see Figure S5 (d)) were inclined to study in advance (ahead) or during the week when those topics were scheduled (preparation) by predominantly employing the reading oriented tactic, which contained the reading materials and general course information, while other learning tactics (i.e., *Reading.Prelab.Oriented*, *Reading.Discussion.Oriented*) and time management tactics (i.e., *Mixed*) were hardly observed. This finding seems to suggest that, the *Selective* strategy group in blended learning was more likely to use active retrieval practice (by accessing the course topics in advance or during the scheduled week) that potentially allows for greater long-term retention [64].

In the MOOC settings, the *Selective* strategy group consisted of students with timely learning practice as shown in Figure S6 (c) who exhibited strong connections between the *Preparing* tactic and the *Diverse.Practice.Oriented* tactic. This group tended to make use of the same learning tactic (*Diverse.Practice.Oriented*) while reviewing the course items. This group highly focused on timely access to the practice oriented tactics (i.e., *Diverse.Practice.Oriented* and *Short.Practice.Oriented*), while the revisiting efforts were quite low (see Figure S11 (c)).

To summarize, the *Selective* strategy groups were characterized by students who directed their efforts towards preparing in advance (i.e., flipped classroom and blended learning) or gaining access to the course in a timely basis (i.e., MOOC). They also regulated their learning through the use of effective learning tactics (i.e., *Diverse.Practice.Oriented*

and *Short.Practice.Oriented*) to supplement the less effective learning tactic (i.e., *Reading.Oriented*). This implies that *Selective* strategy groups were monitoring their learning by evaluating differences between their current status (i.e., learning progress) and standards (i.e., predefined learning goals) which, in turn, activates control processes to reduce disparities (i.e., to engage more intensively in a specific topic) [65].

Mid-Low Achieving Groups. The study found that *Reading.Oriented* was the most popular tactic employed by the students mainly in hybrid learning modalities (i.e., flipped classroom and blended learning) as we could observe that almost all strategy groups in both learning settings used this tactic to complete the learning tasks. Despite its popularity, Dunlosky [48] asserted that reading and re-reading are less useful strategies as they do not provide sufficient benefits for long-term memory and academic outcomes. Accordingly, our findings corroborate Dunlosky's proposition by reflecting on the performance and tactics employed by the *Reading* strategy groups. Particularly, the *Reading* strategy group (Figure S5 (a)) was described as a mid-low performing group that typically used reading (i.e., *Ahead_Reading.Oriented*, *Preparing_Reading.Oriented*) and re-reading (i.e., *Mixed_Reading.Oriented*) as their preferred learning tactics, while other learning tactics were hardly observed. The process model (Figure S9 (a)) revealed frequent transitions occurred between tactics used by the learners: *Ahead_Reading.Oriented*, *Preparing_Reading.Oriented* and *Mixed_Reading.Oriented*. These results indicated that the *Reading* strategy group is well-versed in terms of managing their study time, as they adopted active time management tactics (i.e., study in advance, prepare learning beforehand, and re-study the learning items); however, they failed to optimally use the available learning tactics to support their learning.

In contrast to the *Reading* strategy group, the *Defer* strategy group (Figure S6 (b)) observed among students in the MOOC exhibited the effective use of learning tactics (i.e., *Diverse.Practice.Oriented* and *Short.Practice.Oriented*). However, the inadequate use of effective time management tactics can be associated with their low scores (Mdn = 41.00). The students in this group tended to procrastinate by delaying access to the weekly topics (*Catching.up*). Although they demonstrated frequent activities on practice testing (deemed as a effective learning tactic [48]) (see Figure S11 (b)), the delay to study often led to relatively poor course performance and ineffective self-regulation [66]. Thus, this study suggests that effective learning strategies are not a unidimensional concept that depends solely on effectiveness of learning tactics; they are tightly bound to the effective use of time management tactics.

Lowest Achieving Groups. Three strategy groups showed the lowest academic performance: (i) the *Diverse* strategy groups (identified from flipped classroom and MOOC) and (ii) the *Passive* strategy group (identified from blended learning). Similar to previous research [24], the *Diverse* strategy groups were described as groups that employed various learning (i.e., exercise, quizzes and reading) and time management tactics (i.e., ahead, preparing, revisiting) while progressing in their learning (Figure 4 (c)). Process models (Figures S7 (c) and S11 (a)) also showed active transitions between tactics. However,

the study also found some contradictions in regards to their performance. The *Diverse* strategy groups (identified in both flipped classroom and MOOC) were the lowest achieving group instead of the highest performing group as previously reported in [24]. A possible explanation for these findings is that less effective self-regulated learners often use of sub-optimal study strategies, which lead them to make poor evaluations of their own learning [15], [67], [68] in terms of where to direct their efforts and how much effort to put in achieving desirable learning goals. Similar to the *Reading* strategy groups for the Mid-Low Achieving groups, the *Passive* strategy group (Figure S5 (b)) can be described as a group of students who put their study efforts mainly in reading oriented tactics. Although they were active in preparing and revisiting the previously studied materials, the way they regulated their learning by continuously using an impotent learning tactic (i.e., *Reading.Oriented*) throughout the course was not sufficient to support their learning and academic achievement.

The effectiveness of learning strategies is often linked to the spacing effect. There are two spacing qualities that have been highlighted in Dunlosky et al.'s [48] work: distributed practice and interleave practice. Distributed practice involves planning of learning by spreading study sessions over time; interleaved practice involves scheduling a mixture of learning materials across the study sessions. Both of these spacing practices are recognized as some of the most effective (distributed practice) and promising (interleaved practice) learning strategies to improve learning and academic performance. In contrast, massing practice is considered as one of least effective ones. However, our results present mixed evidence for the endorsement of spacing effects in supporting students' performance. This echoes Winne and Hadwin's [10] assertion that the quality of strategy use should be related to performance.

Accordingly, we discovered that the mid- and lowest achieving groups from blended learning (*Selective*, *Reading* and *Passive*) and MOOC (*Diverse*) preferred to practice distributed learning strategies, in which the students tend to stick to the same learning tactics, before employing them again in later sessions. For example, in the blended learning-based course, students segmented the *Reading.Oriented* tactic into successive learning sessions. i.e., study a topic in advance (*Ahead_Reading.Oriented*), prepare the topic before an in-class session (*Preparing_Reading.Oriented*) and review the topic later after the class (*Mixed_Reading.Oriented*). In general, they took relatively long time to shift from one study session to another with the median idle time of almost a week, while the *Diverse* strategy group took longer than that (Mdn = 16.48 days). This result indicates that students may have chosen effective strategies for their learning (i.e., involves planning of study by spreading learning sessions over time) [48], but a maladaptive delay in their learning may have contributed to relatively poor performance.

It is interesting to note that the highest (*Advanced*) and mid-high (*Selective*) achieving groups from the MOOC were more likely to mass than space their learning, which was evident in short intervals of time between one tactic to another, that is, rapid transitions between tactics (on average of one day). On the other hand, the lowest (*Diverse*) and mid-low

(*Defer*) achieving groups employed more effective learning strategies by using mixed tactics and distributed them across the study sessions (interleaved). However, the extensive delays between tactics proved to be negatively associated with their performance. Contrary to Dunlosky's principles, this study found that MOOC learners benefited from massing, rather than spacing. A possible explanation for this result is that MOOC learners might benefit from self-paced learning, in which the flexibility offered by MOOCs allowed the learners to be highly autonomous in organizing their study. They could independently decide how to regulate their study time and efforts (e.g., cram weeks of material into a short period of time or frequently access the course) as they progress in a course [69]. Thus, the tactics that learners used were not necessarily aligned with the course design. Hence, the degree to which students regulated their learning, such as maintaining motivation and persistence to learn in the MOOC setting, was critical for success or failure in the MOOC [70].

With respect to spaced practice, we found that the highest and mid-achieving groups in the flipped classroom-based (*Active* and *Selective*) and the blended learning-based (*Active*) courses benefited from the interleaved practice. These strategy groups were more likely to use a mixture of learning tactics and kept switching amongst tactics across the course timeline. Moreover, these strategy groups allowed for a short lag between learning tactics (a median of 5 days) that was associated with relatively high academic performance. This result indicates that students from flipped classroom and blended learning courses were more competent in allocating and segmenting their study time, which led to better retention of information [71]. One possible explanation is that, in-class instructions provided opportunities for students to gain certain knowledge and to develop certain skills to help them regulate their learning effectively. Hence, consistent with the previous research [48], [72], [24], the results of the current study suggest that the use of the interleaved practice and practice testing (i.e., self-testing) could ultimately support better learning in both flipped classroom and blended learning settings. However, because the findings on the spacing effect in the MOOC setting contradict earlier notions, further investigation is warranted.

VI. CONCLUSIONS, IMPLICATIONS AND LIMITATIONS

This study shows how multivocality can bring together diverse and theoretically-grounded data analytic methods to provide empirical evidence necessary for the understanding of the diversity of learning strategies adopted by students from multiple learning modalities across diverse disciplines. Our research has further enforced the importance of combining various time management and learning tactics in order to promote effective learning strategies, support self-regulation, and improve academic outcomes.

Taken together, the study has two key contributions. First, it has demonstrated that a creative synergy of multiple data analytic methods allowed for a rigorous evaluation of learning strategies from the perspective of the underlying theory. This study revealed that the learning strategies identified using the proposed data analytic method were consistent with the

expectations from the SRL theory and principles of learning strategies. Moreover, the method proved capable of providing detailed insights into students' learning strategies (i.e., connection, process and time) across three learning modalities (i.e., flipped classroom, blended learning and MOOC) and three subject areas. Secondly, this study confirmed the association of the detected strategies with academic performance across three learning contexts.

This study found that almost all of the most successful strategy groups (*Active* and *Advanced* strategy group) preferred to use practice testing (i.e., *Exercise.Oriented*, *Diverse.Practice.Oriented*, and *Short.Practice.Oriented*) particularly during preparatory activities and they were likely to re-practice them after the study week. This finding suggests that self-testing has a widespread benefit in different learning modalities across various academic disciplines. Self-testing is regarded as one of the most effective learning tactics [48] and a useful technique to promote students' comprehension and long-term recall that is positively associated with academic performance [38]. However, we noticed that the most successful strategy groups in the flipped classroom- and blended learning-based courses tended to use less effective learning tactics, such as reading and re-reading. This might be due to the course design (Computer Engineering and Health Science courses), which required students to complete reading tasks each week. Still, they supplemented less effective tactics with effective ones [48], like problem-solving, quizzes, and pre-laboratory exercises. This evidence indicates that successful strategy groups tended to demonstrate a high level of metacognitive and self-regulation skills. This enabled them to monitor and judge their performance and then make necessary adjustments to their learning tactics and strategies to be aligned with their learning goals.

In contrast to high achieving groups, less successful strategy groups heavily relied on relatively passive reading oriented tactics (i.e., reading and re-reading tactics) during a course. This result seems to suggest that less successful strategy groups had relatively low SRL skills in terms of the selection and adaptation of learning tactics. In the MOOC context, less successful strategy groups seem to have focused on practice testing (effective learning tactic) with little consideration for time management. In particular, the study found that less successful strategy groups in the MOOC spent relatively less time on studying by delaying their access to the course contents (i.e., *Catching.up*) and by allowing extensive delays between learning activities (i.e., longest interval time); this was negatively correlated with their course performance. This finding seems to further support the need for metacognitive skills which refer to the process of monitoring and reflecting on their study time to accomplish a learning goal in MOOCs [47].

Nevertheless, in some cases less successful and more successful strategy groups tended to choose the same strategies, for example, (i) complement less effective tactics (i.e., reading and re-reading) with effective ones (i.e., self-testing) or (ii) use active time management tactics (i.e., preparing lecture beforehand and revisiting after class). However, more successful strategy groups used them more adeptly (i.e., regularity in

performing those tactics and short interval time between tactics) [38] than less successful strategy groups did. Besides, less successful strategy groups were vulnerable to time management deficiencies such as passive procrastination (i.e., *Catching.up* tactic) and maladaptive delays. These results corroborate the idea that all students used regulatory processes to some degree, but learners with strong SRL were distinguished by the use of cognitive and metacognitive strategies to decide, select and use appropriate tactics and strategies in achieving desired learning goals [73], [38].

Implications. *From the methodological viewpoint*, we replicated the data analytic method proposed in [24] for detection and analysis of learning strategies, by testing its applicability to various learning modalities (i.e., flipped classroom, blended learning and MOOC) across diverse academic disciplines (i.e., Computer Engineering, Health Science and Software Engineering). The learning strategies found by using these methods were interrogated based on the established SRL theory and principles of learning strategies. Moreover, we posit that creative synergies of multiple data analytic methods – combined unsupervised machine learning with network and process analytic methods – not only allows for a holistic analysis of integral dimensions of learning (i.e., connection, process and time) in a single study context, but also demonstrates relevance and applicability to diverse learning contexts.

From the development of new learning technology viewpoint, the proposed data analytic method could be used to empower the next-generation of analytics-based technologies for personalised feedback, where feedback is provided based on the tactics and strategies detected. The efficacy of feedback can also be evaluated with the proposed methodology and enable the feedback provision technologies to advice instructors to change some of their feedback strategies.

From the theoretical viewpoint, we conclude that there is a solid common ground for bringing two established perspectives of SRL theory and educational psychology into dialogue; that is, to compare and contrast their understanding of a given learning scenario. In fact, by combining these two perspectives, it is possible to integrate the strengths of both: the SRL [74], [68] perspective can offer a ground theory for the study of students' regulation (i.e., cognition, metacognition, and motivation through SRL phases), while research on learning strategies [48] could provide important points for interpretation of learning strategies in reference to cognitive psychology.

From the practical viewpoint, the findings of this study provide an evidence-based recommendation about effective learning strategies as well as productive self-regulation practices that could be useful in multiple ways. From an instructor's viewpoint, the current study could inform productive educational practices to help learners succeed in various learning settings. Thus, the instructor can play a pivotal role in encouraging the effective use of learning strategies by making necessary adaptation to the course contents, and if necessary, considering modifications to the instructional designs to best suit learners' needs in order to foster and sustain learners engagement with various online learning tasks. From a learner's perspective, this study can inform learners about effective learning strategies (both time management and learning tactics) to accomplish a

given instructional objective.

Limitations. The current study has several notable limitations that need to be carefully addressed in future research. First, the study makes extensive use of digital trace data about learners' interaction with online learning environments. Although trace data have proven beneficial for capturing and examining the latent behaviour of students in an authentic learning setting, they may be insufficient to provide assessment of students' conditions, intentions, and motivations to learn. Therefore, future studies should consider including self-report measures or multi-modal methods that could support interpretation of research findings.

Second, this study relied on an unsupervised method, namely hierarchical clustering technique for detecting learning strategies, as it is deemed adequate to detect student groups from learning activities [75]. Although resulting dendrograms from hierarchical clustering are practical tools for the estimation of the number of clusters, this technique introduces a certain degree of subjectivity in the interpretation of the cluster findings. Future studies should explore methods that can be used to generate or support rigorous cluster solutions.

Third, while this study aimed to provide initial empirical validation of combination of unsupervised machine learning with network and process analytic methods in different learning modalities, the study did not take into account the course design. Thus, future studies of relationships between learning and time management with course design are necessary.

Finally, this study used minimal demographic information about the student populations due to the limited data access granted in the institutional ethical approval. If possible, future studies should report on relevant demographic background or past academic history to allow for better understanding of learners characteristics and factors contributing to the success or failure in a course.

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**Supplementary Document:
Theoretically Grounded Analytics of Learning Strategies: A Multivocal Approach**

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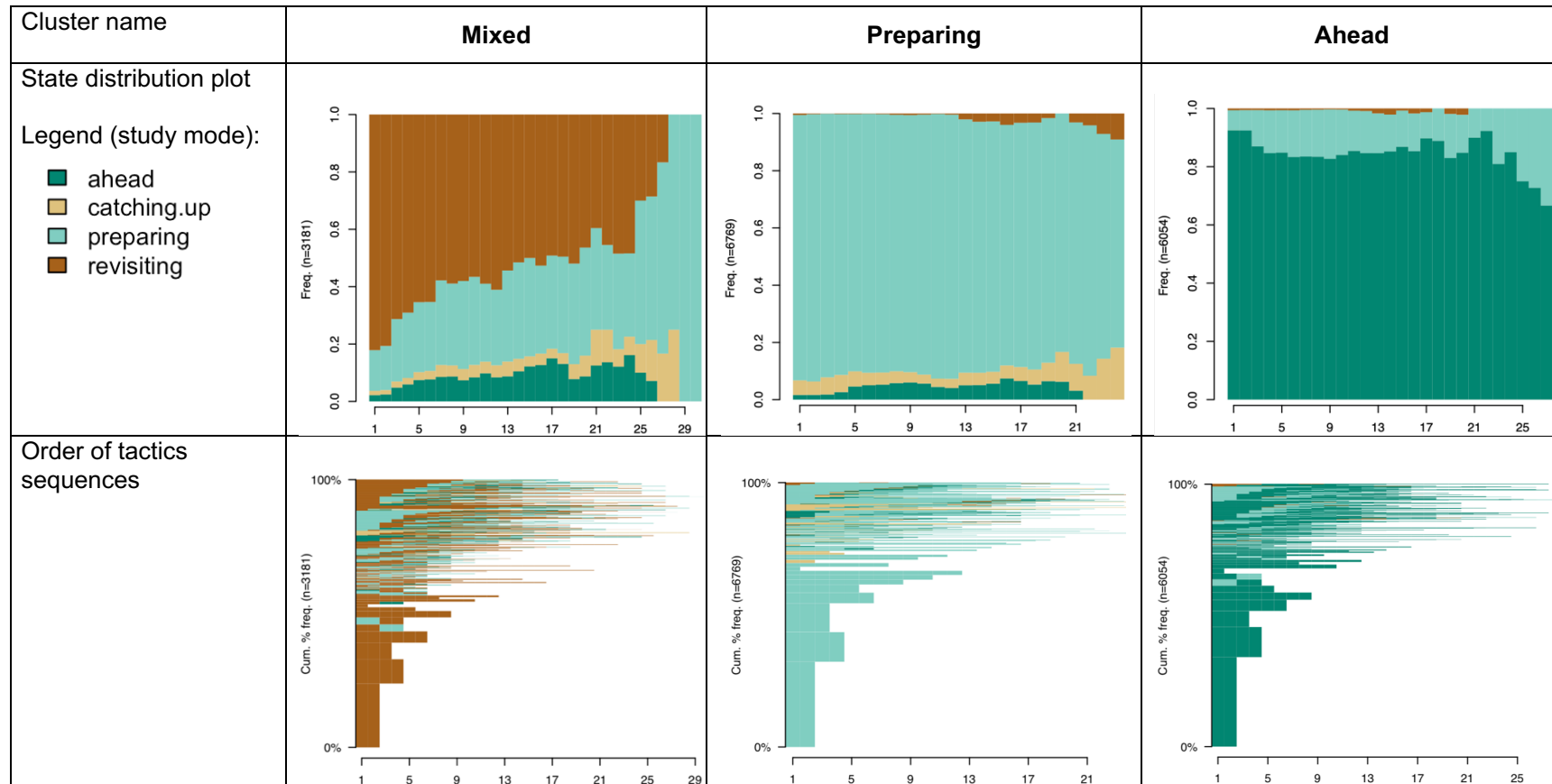
Figure S10: Idle time (in days) between the end of the from-activity and the start of the to-activity across four identified strategy groups in the course based on blended learning.

