ANALYTICS OF SELF-REGULATED LEARNING: A TEMPORAL AND SEQUENTIAL APPROACH

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For Mam

Abstract

In educational settings, the increasingly sophisticated use of digital technology has provided students with greater agency over their learning. This has focused educational research on the metacognitive and cognitive activities with which students engage to manage their learning and the achievement of their learning goals. This field of research is articulated as self-regulated learning (SRL) and has seen the development of several key theoretical models. Despite key differences, these models are broadly defined by thematic variations of the same fundamental phases: i) a preparatory phase; ii) a performance phase, and; iii) an appraisal phase. Given the phasic nature of these models, the conceptualisation of SRL as a phenomenon that unfolds in temporal space has gained much traction. In acknowledging this dimension of SRL, researchers are bound to address the methodological demands of process, sequence, and temporality. Learning Analytics research, however, is largely characterised by the use of statistical models for data interrogation and analysis. Despite their value, several researchers posit that the use of statistical methods imposes ontological limitations with respect to the temporal and sequential nature of SRL. Another challenge is that while learner data are mostly collected at the micro level, (e.g., page access, video view, quiz attempt), SRL theory is defined at a macro level (e.g., planning, monitoring, evaluation), highlighting a need to bridge this gap in order to provide meaningful results. This thesis aims to explore the methodological opportunities and address the theoretical challenges presented in the area of temporally focused SRL learning analytics.

First, the thesis explores the corpus of research in the area. As such, we present a systematic review of literature that analyses the findings of studies that explore SRL through the lenses of order and sequence, to provide insights into the temporal dynamics of SRL. Second, the thesis demonstrates the use of a novel process mining method to analyse how certain temporal activity traits relate to academic performance. We determined that more strategically minded activity, embodying aspects self-regulation, generally demonstrated to be more successful than less disciplined reactive behaviours. Third, the thesis presents a methodological framework designed to embed our analyses in a model of SRL. It comprises the use of: i) micro-level processing to transform raw trace data into SRL processes; and ii) first order Markov models to explore the temporal associations between SRL processes. We call this the "Trace-SRL" framework. Fourth, using the Trace-SRL framework,

the thesis explores the deployment of multiple analytic methods and posits that richer insights can be gained through a combined methodological perspective. Fifth, building on this theme, the thesis presents a systematic analysis of four process mining algorithms, as deployed in the exploration of common SRL event data, concluding that the choice of algorithm and metric is of key importance in temporally-focused SRL research, and that combined metrics can provide deeper insights than those presented individually. 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 approaches for analysis of patterns of self-regulated learning (SRL) as extracted from data generated from authentic learning management systems. Embedding our analyses in a recognised theoretical framework, we investigated how the temporal and sequential dynamics of SRL can be explored through the use of several process-based analytic methods. We also present a systematic review of the corpus of research in the area of temporally focused SRL. This study contributes to the understanding of how certain analytic methods can provide insights into the dynamics of self-regulation; specifically how they provide insights not possible with conventional statistical methods. In summary, this thesis provides the promise of theoretically-grounded insights based on a large scale analysis of digital trace data.

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I am extremely lucky to have had Professor Dragan Gašević as my principal supervisor throughout this journey. His passion and insight are only matched by his sense of care for his students; he is a true inspiration. He has helped me grow as student and teacher, and for that I am eternally grateful.

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I must express my thanks to Eleanor Alty for her relentless support at every turn, even as I careered between crippling self-doubt and groundless self-aggrandisement, and for her scrupulous proofreading. I thank my family, Helen, Philip, and Joanne, for their support and patience throughout. Also thanks to extended family, Dotty, for keeping me on the right track along the way!

I wish I could share my achievements with my dad, Stan, and my beloved sister, Jean, whom I know would be proud of me at this moment. Ultimately, I dedicate this work to a fellow educator, my first teacher, my mother, Vera. I got there in the end, Mam.