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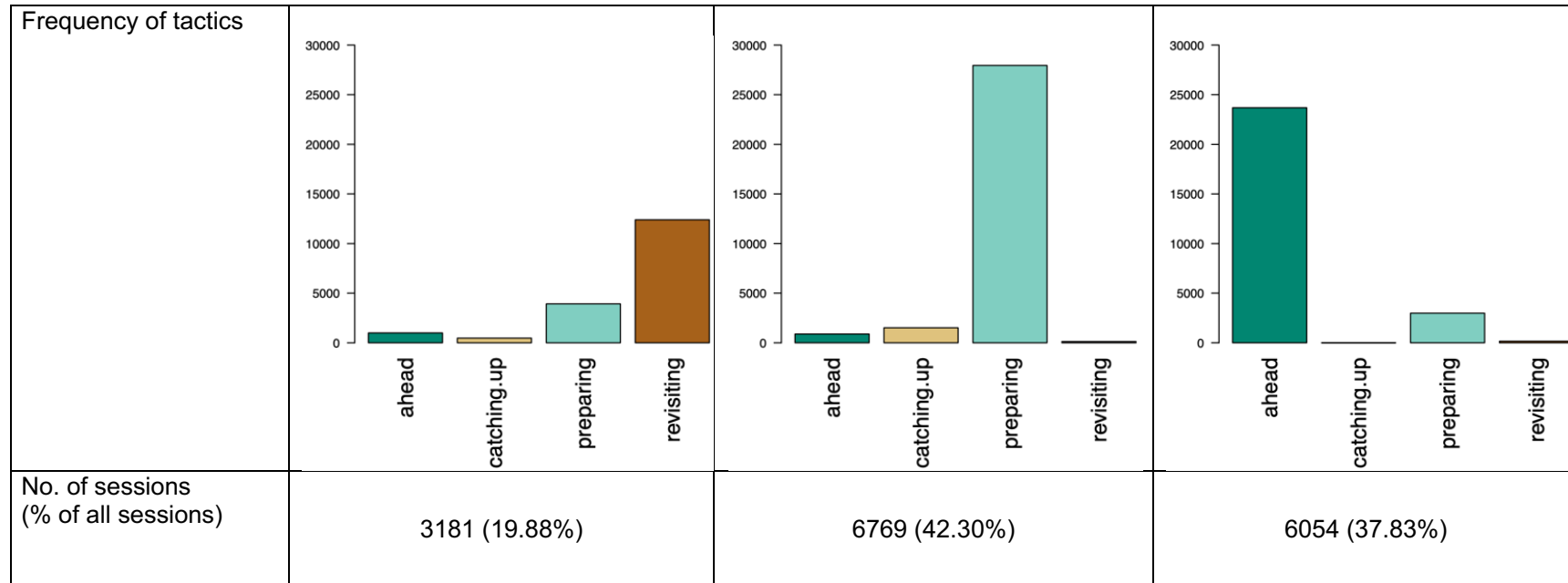
Figure S12: Idle time (in days) between the end of the from-activity and the start of the to-activity across the four identified strategy groups in the MOOC.

Dataset 2: Health Science Course (Blended Learning Course)

Figure S1: Characteristics of the detected time management tactics in the Health Science course

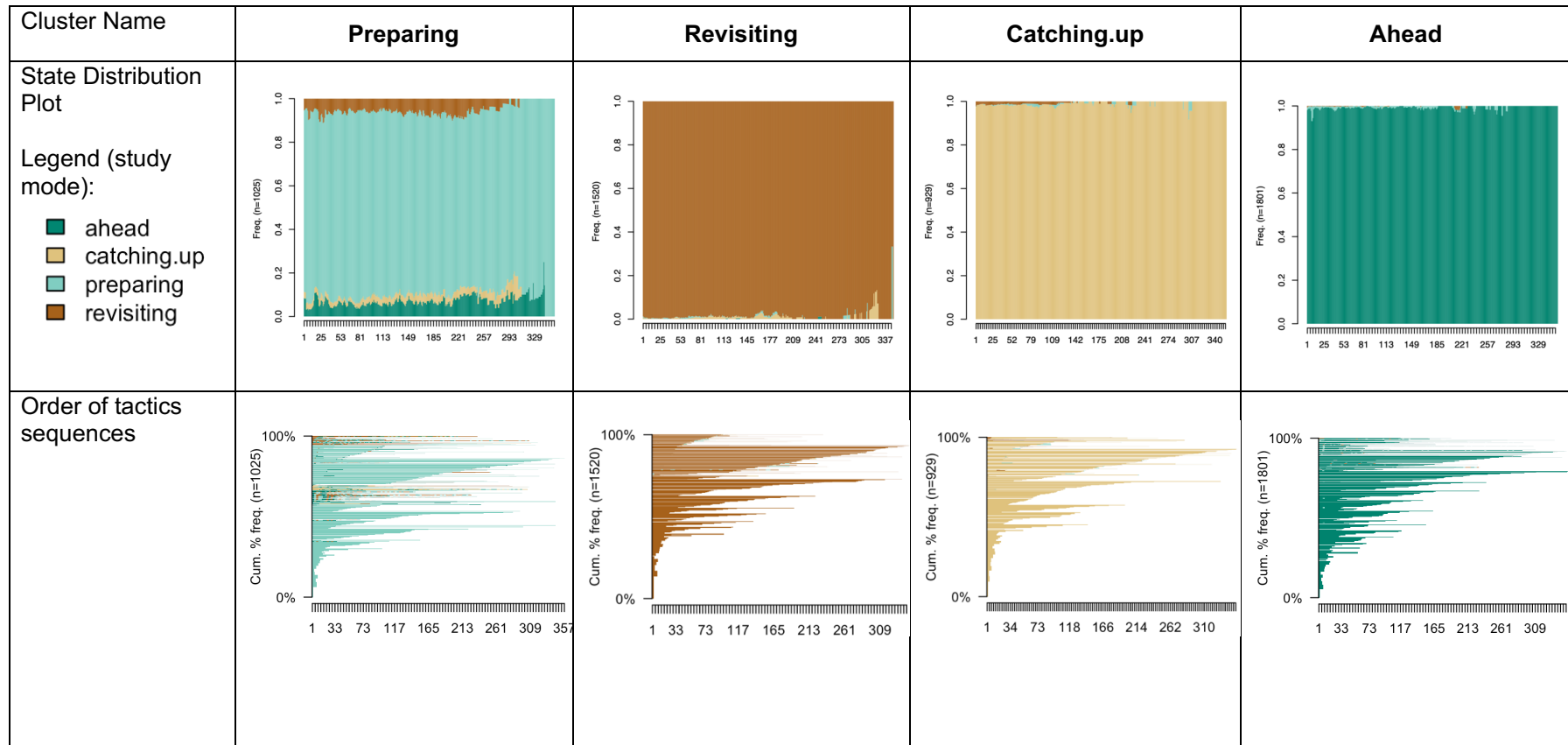


6. MULTIVOCAL ANALYTICS OF LEARNING STRATEGIES



Dataset 3: Introduction to Python Course (Massive Open Online Course)

Figure S2: Characteristics of the detected time management tactics in the Introduction to Python course



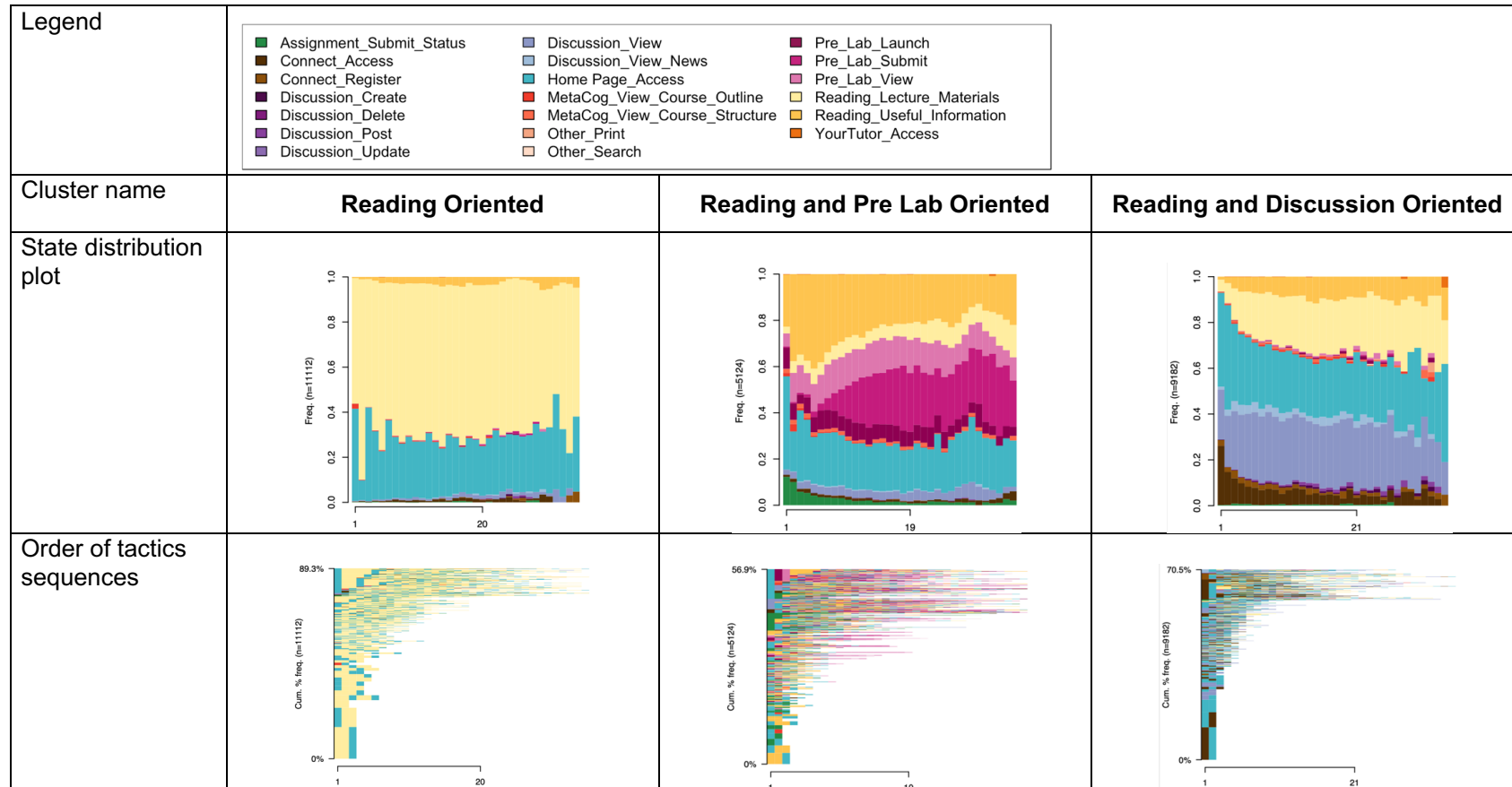
6. MULTIVOCAL ANALYTICS OF LEARNING STRATEGIES

<p>Frequency of tactics</p>				
<p>No. of sessions (% of all sessions)</p>	<p>1025 (19.43%)</p>	<p>1520 (28.82%)</p>	<p>929 (17.61%)</p>	<p>1801 (34.14%)</p>

6. MULTIVOCAL ANALYTICS OF LEARNING STRATEGIES

Dataset 2: Health Science Course (Blended Learning Course)

Figure S3: Characteristics of the detected learning tactics in the Health Science course



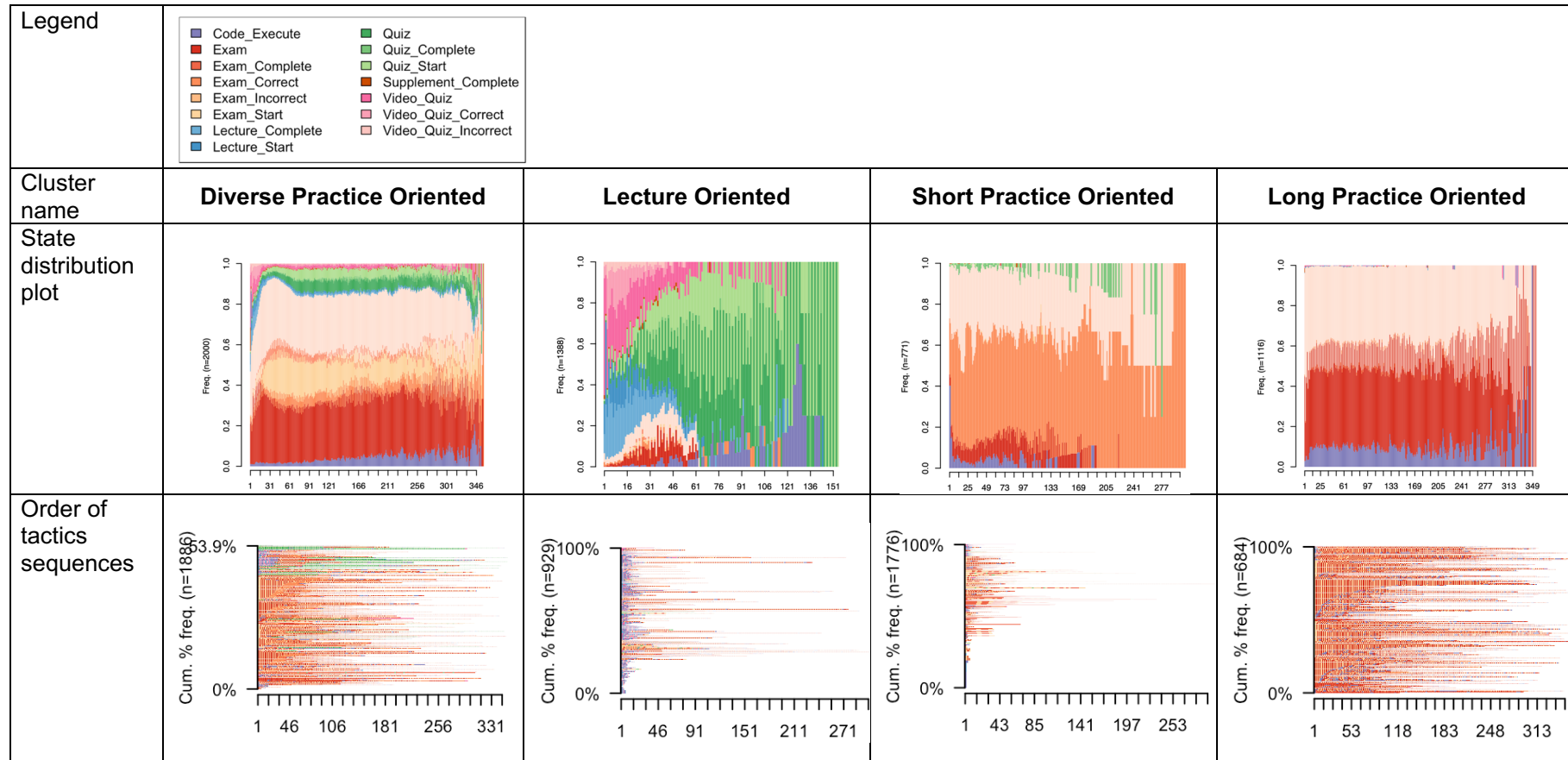
6. MULTIVOCAL ANALYTICS OF LEARNING STRATEGIES

<p>Frequency of tactics</p>			
<p>No. of sessions (% of all sessions)</p>	<p>11112 (43.72%)</p>	<p>5124 (20.16%)</p>	<p>9182 (36.12%)</p>