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 joint authorship:

1. Saint, J., Fan, Y., Gašević, D., & Pardo, A. (2021). Temporally focused Self-regulated Learning: A Systematic Review of Literature

2. Saint, J., Gašević, D., & Pardo, A. (2018). Detecting Learning Strategies Through Process Mining. In V. Pammer-Schindler, M. Pérez-Sanagustín, H. Drachsler, R. Elferink, & M. Scheffel (Eds.), *Lifelong Technology-Enhanced Learning* (pp. 385–398). Springer International Publishing. https://doi.org/10.1007/978-3-319-98572-5_29

3. Saint, J., Whitelock-Wainwright, A., Gašević, D., & Pardo, A. (2020). Trace-SRL: A Framework for Analysis of Microlevel Processes of Self-Regulated Learning From Trace Data [Conference Name: IEEE Transactions on Learning Technologies]. *IEEE Transactions on Learning Technologies*, *13*(4), 861–877. https://doi.org/10.1109/TLT.2020.3027496

4. Saint, J., Gašević, D., Matcha, W., Ahmad Uzir, N., & Pardo, A. (2020). Combining analytic methods to unlock sequential and temporal patterns of self-regulated learning. *Proceedings of the Tenth International Conference on Learning Analytics & Knowledge*, 402–411. https://doi.org/10.1145/3375462.3375487

5. Saint, J., Fan, Y., Singh, S., Gasevic, D., & Pardo, A. (2021). Using process mining to analyse self-regulated learning: A systematic analysis of four algorithms. *LAK21: 11th International Learning Analytics and Knowledge Conference*, 333–343. https://doi.org/10.1145/3448139.3448171

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 conceptualisation, data collection, data analysis, and interpretation, as well as the writing of the final publications.

John Saint

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1 Introduction

John, that is the least of your worries...

— Dragan Gašević, *General Wisdom*

DIGITAL technology in now integral to the design and delivery of education at all levels. Whether these digital resources exist to support face-to-face teaching, blended environments, or complete online platforms, their impact is manifold. The affordances of technology provide learning designers with the tools to create innovative content, and means of engaging the needs of learners who seek a more dynamic form of education. Critically, it is shaping the ways in which students engage with their learning, and how they manage the learning resources available to them. A key outcome of this is the digital imprint students leave as they navigate the various learning management systems (LMSs) that underpin modern education. The data generated from such systems have provided educational researchers with a wealth of opportunities to examine the way in which students navigate their learning resources, and has driven the rise of learning analytics (LA) as a developing field of research (Knight & Buckingham Shum, 2017). This rise has seen the exploration of new ways to research learning and teaching (Viberg et al., 2018), and the re-positioning of educational theories in data-driven contexts (e.g., Winne et al. (2010), Winne and Hadwin (2013), Järvelä et al. (2013)). One theoretical perspective that has enjoyed a particular increase in focus is self-regulated learning (SRL) (Roll & Winne, 2015).

SRL is predicated on the notion that students have agency over their own learning; they have the capacity to use their own meta-cognitive and cognitive skills to reach their learning goals, making use of educational resources, inherent feedback mechanisms, and internal judgement throughout the process (Winne & Perry, 2000; Zimmerman, 2000). Learning resources have grown in sophistication and, with a nod to the constructivist learning theories (Piaget, 1972), this has resulted in recognition of the shift of the shared responsibility of learning from the teacher to the student. For example, consider a student engaging in goal setting and planning at the beginning of an assignment, undertaking and monitoring the status of a key task, then evaluating the outcome before revisiting and re-planning; we view this as a cycle of SRL. Theoreticians of SRL agree that self-regulated learners tend to be more effective than their passive peers (Pintrich & de Groot, 1990; Zimmerman, 1989) and it is incumbent on the LA community to explore ways of analysing and measuring SRL with a view to supporting learners as they navigate it. SRL theorists—Winne and Hadwin (1998), Zimmerman (2000), Pintrich (2000), and Boekaerts (1996)— have all developed their models through iterations of empirical testing and literature synthesis; the use of such models answers the call, articulated by Gašević et al. (2015), that LA research should always have a strong basis in recognised theories of learning. Conceptually, SRL can be viewed from two perspectives: i) as a set of learner characteristics or traits, as emphasised in the Efklides (2011) model, and; ii) as a strategy-driven cyclical process, as emphasised by Winne and Perry (2000).