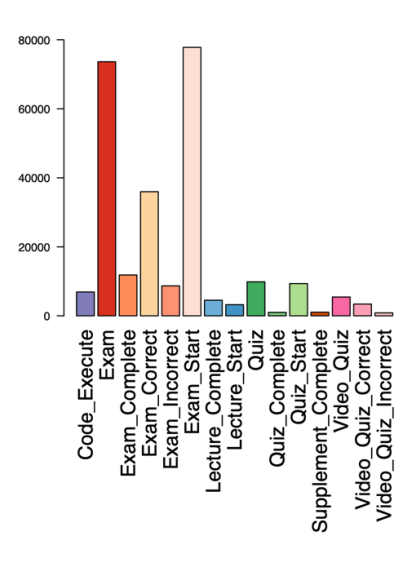
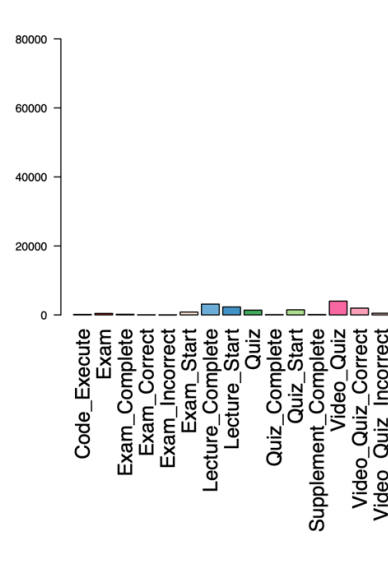
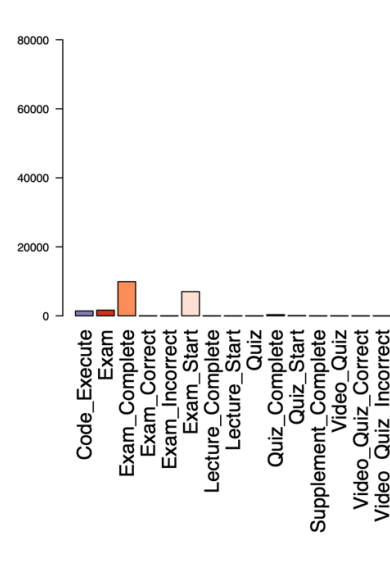
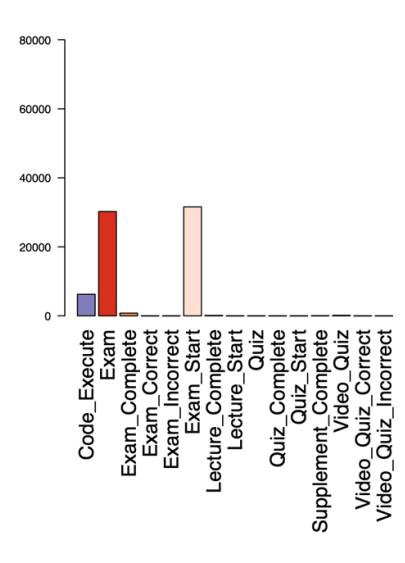
6. MULTIVOCAL ANALYTICS OF LEARNING STRATEGIES

Dataset 3: Introduction to Python Course (Massive Open Online Course)

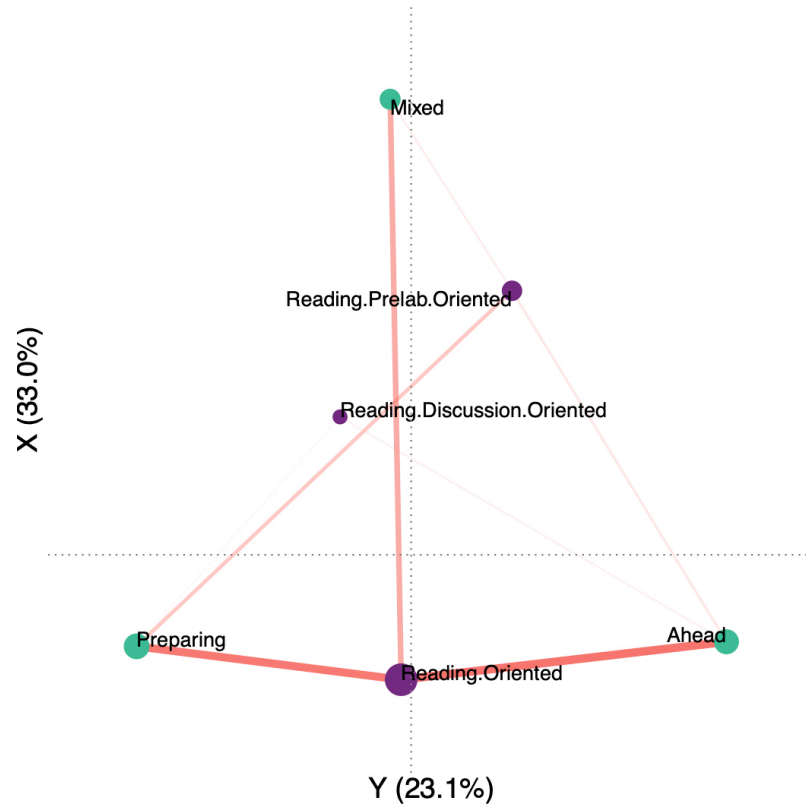
Figure S4: Characteristics of the detected learning tactics in the Introduction to Python course



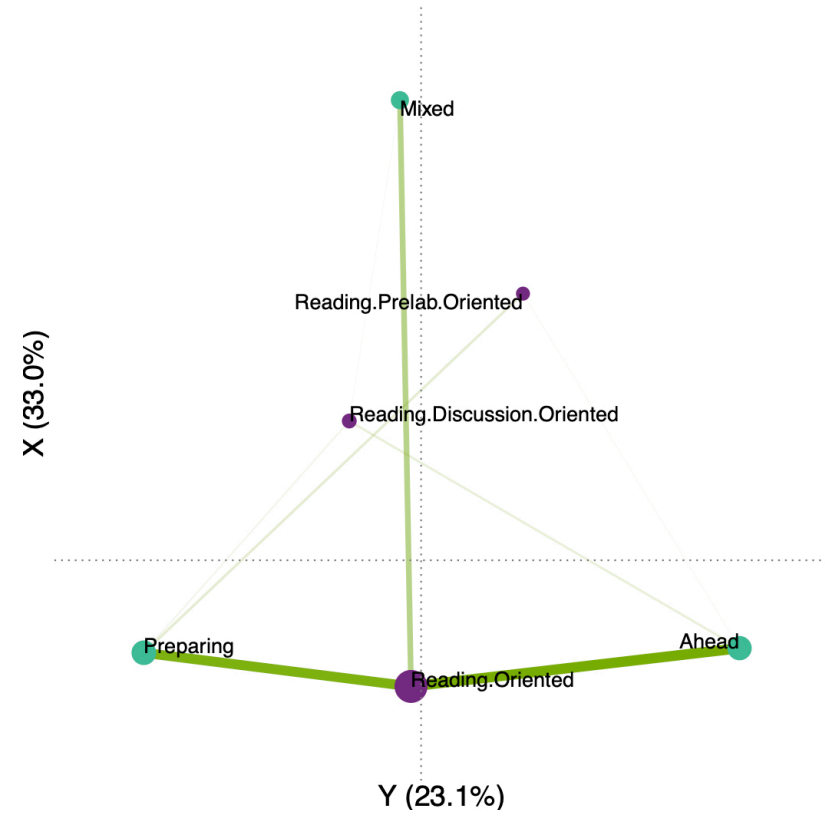
6. MULTIVOCAL ANALYTICS OF LEARNING STRATEGIES

Frequency of tactics				
No. of sessions (% of all sessions)	2000 (37.87%)	1391 (26.34%)	772 (14.62%)	1118 (21.17%)

Dataset 2: Health Science Course (Blended Learning Course)



(a) Reading Strategy Group



(b) Passive Strategy Group

6. MULTIVOCAL ANALYTICS OF LEARNING STRATEGIES

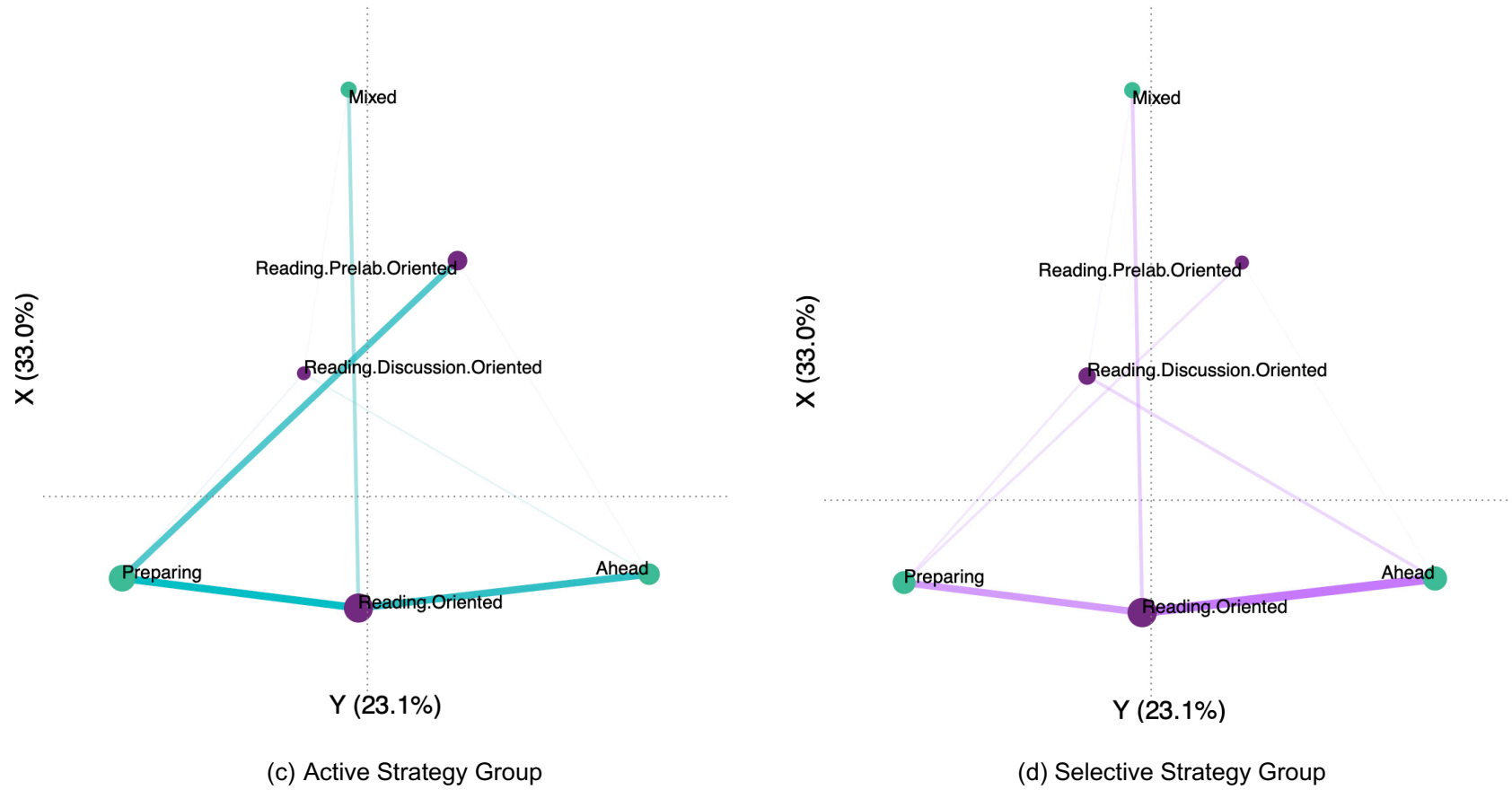
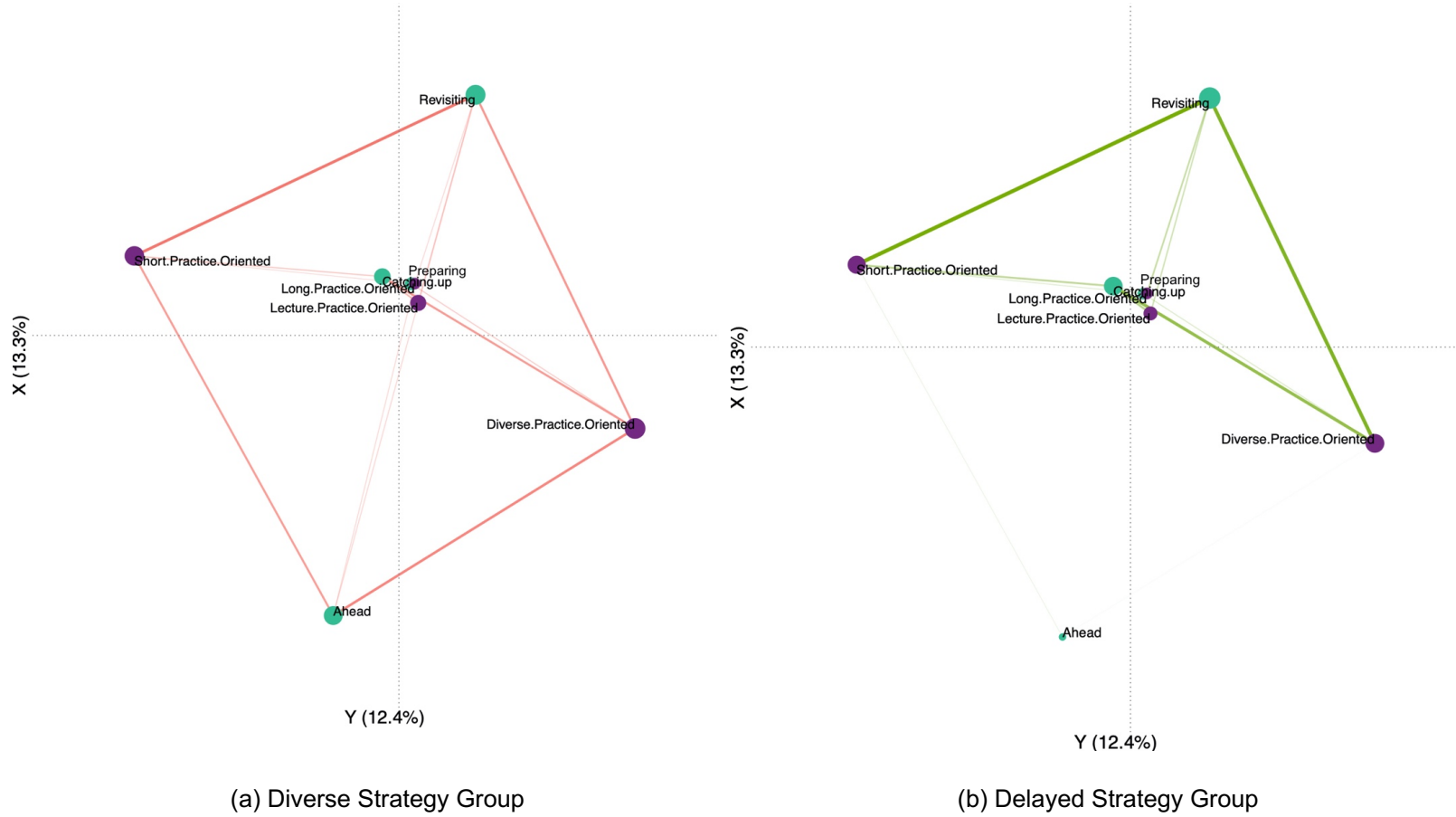


Figure S5: Epistemic network models identified in the course based on blended learning. The green nodes represent time management tactics, while the purple nodes represent learning tactics.

Dataset 3: Introduction to Python Course (Massive Open Online Course)