The latter view positions SRL as an ongoing process which unfolds and develops over time. In this temporal context, Panadero (2017) highlights a key factor; all of the major models are defined by thematic variations of the same fundamental cycle of SRL: i) a preparatory phase, ii) a performance phase, and iii) an appraisal phase. This conceptualisation directs a focus onto the dynamics of SRL in terms of order, sequence and temporality. In acknowledging the temporal dimension of SRL, researchers are bound to accept a change in methodological viewpoint. A large section of quantitative LA research is underpinned by statistical modelling for data analysis and discovery. Indeed, many of these studies, (e.g., Paans et al. (2019), and Greene et al. (2019)) provide critical insights into SRL. This notwithstanding, an opinion suggests that this variable-centered view, as typified by statistical analysis, imposes ontological limitations in temporally focused studies (Reimann, 2009). In short, how do we talk about the way in which learners move between and interact with the various elements and artefacts in a modern educational environment? How do we measure it? This, in itself, requires a fundamental shift in perspective. For example, statistical analysis could indicate levels of relative engagement in learning activities, such as planning, engagement and reflection in groups of learners. This would not, however, provide insights into the likely sequences in which these activities were tackled, or how closely these activities happened together in time. These types of temporal and sequential dimensions have synergy with the notion of learning as a fluid and semi-cyclical process. Molenaar (2014) recognised the paradigmatic shift implicit in this notion and highlights the need for common understanding of how temporal dimensions can inform a research narrative and an understanding of the appropriate methods to analyse these dimensions.

Despite the increasing conceptual importance of the temporal dimensions of SRL, there is no systematic treatment of the research in this area. SRL as a trait and as a process is a key concept in learning and teaching theory that has gained enormous traction, and the number of SRL studies is testament to its importance. More telling is the number of SRL systematic reviews of literature; Devolder et al. (2012), Wong et al. (2019), and Cerón et al., 2021, are just three examples of fourteen reviews undertaken in recent years (see Chapter two). Given that researchers are recognising the increasing importance of the notion that learning is a process that unfolds in sequences over time (Molenaar, 2014; Reimann, 2009), the work by Knight et al. (2017) and Chen et al. (2018)

represents a significant step in furthering the cause of temporally focused LA. The Knight and Chen journal collections provide compelling reasons to consider the temporal dimension, and this dimension synergises strongly with SRL (Butler & Winne, 1995; Winne, 2014). Despite this, there are no published systematic reviews of literature in temporally focused LA, and, more specifically, SRL in the context of time, sequence, and order. This is a significant research gap, and one which this thesis aims to address in order to provide a comprehensive empirical context for researchers hoping to further this important stream of research.

Process analytic methods have been deployed in many studies to measure the dynamics of learner behaviours, but the results have been variable, and subject to the nuances of data collection and curation methods. If we accept Reimann's view that variable-centric, statistical measures have ontological limitations in this context (2009); then it follows that the temporal and sequential dimensions of SRL demand explicit consideration of methods to measure them. With this in mind, we argue that viewing this dimension through the lens of frequency, time, and probability, has great promise. Although frequency of learner engagement with a particular action (or action sequence) is dimensionally limited, an additional measure of transition frequency between actions can provide a clearer view of the sequential nature of the inherent relationship. In this context, time (in its manifestation as a measure of duration) can also be seen to articulate a view of sequentiality (Ahmad Uzir et al., 2019). Winne (2010), in his conceptualisation of SRL as a sequence of events, provides compelling reasons for the use of probability to articulate likely sequences. We argue that all such associative measures provide the promise of articulating the dynamics of SRL that cannot be achieved by using aggregated frequency measures. This richness can be further augmented when sample groups are delineated by characterisations, derived from supervised or unsupervised methods (Jovanović et al., 2017). We argue that although process analytic methods have been explored with some success in LA research, their interpretation has been rarely systematic. This is not an overt criticism, but an acknowledgement that many of these studies represented valuable explorations of novel methods, and exhaustive metric interpretation was not always a priority (e.g., Bannert et al., 2014; Sonnenberg and Bannert, 2015). We further argue that, in context of the study of SRL and its related dimensions, process analytic research is not as mature as statistical analytic research. Up to this point, LA is dominated by statistical analytics which do not provide the dimensional insights to reflect the true dynamics of learning. This represents a methodological gap which this thesis seeks to address, as, we argue, the insights derived from temporally focused process analytics can more authentically inform learning design and learning interventions.

In terms of study data collection, the choice of self-report or digital trace data collection is key. Process analytic methods have been used in SRL research, based on self-report data collection, with some success (e.g., Heirweg et al. (2020), Engelmann and Bannert (2021)). Whilst these provided rich insights, the veracity of self-report capture, for example, has been called into question by Winne and Jamieson-Noel (2002), who uncovered disparities between students' reporting of their own study tactics and their actual behaviours; students tended to demonstrate a positive bias in their self-perception of achievements. Bjork et al. (2013) also detected evidence of faulty models of learning and recall. Critically, Zhou and Winne (2012) reported on a study in which self-reported perceptions of goal orientation correlated more weakly than trace measures. In the context of this thesis, these are key motivations for exploring the promise of analysing SRL processes through the capture of learner trace data, as extracted from authentic digital learning platforms. More importantly, the promise of producing analytical systems that have relevance in authentic settings is something that cannot come directly from experimental studies.

It is critically important to embed LA process analytics in recognised models of learning to make them meaningful and valid. Gašević et al. (2015) emphasised this point in relation to broader LA research, but it takes on a critical aspect in relation to SRL, where a number of theoretical models have been developed and extensively tested (Pintrich, 2000; Winne & Hadwin, 1998; Zimmerman, 2000). Trace data are normally captured at micro level, which relates to the atomic actions that are initiated when a learner interacts with any aspect of the LMS; *clicking on course materials*, *watching videos*, or *accessing a dashboard*, could be examples of this. SRL models are articulated at the macro level (Molenaar, 2014); *planning or preparing*, *monitoring*, or *reflection*, could be examples of this. This necessitates the use of some method to code micro-level action sequences to recognised macro constructs of SRL. This is challenging and, whilst the framing of such analyses in SRL coding frameworks has been well researched using self-report instruments and discourse-based collection methods (e.g., Greene and Azevedo (2009), Bannert et al. (2014)), very little such work has been undertaken using trace data. Building on our argument in the previous paragraph, trace data collection promises an unobtrusive and authentic capture of learner behaviour, and the dearth of SRL-framed trace data studies represents a gap which this thesis aims to address. The SRL trace data studies by, for example, Malmberg et al. (2014) and Siadaty et al. (2016), are valuable but cannot be truly construed as authentic or unobtrusive. We argue that the capture of SRL behaviours in such settings is an important step in the pursuit of impactful SRL research. Building on our earlier process analytic work, we perceive the need for a cohesive framework of methods to facilitate the transformation of authentic trace data, using a coding system based on a recognised model of SRL, and a way of analysing the temporal and sequential dynamics of the captured SRL processes. We argue that without embedding a theoretical model or framework, analysis of SRL is contextual and subjective. No technique currently exists to align authentic trace data to equivalent SRL processes, which is what must happen to push SRL research forward. One key outcome is the potential generation of a set of SRL frameworks that facilitate a transfer of analytic methods across different LMSs.

The systematic comparison and combination of analytic methods is one which brings value, but there are limited examples that deployed such combinations in the analysis of SRL trace data. To properly assess the available analytic methods, a systematic comparison is key. We know that combining analytic methods can provide richer outcomes than relying on a single method (e.g., Ahmad Uzir et al. (2020)). A key weakness around single-metric interpretation is the notion of scale. Using an absolute measure of frequency or duration as a metric, may mean that researchers may lose its value in a relative sense. Conversely, when relative scales, such as probability, are employed, the loss of absolute scale may be deceptive. To alleviate this, we argue that the combination of analytic methods, and the metrics they generate, has the promise of providing dimensional insights into SRL. As yet, no such assessment of this, and other issues, has been systematically addressed. In addressing this gap, we hope to facilitate a more informed use of process analytic metrics (in combination or otherwise) than currently exists. The consolidation of analytic methods has implications for the quantitative interpretation of SRL processes, and the broader qualitative interpretation of SRL behaviours. We suggest that the use of process analytic methods should be subject to explicit and considered assessment, but the means to do this is currently unsupported by any systematic overviews of the methods, the metrics they provide, and their importance in context of SRL. This is a gap this thesis seeks to address. Building on this theme, we believe that rich insights can be derived from the combination of certain process analytic metrics.