6. MULTIVOCAL ANALYTICS OF LEARNING STRATEGIES

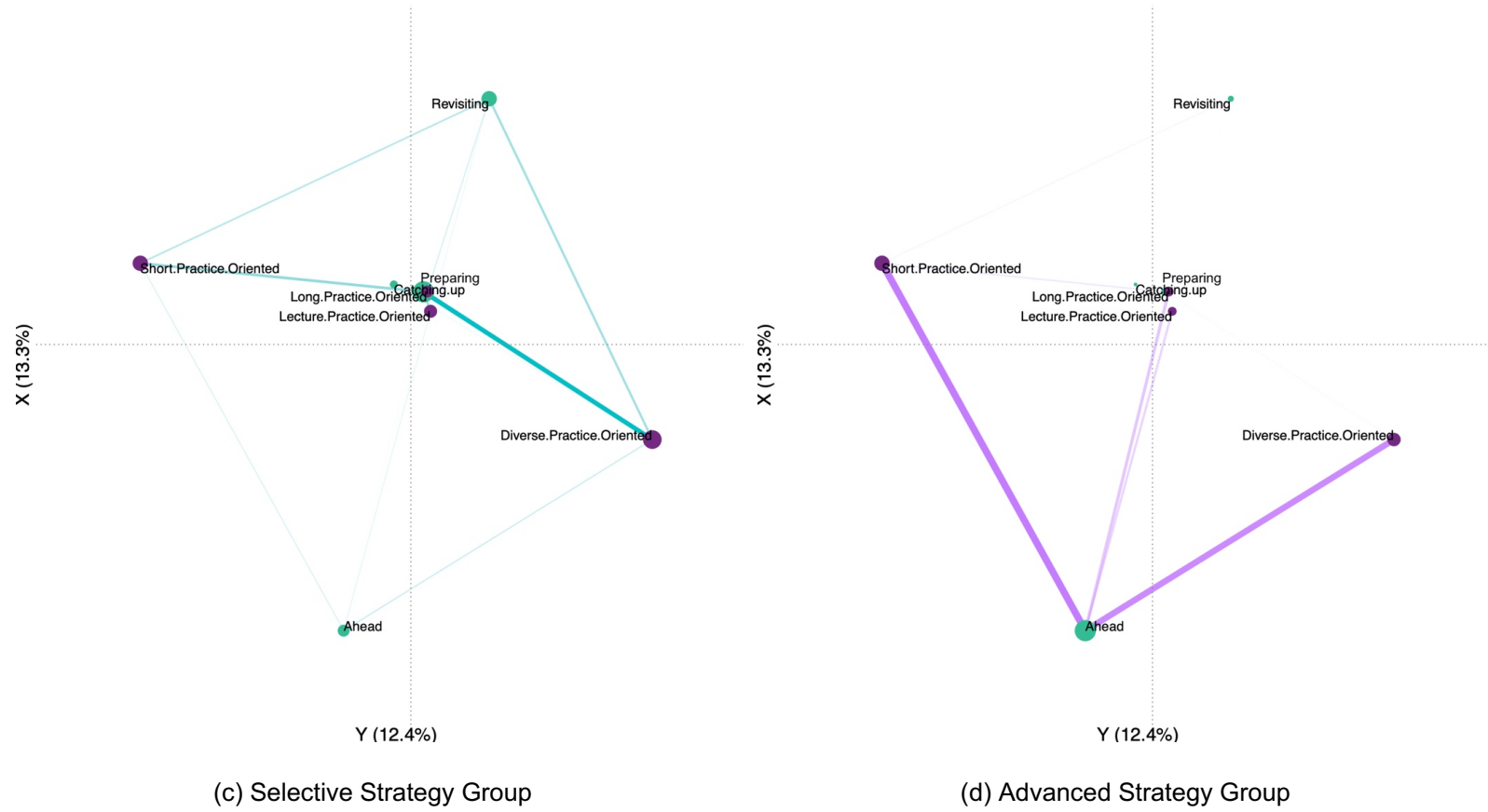


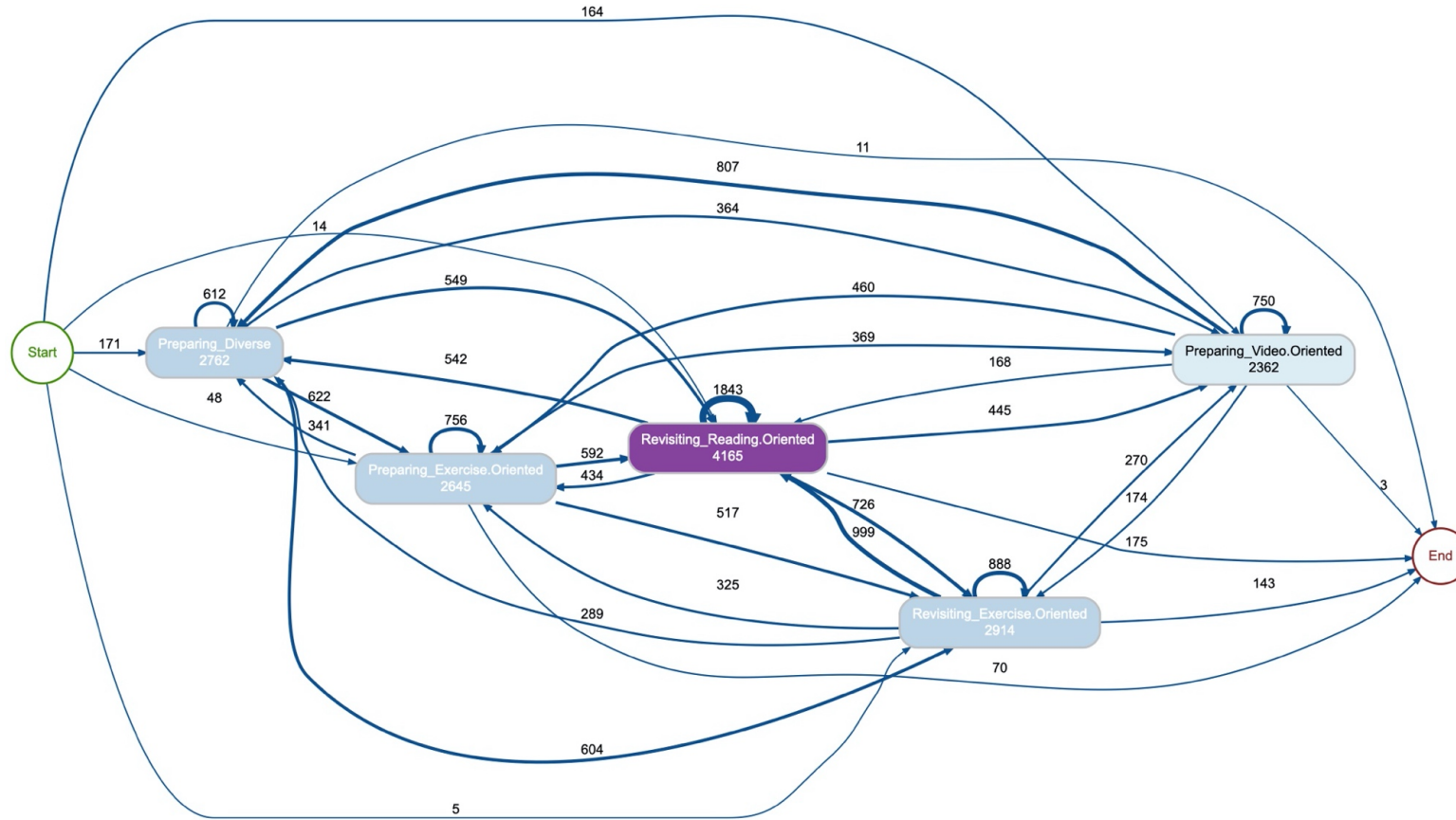
Figure S6: Epistemic network models identified in the MOOC. The green nodes represent time management tactics, while the purple nodes represent learning tactics.

Time Management and Learning Tactics Used Across Strategy Groups

Figures S7 – S12 present two dimensions of the temporal patterns presented in the process models include the process (i.e., transition from one tactic to another), and time (i.e., interval time between enactment of one tactic to another) across identified strategy groups.

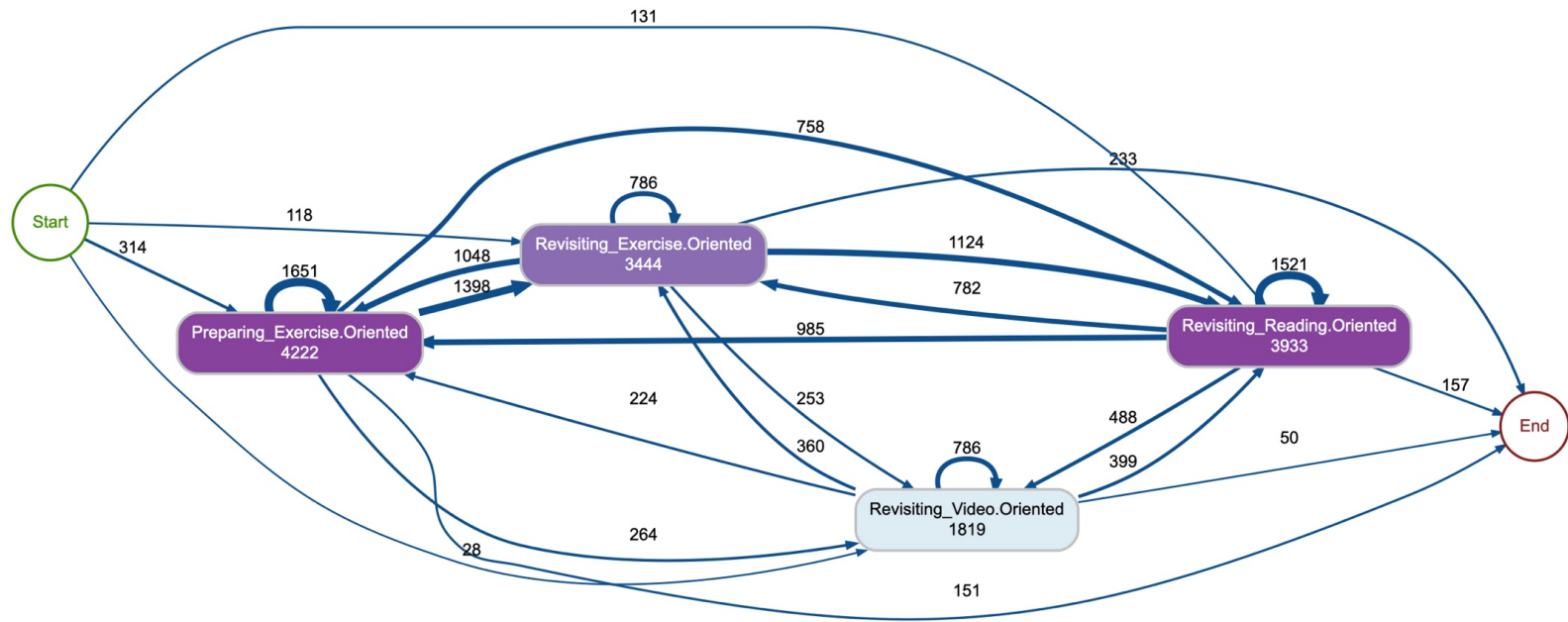
- **Process:** the process models in Figures S7, S9, and S11 present the frequency of learning activities and transitions between consecutive activities. The numbers in the boxes, in the visual depiction of the process models, are absolute frequencies of activity instances, while the numbers associated with edges represent absolute frequencies of transitions between consecutive activities. The gradient of the node color indicates the frequency of activities (e.g., the darker the color, the higher is the frequency of activities).
- **Time:** the process models in Figures S8, S10, and S12 show the idle time (in days) between the end of one activity (from-activity) and the start of the next activity (to-activity) across the identified strategy groups. Darker line color represents longer idle time.

Process Models: Computer Engineering Course (Flipped Classroom Course)



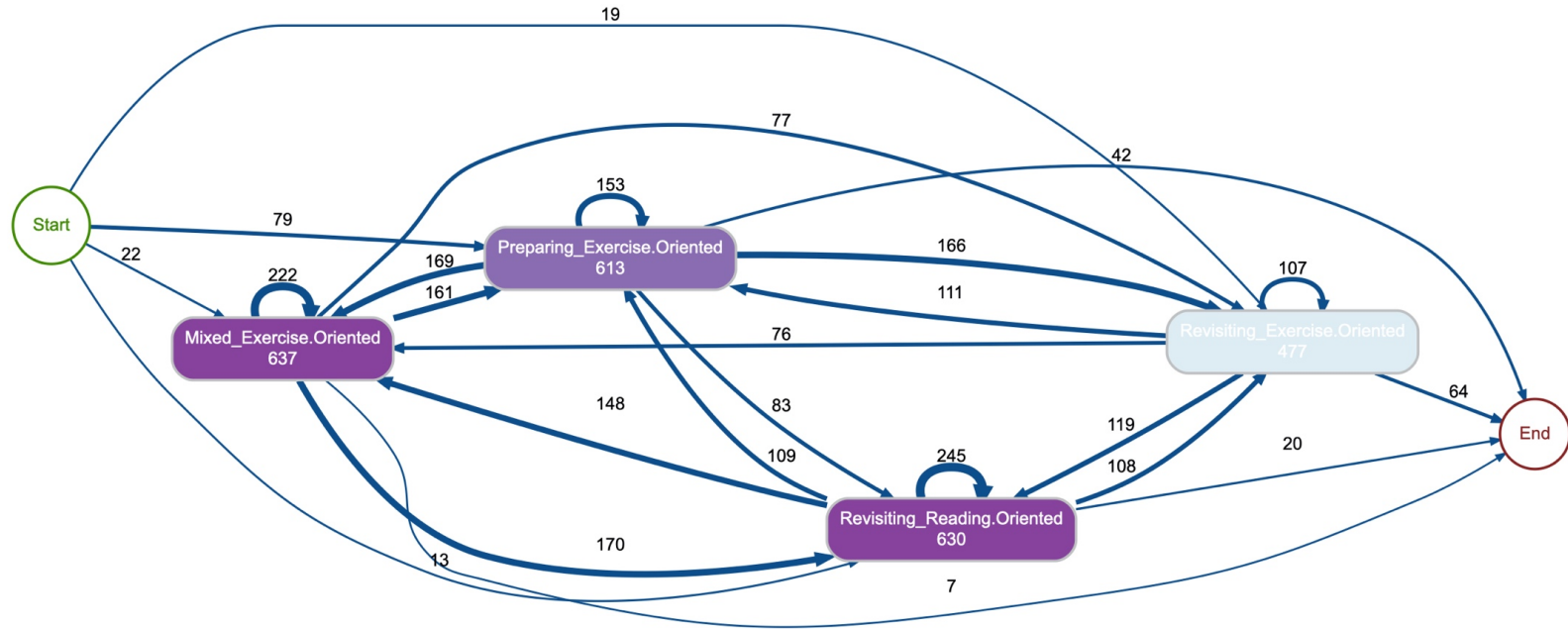
a) Active Strategy Group

6. MULTIVOCAL ANALYTICS OF LEARNING STRATEGIES



(b) Selective Strategy Group

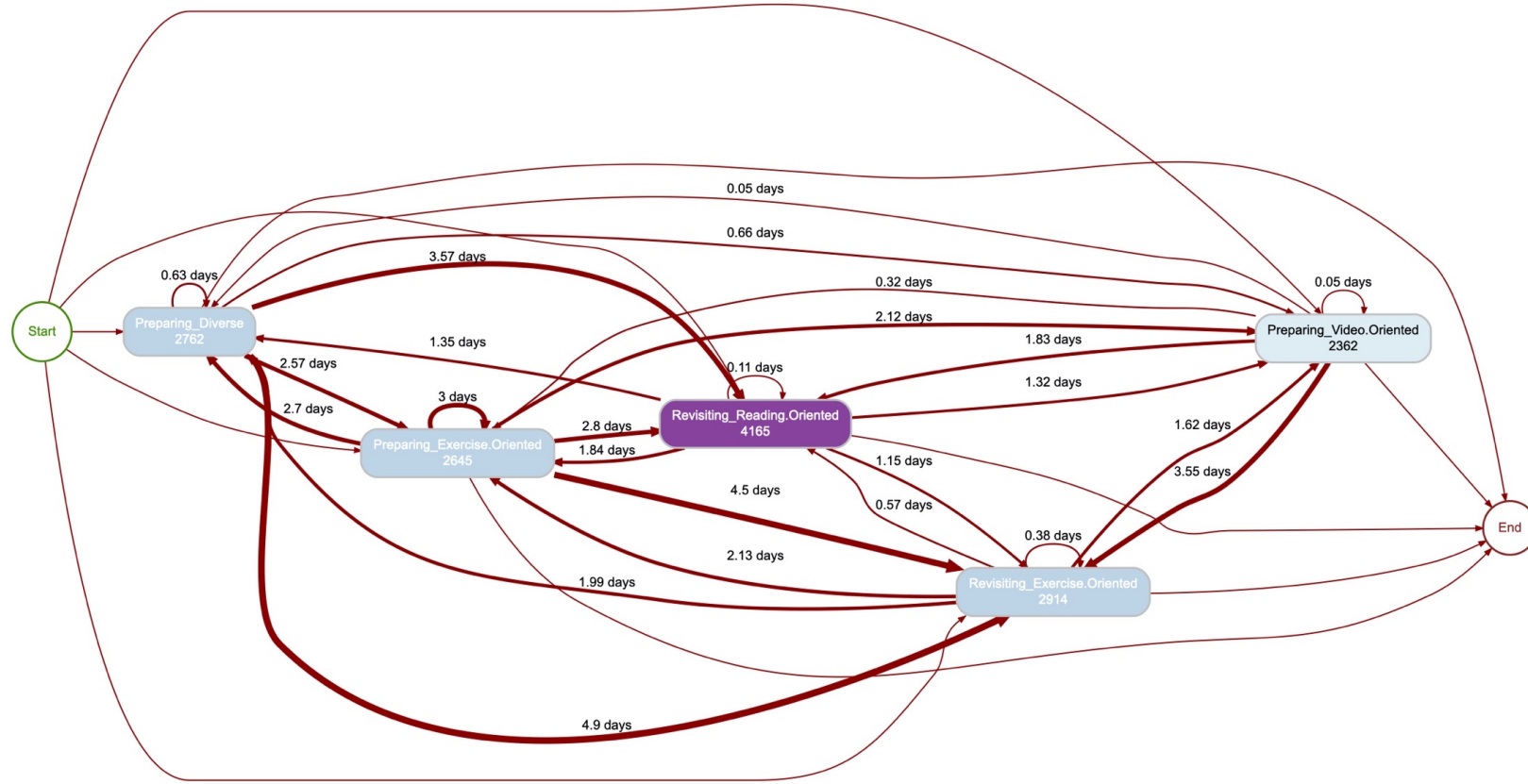
6. MULTIVOCAL ANALYTICS OF LEARNING STRATEGIES



(c) Diverse Strategy Group

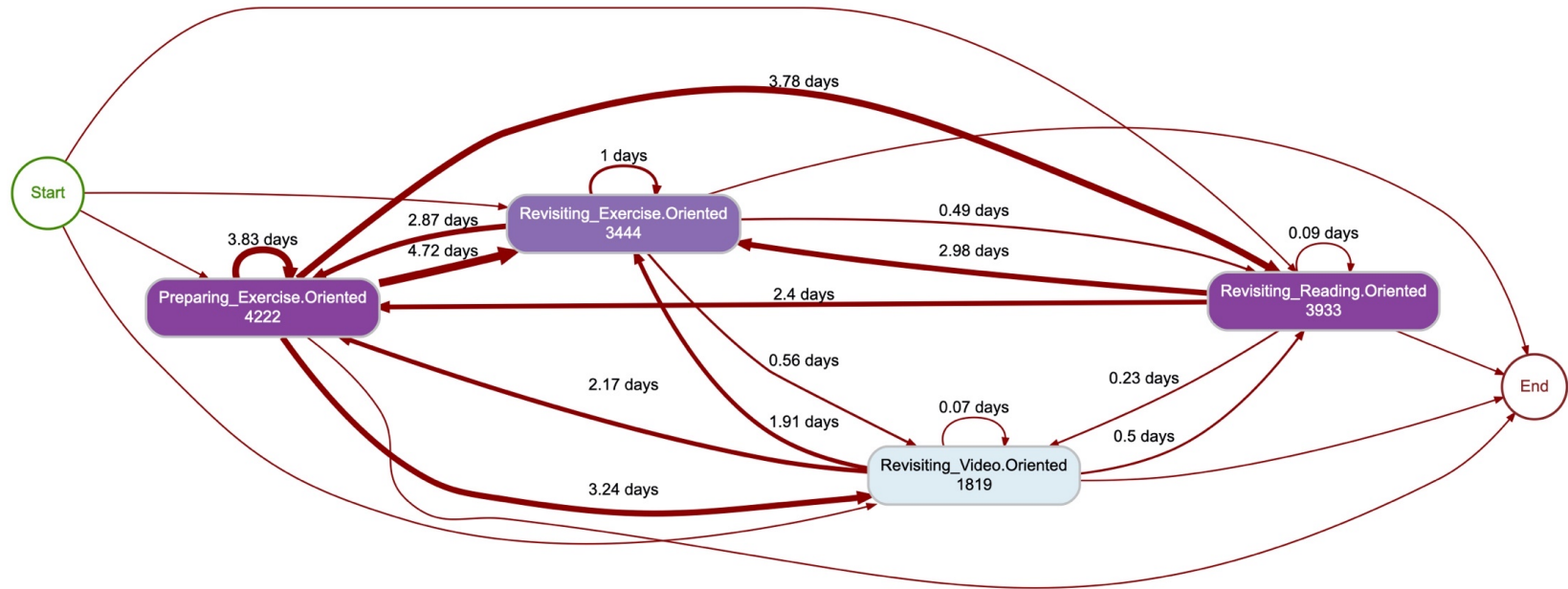
Figure S7: Process models focused on frequency of occurrence for the learning processes of the three identified strategy groups in the flipped classroom.