Different process analytic methods have strengths and weaknesses that are not routinely discussed when deployed in studies. Here we focus on the systematic assessment of these methods and their metrics. We want researchers to more explicitly consider which methods/algorithms they use, and be creative in combining them, or even designing new ones. This, we argue, will benefit temporally focused SRL research, going forward.

A key methodological decision is the choice of analytic method to model and visualise the results. In the four applied studies undertaken to support this thesis, two methods are utilised. Firstly, process mining (PM) is an event-based method that derives sequential and temporal analyses from log data files. Taking event log files as its input, process mining utilises discovery algorithms which allow the identification of common logical arrangements of logged event classes in a temporal and sequential space (van der Aalst, 2016). Although it was conceived in commercial and industrial settings, it is steadily gaining traction in LA research circles. Secondly, epistemic network analysis (ENA) is an analytic technique that positions events in a network space and emphasises temporal co-occurrence, as opposed to the sequential association emphasised in process mining. Connections are established through relative weighting, and statistical techniques are employed to compare the salient properties of networks generated (Shaffer et al., 2016). In the broader area of temporally focused SRL, other methods, for example, transition graphs, lag sequential analysis, and hidden Markov models, are employed. All of these methods promise a view of SRL dynamics that cannot truly be realised using conventional frequency measures and statistics, and combining them provides the prospect of richer insights into SRL. We use these analytical methods to aid the discovery of SRL processes from trace data origins, and explore the promise of comparing and combining their outcomes.

In summary, this thesis explores a corpus of research in the area of temporally focused SRL as context for subsequent applied studies. First, we present a systematic review of literature that analyses the findings of studies that explore SRL through the lenses of order and sequence, to provide insights into the temporal dynamics of SRL. Second, the thesis demonstrates the use of a novel process mining algorithm to analyse how certain temporal activity traits relate to academic performance. Third, the thesis presents a methodological framework designed to embed our analyses in a model of SRL. It comprises the use of: i) micro-level processing to transform raw trace data into SRL processes; and ii) first order Markov models to explore the temporal associations between SRL processes. Fourth, the thesis explores the deployment of multiple analytic methods to explore the insights gained through a combined methodological perspective. Fifth, building on this theme, the thesis presents a systematic analysis of four process mining algorithms, as deployed in the exploration of common SRL event data.

1.1 Research goals and questions

The work presented in this thesis was conducted with four main research goals. The first was to examine the empirical landscape of data-driven SRL in the context of sequence and temporality, and articulate the collective outcomes of a body of research which focused on learner event dynamics, as opposed to variable-centric correlative measures. SRL is a well-researched discipline, and it has inspired a sizable number of reviews of literature; a testament to its importance in the area of educational research. Despite this, and the increasing focus on temporal dimensions in LA and SRL (Molenaar, 2014; Reimann, 2009), there has been no review of SRL in the context of a process that unfolds over time. To address this gap, the thesis presents a systematic review of studies which analyses SRL in this temporal and sequential context, the methods used, and the insights uncovered. As such, the first research question is:

Research Question 1:

To what extent has learning analytics research addressed the notion of self-regulated learning as a process that unfolds over time?

It is important to note that research question 1, although principally addressed by our systematic review of literature, has a key influence over the exploration of the remaining research questions. The second goal was to outline a way of providing novel, temporally focused insights into the ways in which learners navigate various study modes, as extracted from trace data. We were motivated to explore ways in which we could articulate the behaviours of contrasting groups of learners, and, critically, the behavioural differences and commonalities between these groups, using event or process-based (as opposed to variable-centric) analytic methods. As such, our second research question is:

Research Question 2:

How effectively can we measure the temporal dynamics of learning strategies in delineated student groupings, using process analytic techniques?