6. MULTIVOCAL ANALYTICS OF LEARNING STRATEGIES



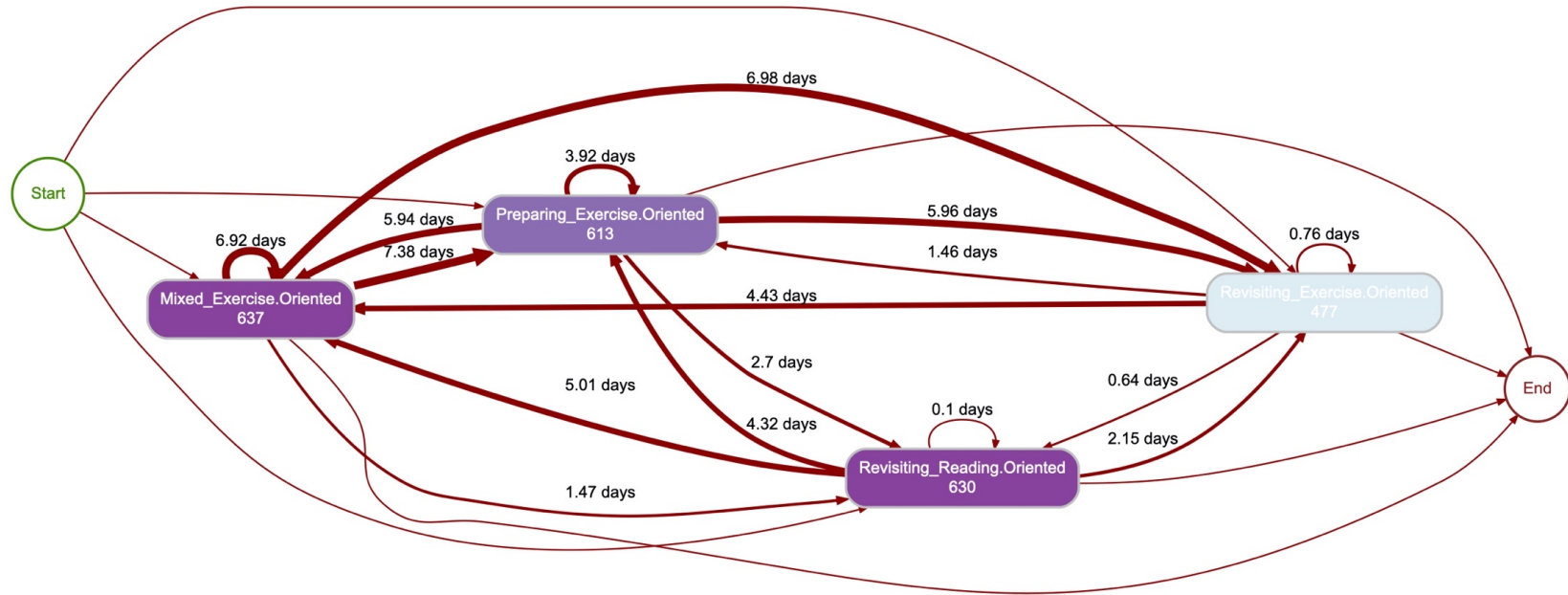
a) Active Strategy Group

6. MULTIVOCAL ANALYTICS OF LEARNING STRATEGIES



(b) Selective Strategy Group

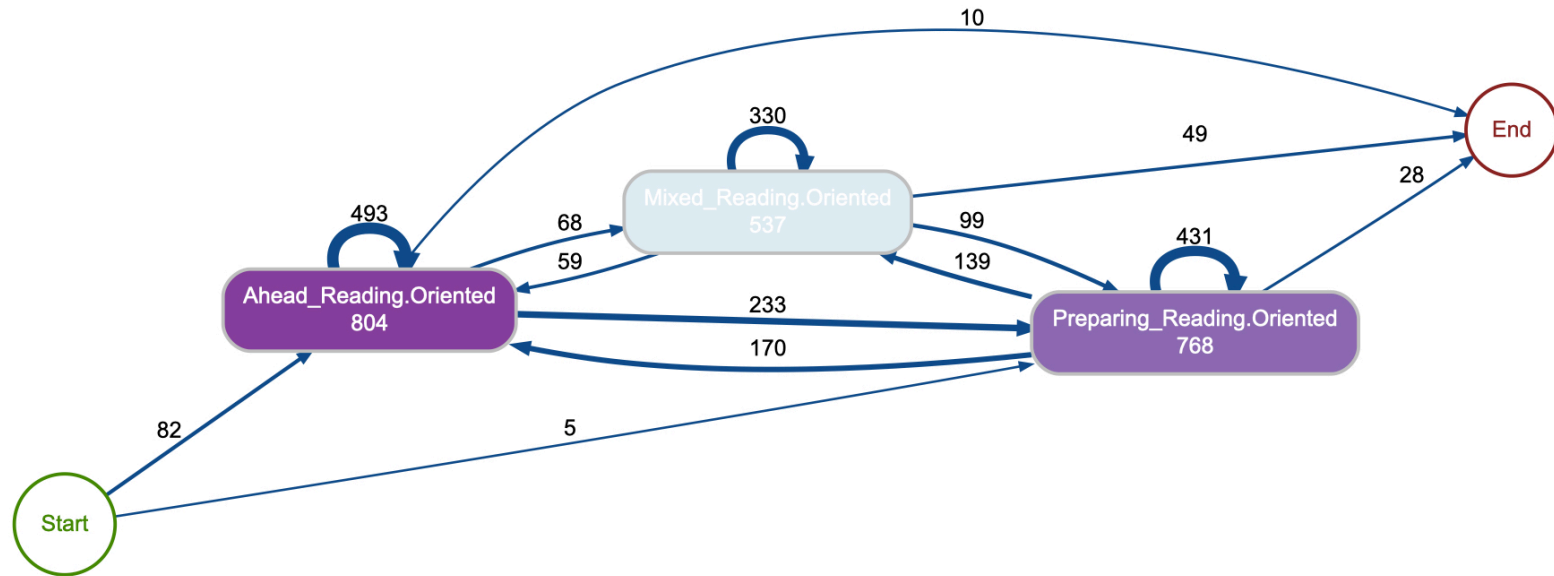
6. MULTIVOCAL ANALYTICS OF LEARNING STRATEGIES



(c) Diverse Strategy Group

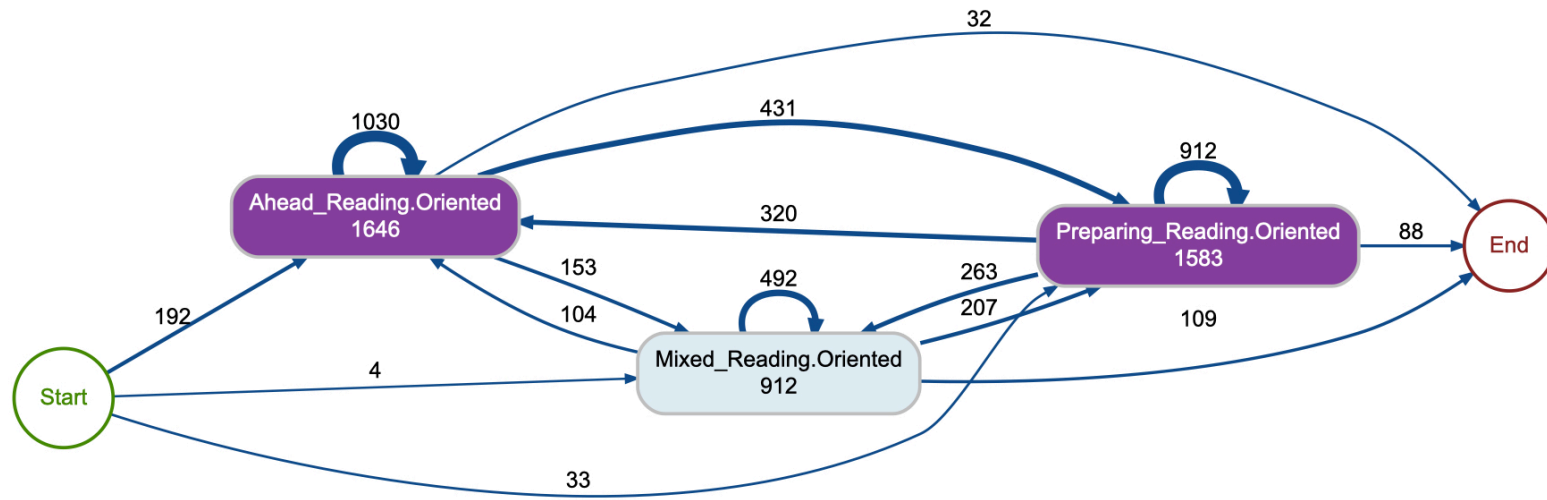
Figure S8: Idle time (in days) between the end of the from-activity and the start of the to-activity across the three strategy groups identified in the course based on the flipped classroom model.

Process Models: Health Science Course (Blended Learning Course)



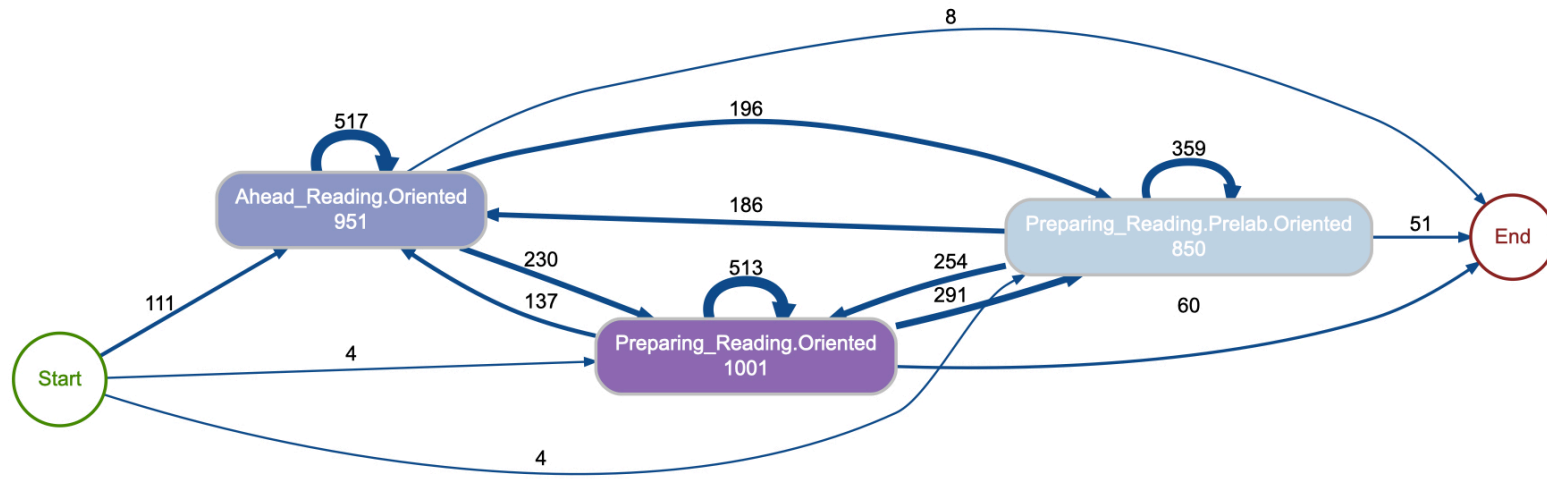
(a) Reading Strategy Group

6. MULTIVOCAL ANALYTICS OF LEARNING STRATEGIES



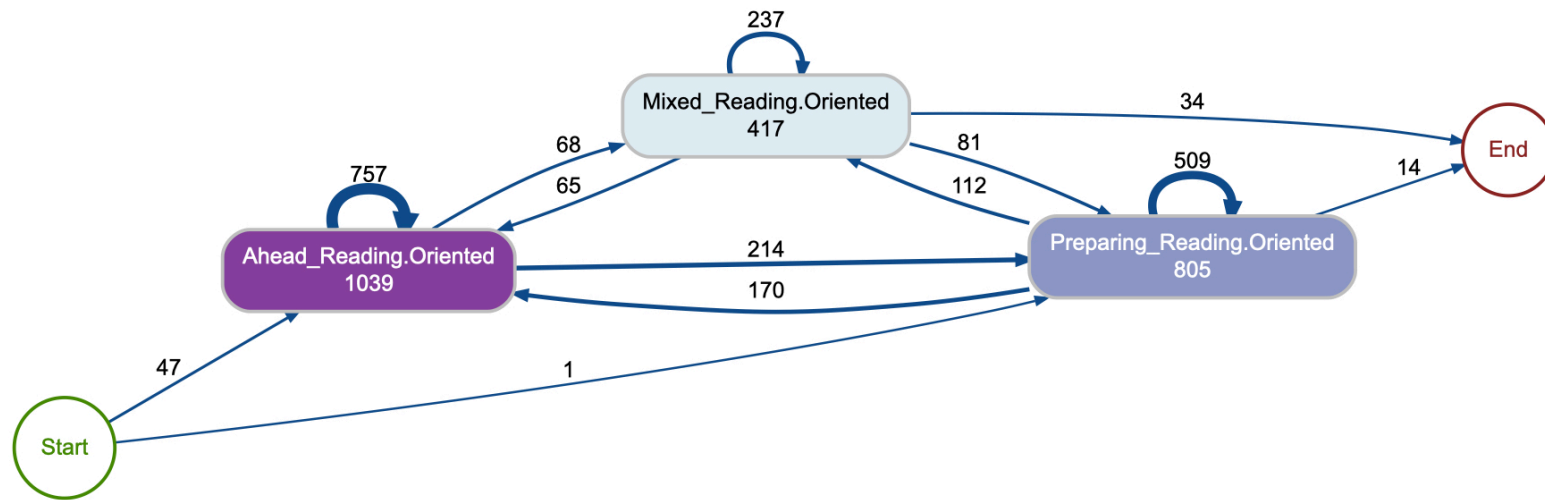
(b) Passive Strategy Group

6. MULTIVOCAL ANALYTICS OF LEARNING STRATEGIES



(c) Active Strategy Group

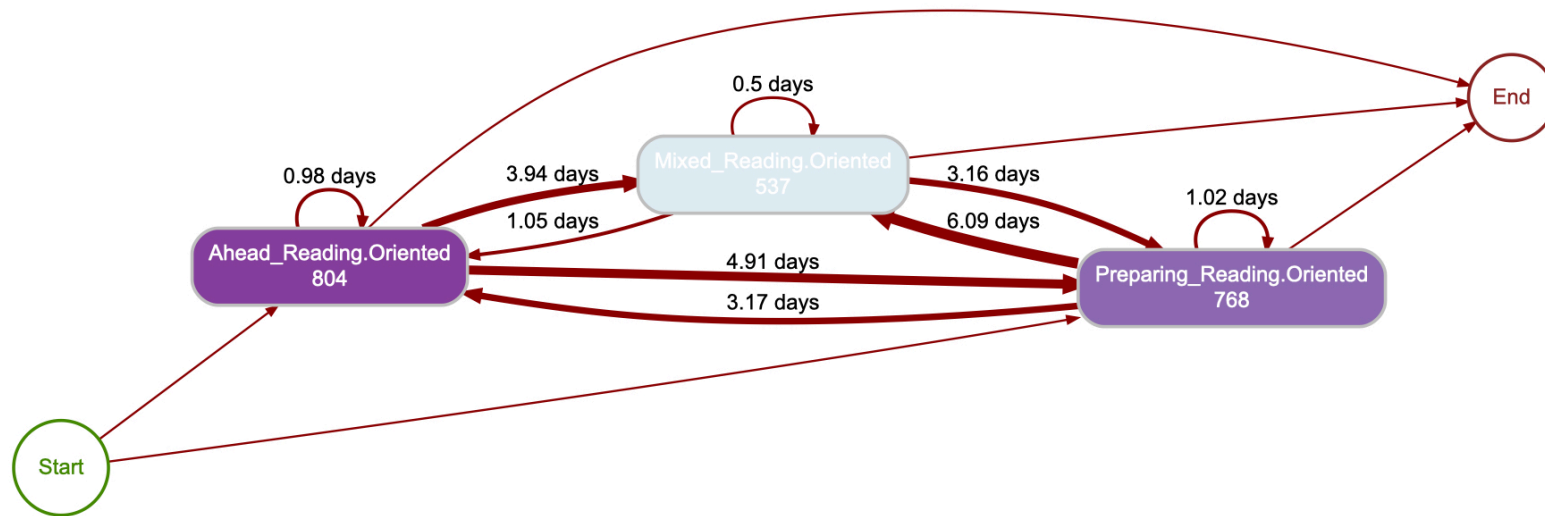
6. MULTIVOCAL ANALYTICS OF LEARNING STRATEGIES



(d) Selective Strategy Group

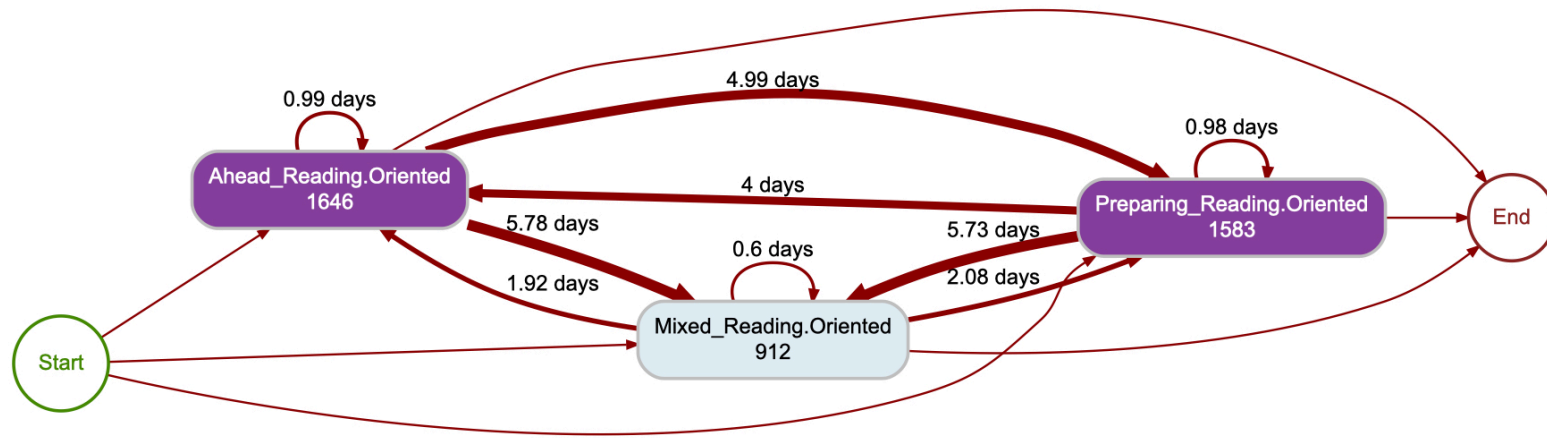
Figure S9: Process models, based on the frequency of occurrence, for the learning processes of the four identified strategy groups in the course based on blended learning.

6. MULTIVOCAL ANALYTICS OF LEARNING STRATEGIES



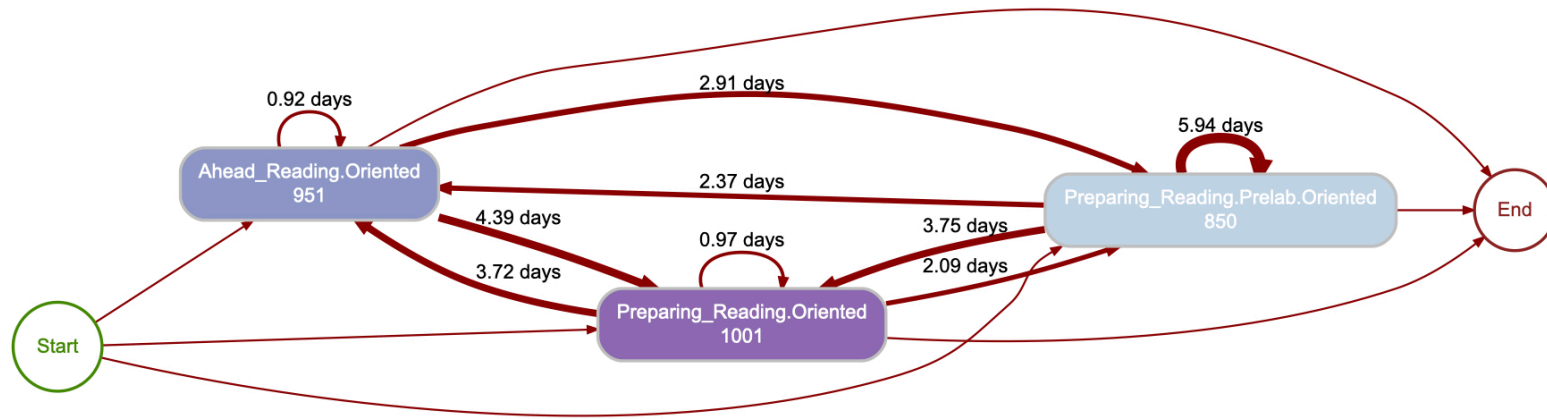
(a) Reading Strategy Group

6. MULTIVOCAL ANALYTICS OF LEARNING STRATEGIES



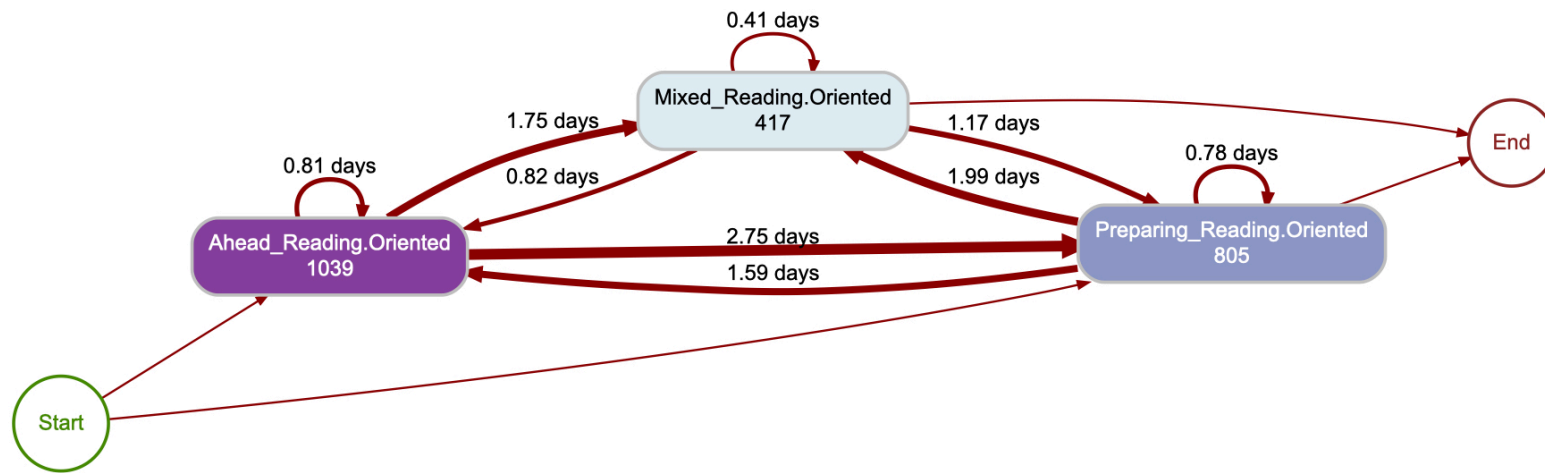
(b) Passive Strategy Group

6. MULTIVOCAL ANALYTICS OF LEARNING STRATEGIES



(c) Active Strategy Group

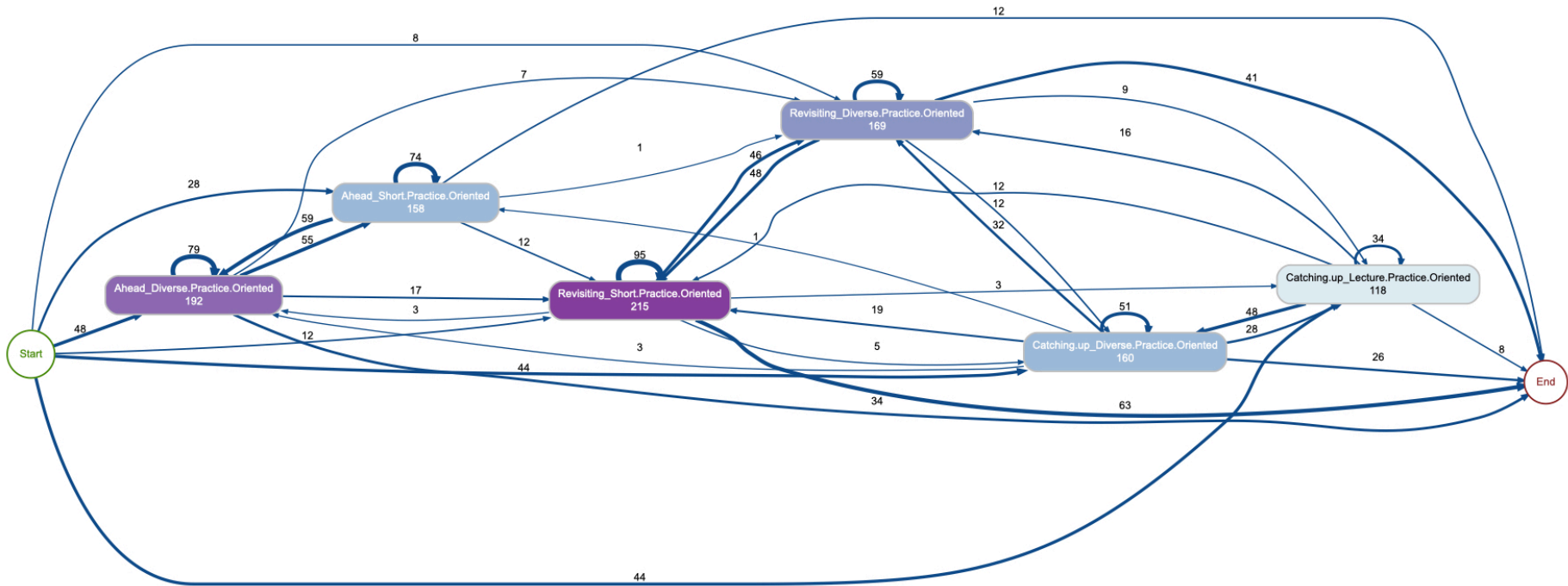
6. MULTIVOCAL ANALYTICS OF LEARNING STRATEGIES



(d) Selective Strategy Group

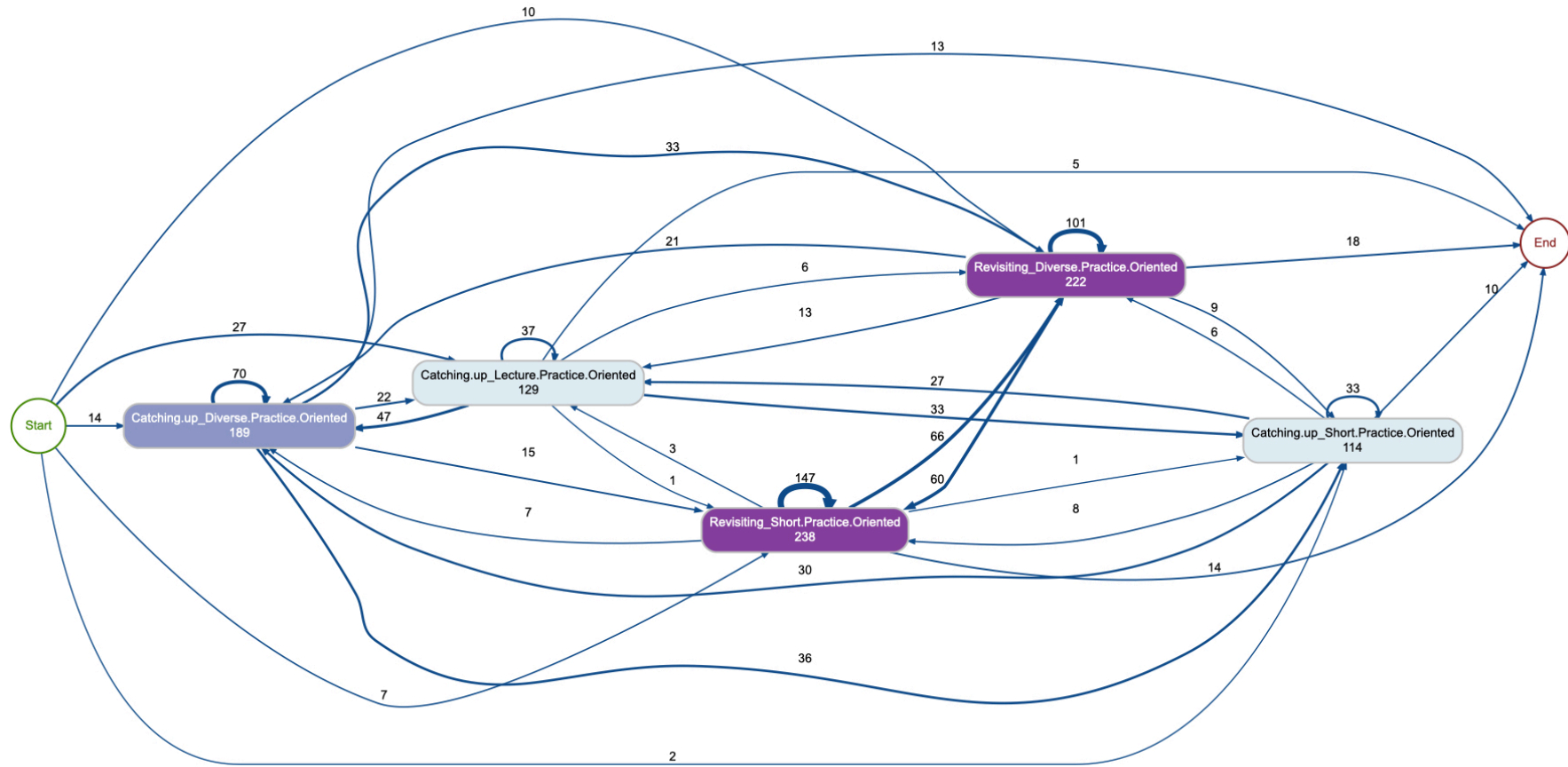
Figure S10: Idle time (in days) between the end of the from-activity and the start of the to-activity across four identified strategy groups in the course based on blended learning.

Process Models: Introduction to Python Course (Massive Open Online Course)



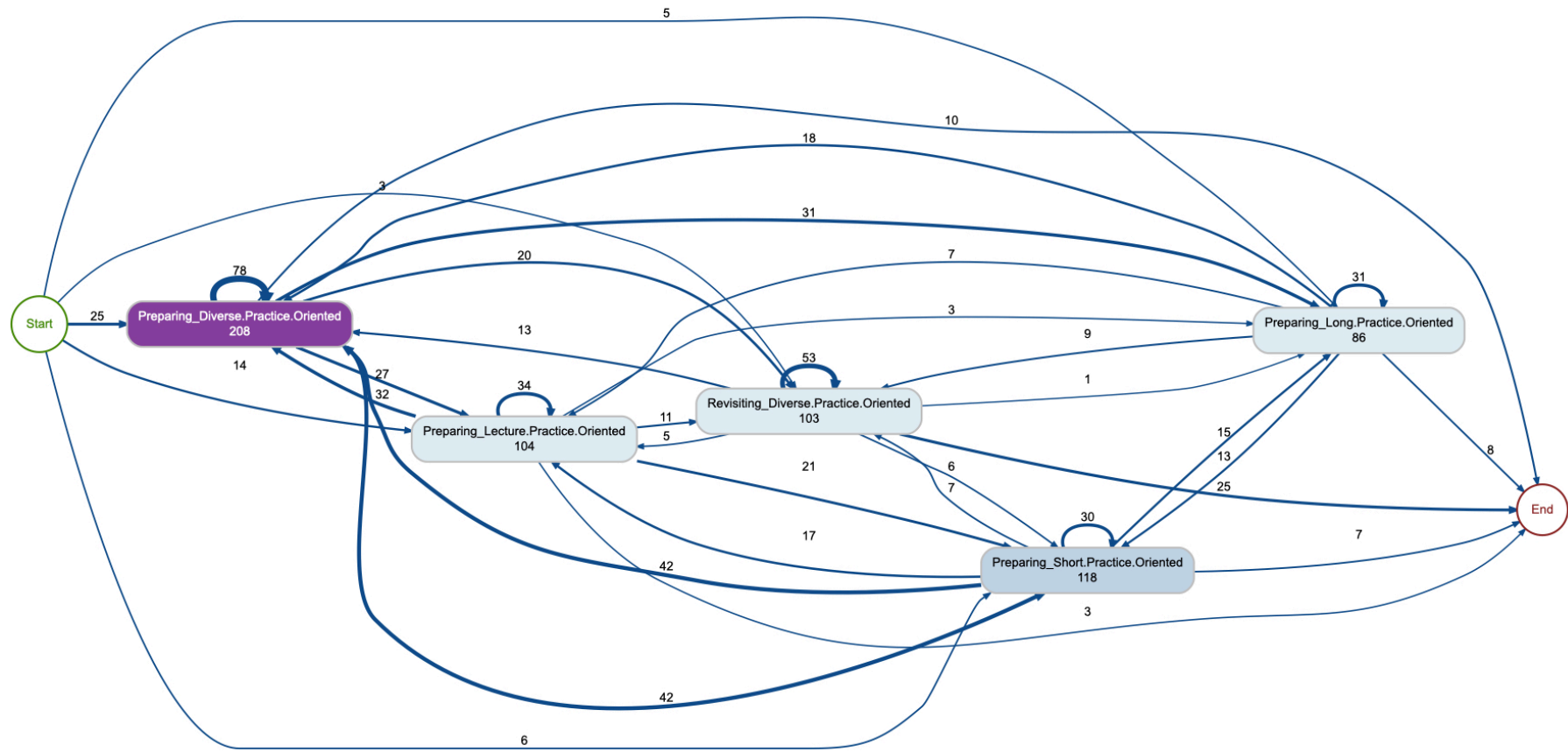
(a) Diverse Strategy Group

6. MULTIVOCAL ANALYTICS OF LEARNING STRATEGIES



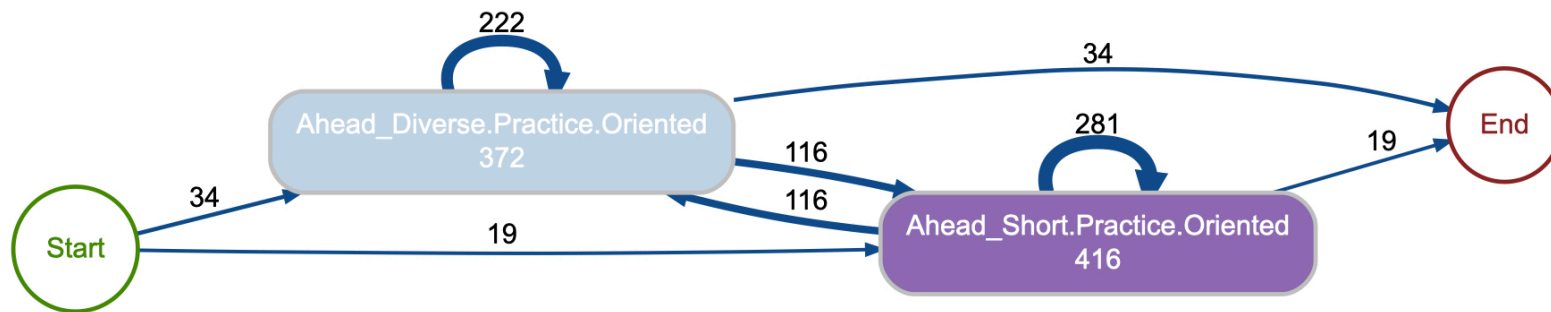
(c) Defer Strategy Group

6. MULTIVOCAL ANALYTICS OF LEARNING STRATEGIES



(d) Selective Strategy Group

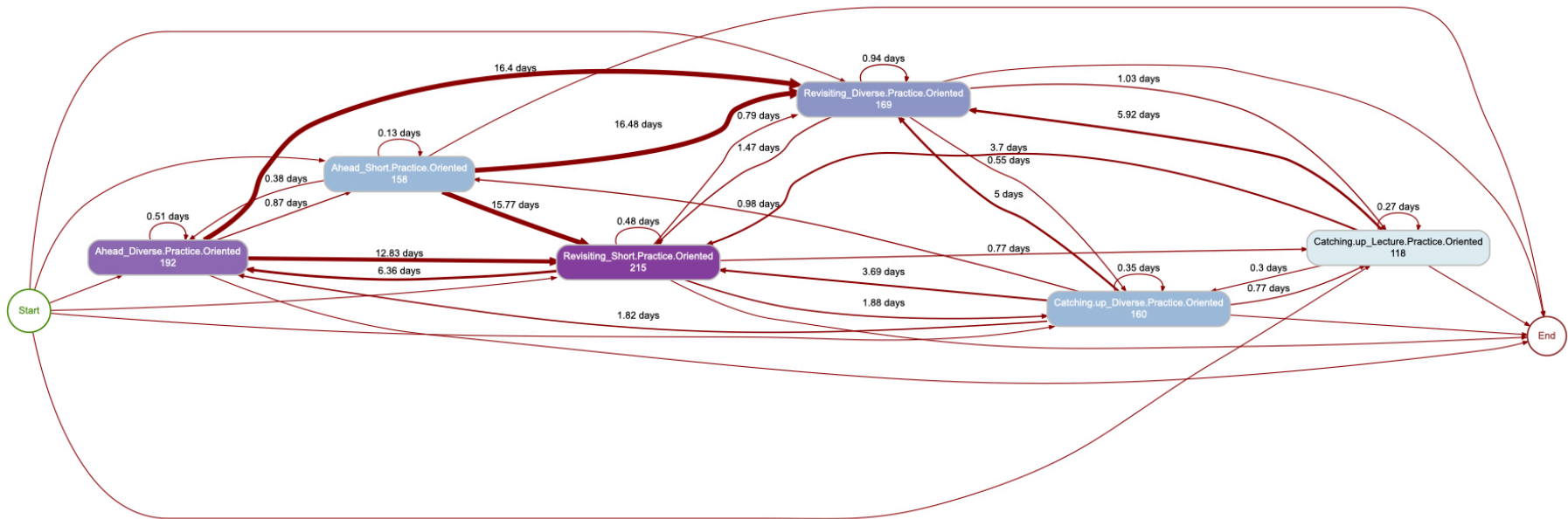
6. MULTIVOCAL ANALYTICS OF LEARNING STRATEGIES



(d) Advanced Strategy Group

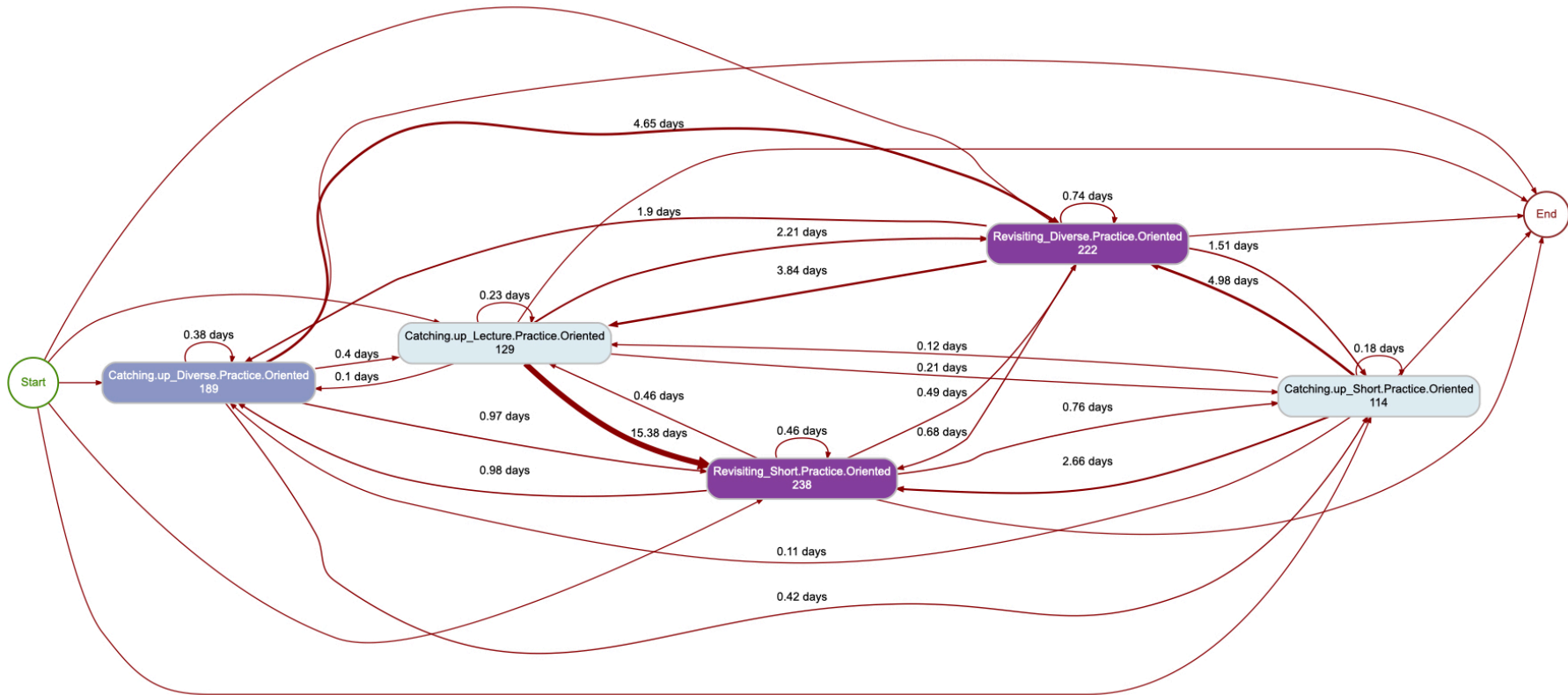
Figure S11: Process models, based on the frequency of occurrence, for the learning processes of the four identified strategy groups in the MOOC.

6. MULTIVOCAL ANALYTICS OF LEARNING STRATEGIES



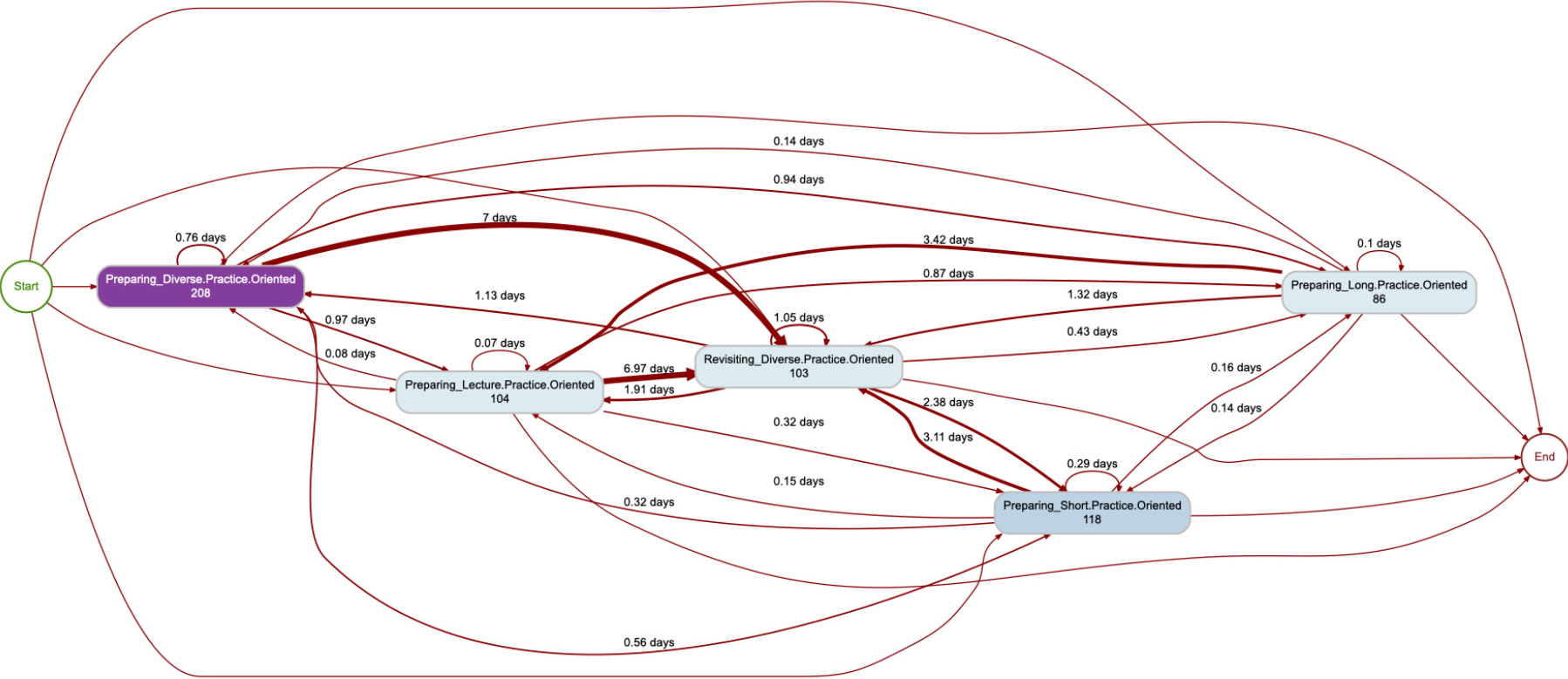
(a) Diverse Strategy Group

6. MULTIVOCAL ANALYTICS OF LEARNING STRATEGIES



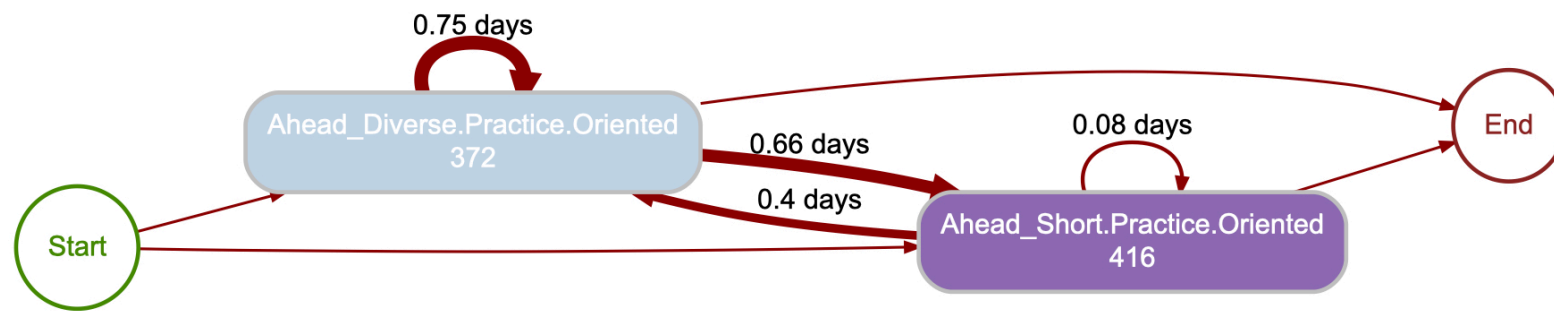
(b) Defer Strategy Group

6. MULTIVOCAL ANALYTICS OF LEARNING STRATEGIES



(c) Selective Strategy Group

6. MULTIVOCAL ANALYTICS OF LEARNING STRATEGIES



(d) Advanced Strategy Group

Figure S12: Idle time (in days) between the end of the from-activity and the start of the to-activity across the four identified strategy groups in the MOOC.

6.3 Summary

Building on the work presented in Chapter [five](#), the study in this chapter (Chapter [six](#)) seeks to check the validity and generalizability of the proposed method in a range of different educational contexts, including blended and purely online learning modes. To achieve this, large amounts of data, obtained from courses operated in various learning modalities (flipped classroom, blended learning, and MOOC) were analysed using a range of learning analytics methods interpreted using a multivocal approach. A valuable contribution of multivocality in this study is that the potential of the approach to examine tactics and strategies from multiple perspectives by using multiple analytics methods. Then, bringing together the findings of individual methods through the practice established in productive multivocality.

In essence, there are three major contributions to the work presented in this chapter. Firstly, we address research question four (RQ4) by replicating the proposed analytics methods across different learning contexts (flipped classroom, blended learning, and MOOC) on separate courses (i.e., computer engineering, public health, and software engineering). This study demonstrates that the proposed method is equally well applicable both in blended and online learning contexts, and the benefits of these methods are applicable across different learning modalities. Accordingly, we identify three strategy groups from the flipped classroom-based course (*Active, Selective and Diverse*); four strategy groups from blended learning-based course (*Active, Selective, Reading and Passive*) and MOOC (*Advanced, Selective, Delayed and Diverse*) respectively. Note that the detected learning strategies are varied and distinct in terms of the composition and regularity of tactics as well as the academic achievement of students.

Secondly, to address research question three (RQ3), we prove that both ENA and process mining are effective methods for gaining insights into temporal aspects of student's learning in terms of the process (i.e., transition from one tactic to another) and connection (i.e., the link between time management tactics and learning tactics) across three learning modalities and subject areas. This study shows that the learning strategies identified by using the proposed analytics method are consistent with the SRL theory (Winne & Hadwin, 1998) and principles of learning strategies (Dunlosky, 2013; Dunlosky et al., 2013).

Finally, to address research question two (RQ2), we demonstrate that the results of the Kruskal Wallis test have shown a significant association between the identified strategy groups and the academic achievement of students in the course. Besides, pairwise tests show that all the pairs of identified strategy groups in the flipped classroom, blended learning, and MOOC are significantly different with effect sizes (r) ranging from small to large.

Taken together, the works presented in Chapter [two](#) – Chapter [six](#) demonstrate how learning analytics methods and trace data can be useful for the measurement of latent constructs of student learning, particularly in presenting and interpreting meaningful tactics and strategies in blended and online learning settings. Ultimately, the generalizability of the proposed methods across three

learning contexts, as presented in this chapter (Chapter [six](#)) regards as a final investigation of this thesis. At the same time, our future work in this domain was discussed in Chapter [seven](#).

7

Conclusions and Future Directions

There is no real ending. It's just the place where you stop the story.

— Frank Herbert, *Magic Apples: Reflections to Mull*

The overarching idea of this thesis is to use trace data collected in learning environments to provide new insights into students' time management practices and related constructs using a range of learning analytics methods. In this thesis, we present novel and theoretically-grounded learning analytics methods that are validated across diverse online learning contexts. In particular, we demonstrate that time management is a pivotal construct in student's learning. In this chapter, we briefly summarize the key findings, contributions, and implications of the work presented in this thesis. We then discuss the key findings according to the four research questions presented in Section 1.1. Next, we outline the directions for future research, followed by the reflections on this research works. Finally, we conclude with a short overview of the thesis and a summary of its key contributions.

7.1 Summary of the present work

Table 4 summarizes the key contributions, findings and implications of the work presented in this thesis, as follows:

Table 4. Summary of the present work

Chapter 2	Detection of Time Management Tactics and Strategies
Contributions	Introduced a new definition of time management tactics and strategies. Developed a novel method, based on sequence mining, to detect time management tactics and strategies. Examined the association between strategies and academic performance.
Results	RQ1: Sequence mining based method enabled the detection of time management tactics and strategies from trace data.

RQ2: Detected time management strategies were positively associated with course performance.

Implications	<p>Real-time identification of time management tactics and strategies.</p> <p>Demonstrated that learners' choices of time management strategy are associated with their course performance.</p> <p>The proposed method can be used to discover time management tactics and strategies, and thus it could potentially inform the provision of feedback for effective study time practice.</p>
Chapter 3	Temporal Representation of Learners' Decision
Contributions	<p>Developed a new method, based on process mining, for automated detection of time management tactics and strategies.</p> <p>Applied the new process mining-based method to detect temporal differences across strategy groups.</p>
Results	<p>RQ1: The proposed method based on process mining generated meaningful results in terms of diversity, distributions, and coverage of time management tactics and strategies detected from trace data.</p> <p>RQ2: Identified significant differences in academic performance among students who followed different time management strategies.</p> <p>RQ3: Discovered clear differences in the temporal patterns (i.e., process and time) in the enactment of time management tactics across distinct strategy groups.</p>
Implications	<p>Provided an interpretable method for identification of time management tactics and strategies.</p> <p>The proposed method can be used to capture temporal changes in the learning process to unveil learners' decision on time management strategies.</p>
Chapter 4	Network Representation of Students' Learning
Contributions	<p>Demonstrated the interconnection between time management and learning strategies.</p> <p>Contributed both qualitative and quantitative descriptions to enhance insights into the learning process.</p>
Results	<p>RQ3: Revealed the selection of time management and learning strategies plays an important role in students' learning, and ultimately, academic performance.</p>
Implications	<p>The proposed analytic method can facilitate the investigation into mutual connections between time management and learning tactics.</p>

Revealed associations of learning and time management practices with academic performance.

Chapter 5 Analytics of Time Management and Learning Strategies	
Contributions	<p>Proposed a novel method that integrated both time management and learning tactics as components of learning strategies.</p> <p>Applied process and network analytic methods to offer novel insights into learning strategies.</p>
Results	<p>RQ4: Detected distinct learning strategies that were aligned with the principles documented in educational psychology.</p> <p>RQ3: Detected a substantial temporal difference (i.e., process and connection between tactics) between the strategy groups.</p> <p>RQ2: Identified learning strategies were strongly associated with academic performance.</p>
Implications	<p>Provided a holistic view of SRL in terms of the use of learning strategies in online settings.</p> <p>Offered deep insights into relevant temporal dimensions of students' learning.</p> <p>Allowed for a close inspection of the role of learning strategies according to educational psychology.</p>
Chapter 6 Multivocal Analytics of Learning Strategies	
Contributions	<p>Replicated the combined method proposed in Chapter five across different courses and contexts.</p> <p>Validated the method for rigorous evaluation of learning strategies.</p>
Results	<p>RQ4: The combined analytic method is equally well-applicable across three learning modalities and subject areas.</p> <p>RQ3: Demonstrated detailed insights into students' learning strategies (i.e., connection, process, and time) across three learning modalities.</p> <p>RQ2: Identified strategy groups across different learning contexts strongly associated with academic performance</p>
Implications	<p>Ensured reliability of the proposed combined methods across different learning contexts.</p> <p>Enhanced interpretability, validity, and applicability of our proposed methods.</p>

7.2 Impact of the present work

7.2.1 RQ 1: Novel methods of detection tactics and strategies

In both Chapter [two](#) and Chapter [three](#), we describe novel methods to detect time management tactics and strategies. The primary motivation behind the development of the methods are: (i) to provide a comprehensive analytic methods for detecting patterns of students' time management on online learning platforms, and (ii) to serve as a groundwork for analytics of time management through the lens of self-regulated learning.

In Chapter [two](#), we first present a study that repurposed the method proposed by Jovanovic et al. (2017) for the detection of time management tactics and strategies. Building on Jovanovic et al. (2017)'s work, we applied a combination of a sequence mining method and agglomerative hierarchical clustering to detect patterns in learning activities, which helped us identify time management strategies. Following the work in Chapter [two](#), the study presented in Chapter [three](#) attempted to overcome some of the issues concerning subjectivity introduced by agglomerative hierarchical clustering. We developed an automated method to detect time management tactics using process mining and unsupervised clustering methods.

Our methods for detecting tactics and strategies rely on a linear pipeline. Note that each component of the pipeline (i.e., analytics method) has its well-defined place and role. As such, in each step, different analytics methods are used for very specific analysis. The overall analytics process consists of three phases: (i) the labelling of learning actions with the mode of study (preparing, revising, catching-up, and ahead) is automatically performed according to the time when students carry out an action, which is identified based on timestamps available in trace data and validated against the course design, (ii) the detection of tactics is an automated identification of sequences of time-related enactment of learning actions within a learning session, and (iii) the detection of strategy groups using an unsupervised machine learning algorithm to cluster similar learning patterns identified in the preceding step. The findings demonstrate that time management patterns, indicative of time management tactics, can be detected from students' learning sessions. Time management tactics, automatically detected, can further lead to the identification of time management strategies. In doing so, the thesis provides a clear and descriptive approach to ease future replication, adoption, and adjustment of the methods for different learning contexts.

In addition, Chapter [two](#) offers a new functional definition of time management tactics and strategies with the intention to increase interpretability of analytics of time management where: *“time management tactics can be defined as a sequence of time-related decisions and enactment of learning actions during a learning session to meet the requirements of specified tasks, whereas strategies represent sets of enacted time management tactics made up by selecting, combining, or redesigning those tactics as directed by a learning goal.”* (Ahmad Uzir, Gašević, Matcha, Jovanović, & Pardo, 2020, p. 4). This thesis is heavily grounded in Winne and Hadwin (1998)'s model of SRL and Dunlosky (2013)

learning strategies principles. In this way, we provide one of the first examples showing how the development of learning analytics methods that can be linked to existing educational theories.

7.2.2 RQ 2: Associations with academic performance

According to Messick (1995), validity is defined as a multi-faceted construct that may be divided into three core types, namely (i) structural validity, or the extent to which a metric or measurement actually describes the construct it is intended to capture, (ii) generalizability, or the extent to which a measurement captures the same construct across populations, and (iii) external validity, such as supportive or dissuasive evidence arising from related constructs. In this thesis, we seek to demonstrate the validity of the learning analytics methods for the detection of time management tactics and strategies by demonstrating their external validity through the association with academic performance (i.e., the students' scores).

The external validation is tested and presented in all chapters (Chapter two – Chapter six) except for Chapter four. We find significant associations between time management strategies and academic performance. This finding further corroborates the idea that more active and directive time management strategies are often positively associated with academic performance. It is important to note that not a single study presented in this thesis has reported a negative association between time management strategies and academic performance, thus suggesting the stability and robustness of the proposed methods across different learning contexts.

By providing validated and theoretically-grounded analytics of time management, the adoption of the proposed method can help researchers and practitioners to improve the interpretation of students' behaviour regarding time management strategies. Furthermore, our research clearly points to the need to take time management aspects into consideration when developing approaches that aim to advance the understanding of learning and optimize learning. For example, the incorporation of suggestions on time management into feedback for students can stress the importance for students to exercise metacognitive control and monitoring of learning, which in turn can improve their academic performance.

7.2.3 RQ 3: New insight into temporal dimensions

In addition, to verify our methods, it is essential to understand if the decisions that students make can influence their levels of regulation and academic performance. With the ability to process large quantities of data in an automated manner, learning analytics methods can provide enriched and meaningful insights into students' learning processes over extended periods (e.g., course duration).

Our research on the temporal dimension of learning has uncovered how patterns and processes of SRL unfold over time. According to Chen et al. (2018), temporal dimensions relate to the passage of time in learning (e.g., how long and how often students engage), whereas the sequential dimensions are the order in which learning tasks take place. Thus, a combined temporal and sequential

analysis offers a new perspective on time management and ways to improve SRL as a whole.

Overall, our results reveal clear differences in the temporal patterns between the students who employ different time management strategies in terms of their process (i.e., transition from one tactic to another), connection (i.e., the link of time management tactics and learning tactics) and time (i.e., interval time between the enactment of one tactic and another). Moreover, the thesis also identifies important differences concerning SRL skills and academic performance, as evidenced in Chapter [three](#), Chapter [five](#), and Chapter [six](#).

There are several significant contributions with respect to this research question. The first study into the temporal dimension is presented in Chapter [three](#). In this chapter, we demonstrate that temporal data about students' interactions with online environments can be analyzed using process mining methods. As such, we present empirical evidence on what, how, and how long students enact their time management tactics across different time management strategy groups and academic achievement. Second, in Chapter [four](#), we demonstrate that ENA combined with sample t-test can offer both qualitative and quantitative descriptions to add precision into the comparison of learning processes between high and low performing groups. Finally, the same process mining method is reapplied in the follow-up studies reported in Chapter [five](#) and Chapter [six](#). We combine the use of process mining with epistemic network analysis to compute and visualize combinations of time management and learning tactics as a way to analyze learning strategies holistically. Given that learning is a complex phenomenon, our results point to the need for creative synergies of multiple learning analytics methods in order to provide richer insights into relevant learning dimensions than individual methods alone can achieve.

7.2.4 RQ 4: Ensuring validity and generalizability

As this thesis seeks to contribute to broad educational research and practice, Chapter [six](#) replicates the use of the learning analytics method proposed in Chapter [five](#) on the data sets collected in different learning contexts, including courses based on the flipped classroom, blended learning, and MOOC delivery modalities. To enhance the interpretability, validity, and generality of our proposed method, Chapter [six](#) demonstrates the importance of the diversity of methodological approaches, large-scale learning data, and multi-lens (theoretical) perspectives. This chapter provides a rich and theoretically meaningful analysis of time management. In particular, the study presented in this chapter emphasizes the significance of multivocality in learning analytics methods for study time management and other relevant learning constructs. In summary, multivocality is an effort that brings together theoretical and methodological understandings to provide valuable insights into students' learning.

Taken together, we conducted a study, as reported in Chapter [six](#), with two aims: First, the study was devoted to produce empirical evidence that can support the generalizability of the proposed learning analytics method for the analysis of time management. This study is done by reapplying the

method to the data sets collected across three learning contexts. The proposed method was found to be able to provide detailed insights into students' learning strategies (i.e., connection, process, and time) while students carried out online tasks. Second, we validated that a creative synergy of multiple learning analytics methods can allow for a rigorous evaluation of learning strategies that are meaningful from the perspective of relevant theories and are associated with academic performance. This study revealed that learning strategies found by using the proposed analytics method were consistent with the SRL theory and principles of learning strategies (Dunlosky, 2013; Winne & Hadwin, 1998). Winne and Hadwin (1998)'s SRL perspective can offer a ground theory that can guide the analysis of students' regulation, i.e., cognition, metacognition, and motivation constructed through SRL phases while Dunlosky (2013)'s perspective can provide theoretical points of the articulation of effective learning strategies.

7.3 Directions for future research

There are also several promising directions for future research to expand and replicate the findings of this thesis. In addition, given that the majority of the studies presented in this thesis are focused on trace data and learning analytics methods, several limitations need to be carefully considered in the future.

Trace data have proven beneficial for capturing and examining latent learning constructs in authentic learning settings. However, trace data have a limited capacity in terms of facilitating the interpretation of the underlying reasons behind behavioural patterns. For instance, it is not immediately clear why students decide to adopt certain tactics and strategies and what might have motivated their actions. A possible approach for future investigation is to use self-reported instruments such as think-aloud protocols, interviews, or surveys to complement insights obtained from trace data. In this way, combinations of both trace data and self-reported data can provide additional evidence towards deepening the understanding of students' time management practices in blended and online learning environments.

Recent research has recognized the importance of grounding learning analytics in feedback theories to provide personalized feedback at scale (Pardo, 2017; Pardo, Poquet, Martinez-Maldonado, & Dawson, 2017). This line of research includes the formation of feedback messages that are parameterized based on the indicators captured by learning analytics. Considerable work has been demonstrated in the work by Pardo and colleagues on feedback provision (Pardo, 2017). According to Pardo et al. (2017) the idea behind analytics-based personalized feedback is to combine digital trace data typically captured by computer-mediated technology with the instructor knowledge to provide more elaborated and personalized feedback to individual learners in an instructional and timely manner.

In the literature, feedback is seen as a crucial way to facilitate students before they are able to gain their own cognitive footing (Azevedo et al., 2013; Butler & Winne, 1995; Winne & Hadwin,

2013). In a follow-up to this line of research, several studies have investigated feedback and its importance in promoting effective learning and overall academic achievement (Tanes, Arnold, King, & Remnet, 2011; Thornock, 2016; Van Der Kleij, Eggen, Timmers, & Veldkamp, 2012; Zingoni & Byron, 2017). There was, however, a lack of empirical studies of learning analytics-based feedback aimed to promote effective time management behaviour in student learning or to provide clear guidelines on the ideal time frame to send feedback to the learners.

Hence, another important direction is to translate the results presented in this thesis by applying the proposed learning analytics methods for time management into actionable feedback to help students develop effective time management. The contribution of the present work is to propose the desirable duration of feedback (i.e., how long learning analytics-based feedback related to the students' time management practices) should be given to the learner to support SRL skills and to promote positive academic outcome.

7.4 Reflection

This following section reflects upon the process of completing this thesis, from the preparing the data, through analysing it, interpreting results, and writing up. It addresses some of challenges which were encountered at each of these phases and emphasizes particularly the importance of each phases to resolve the research questions I hoped to answer.

This research began with data cleaning and preparation of initial raw data which extracted from online learning environments. The data were obtained from large cohorts of students, from three learning delivery modalities and from different institutions. I must admit that not all digital data was always in the best condition. It required much work and careful thought just to ensure that the data was ready for analysis. During my first year, I spent most of my time cleaning, understanding, and re-analysing the data. I did mistakes at the beginning of the study, in which I needed to keep re-running the analysis iteratively and checking the logs after fixing each error due to poorly formatted and duplicated data. Although it may initially have seemed daunting and tedious tasks, it was well worth the effort to get familiar with the data, to identify data quality problems, and to discover first insights into the data. The important lesson learned here is that data cleaning and preparation is a critical first step in any machine learning because quality of the results can be determined by the data that you feed them.

After I created a fully comprehensive dataset, I would start with data analysis. I used the R language for data analysis. Why R? Initially, R was recommended by my supervisor and I had never heard of it before. I then started to learn R, but I did struggle with it mostly due to my limited experience in programming. So, then I attend several R training workshops to learn effective ways to analyse data using R. At first, I found it quite hard and frustrating because I encountered many errors and failures while running my R scripts. Fortunately, I had a supportive supervisor and research partners who guided me through this. I would say that I took at least two months before I

was familiar enough with R to start enjoy working with it.

I started the data analysis process by replicating the foregoing analytical method used in the prominent literature relevant for my study context. This meant I had a starting point to explore methods that I could adopt and adapt to my study. I found that this method was relevant in terms of detecting time management tactics and strategies. However, there were still some gaps in the analysis. To bridge this gap, I tried to find other methods that could provide answers to my research questions. I then started to apply other methods that would suit my research context better. This involved a fair amount of trial-and-error attempts. Apart from data preparation, I also spent more time on data analysis. I explored many unsupervised machine methods to find the most appropriate approach to answer my research questions. This work was not a linear process, but more of a well-rounded journey, in which I was constantly reading, analysing, writing, and refining throughout the whole period of my study. Over time, I was able to extend my understanding, adjust my approach to overcome some initial issues, and develop a method which I thought was appropriate to the nature of my particular research questions. In the end, this led me to do something completely new.

To do this I was not working completely independently. I was working closely with my research partner and fellow PhD student (Wannisa Matcha), sought expert advice and help to ensure accurate, reliable, and relevant analysis. Apart from that, I had weekly meetings and presented results of analysis to my principal supervisor. If the results were not satisfying enough, he will guide and suggest new ways to explore. I cannot express enough how important it was to have an excellent supervisor who meets with you regularly and provides you with the expertise and guidance that is essential to complete a PhD.

My thesis is based on the inclusion of papers that are already published or submitted for publication. This required writing a number of academic papers, which constitute the chapters of the final thesis. However, the main challenge was to put all these individual papers into the thesis that offers a consistent story. For me, writing is hard work and I consistently struggled during the final writing phase, that involved writing the thesis introduction and conclusion as well as the introductions into and summaries of individual chapters. My main trouble while writing was that I keep writing and deleting sentences, which at the end of the day resulted in ending up with nothing on my work sheet. After reflecting on the writing process, I realized that I needed to modify my writing approach because obviously I could not achieve the perfection in my first draft and yet, make no substantial progress. I still remember one piece of advice from my friends when we talked about this who suggested “don’t get it right yet, get it written”. So, I took that advice and started to focus and dedicated at least two months to the intensive writing of the final thesis document. After the introductions and summaries of the five papers chapters and the thesis introduction and conclusion chapters had been written, I then started to revise, rewrite and refine chapter by chapter before submitting to my supervisors. It took at least four to five times of review, revise and rework iteratively before this thesis was ready for submission. I found that the lengthy comment, feedback and

constructive criticism from my supervisors were extremely helpful in improving the quality of the thesis, although receiving feedback from them could be a nerve-wracking experience – all the times.

In summary, reflecting on my experience, I have learnt so much through my PhD. I managed to produce a coherent and approximately 45,000 word-long thesis, published one journal and two conference papers, and another two papers are submitted for review in journals. My PhD stretched me intellectually and emotionally, but I am immensely proud of what I have achieved and actually enjoyed much of the journey. Thanks again to my principal supervisor and my mentor, Professor Dragan Gašević who is the reason behind my success.

7.5 Conclusions

In conclusion, this thesis has proposed a novel methodological approach that offers first insights into time management and learning strategies through the lens of established educational theory and principle. In addition, the work presented in this thesis also provides further evidence about the importance of adopting a range of learning analytics methods to enhance our understanding of the temporality of regulation processes and their association with academic performance. Ultimately, the novel methods proposed in this thesis can enhance the precision in measuring time management and other latent constructs that are hard to be achieved with self-reported measures alone.

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