Having established one novel method of analysing learner behaviours, the third goal was to explore ways in which we could embed these temporally focused analyses in a theoretical model of SRL. Inspired by the micro-level analytic process method developed by Greene and Azevedo (2009), and deployed in an experimental trace data setting by Siadaty et al., 2016, we wanted to develop an approach and a tool to automate the codification and transformation of raw log data into SRL processes. Furthermore, we wanted to assess the efficacy of our process analytic techniques (used to address research question 2) in uncovering insights from the newly generated SRL process data. As such, our third research question is:

Research Question 3:

Table 1. Overview of the research questions by individual chapters.

		Research questions			
Chapter	**Title**	RQ 1	RQ 2	RQ 3	RQ 4
Chapter 2	Temporally focused Self-regulated Learning	✓			
Chapter 3	Exploration of Temporality and Probability from Trace Data		✓		
Chapter 4	Embedding Trace data in SRL		✓	✓	
Chapter 5	Comparing Discovery Algorithms		✓	✓	✓
Chapter 6	Comparing and Combining Process Mining Metrics		✓	✓	✓

To what extent can we develop a framework to ground temporally focused analysis of learning in a theoretical model of self-regulated learning?

In SRL research, the use of multiple analytic methods is less common, but can be seen to provide effective results (e.g., Matcha, Gašević, Ahmad Uzir, Jovanović, Pardo, et al. (2019), Ahmad Uzir et al. (2020)). Therefore, the fourth goal was to assess the relative efficacy of a number of process analytic methods, using a common set of SRL process data, and to explore the potential of combining these methods and ascertain if the combination provides a richer, more dimensional view of SRL. As such, our fourth and final research question is:

Research Question 4:

To what extent can we combine analytic methods to further explore self-regulated learning from a perspective of temporality and sequence?

1.2 Methodology

The research presented in this thesis is underpinned by a systematic review of literature and four trace data-driven studies. The studies made use of three datasets taken from two LMSs. Two of the datasets come from what we term as a 'bespoke' LMS, meaning that it was not commercially available at the time of the study. It should be stressed that we view this LMS as entirely authentic in the sense that it operated with the full functionality of a commercial LMS, and generated genuine learner engagement data. The third dataset was generated from a Moodle LMS (see Table 2).

These data were processed, quantitatively analysed, qualitatively interpreted, using a variety of analytic methods. In this section, we outline the learning analytics methods used in this thesis mapped to research questions 2 to 4 (see Table 3).

To address research question one (RQ1), we explored the state of the art of data-driven SRL research that emphasises the methodological importance of temporality and sequence, as opposed to conventional statistical analysis. To capture the relevant literature for this study, we targeted seven journal databases using various keyword searches based around self-regulated learning, process and sequence analyses, and temporality. The final pass provided a corpus of 53 papers.

Table 2. Summary of the datasets used in the thesis

Dataset	Course	Learning Modalities	Year	Course Duration	Total Students	Chapters
Dataset 1	Computer Engineering	Flipped Classroom (Bespoke LMS)	2014	13 Weeks	290	Chapter three Chapter four
Dataset 2	Computer Engineering	Flipped Classroom (Bespoke LMS)	2014 — 2016	13 Weeks	239	Chapter five
Dataset 3	Engineering Mobile Apps	Flipped Classroom (Moodle)	2019	13 Weeks	726	Chapter six

Table 3. Analytical methods mapped to chapters and research questions

Chapter	RQ	Delineation	SRL transformation	Analytic discovery method
3	2	Unsupervised	n/a	PM (FOMM)
4	2, 3	Unsupervised	Micro-level Processing	PM (FOMM)
5	2, 3, 4	Performance	Micro-level Processing	PM (FOMM, BupaR Time, BupaR Frequency), ENA
6	2, 3, 4	Content Access	Micro-level Processing	PM (FOMM, Fuzzy Miner, Inductive Miner, Heuristics Miner)

To address research question two (RQ2), we used a variety of process mining algorithms across four studies, and in one study, epistemic network analysis (see Table 3). We used a process mining algorithm based on first order Markov models in all of our studies, that is, pMineR (Gatta, Lenkowicz, et al., 2017). In the studies reported on in Chapter three and Chapter four, we used pMineR solely as our process discovery method. This provided us with a transition probabilistic view of learner engagement in the context of order of temporality. In studies reported on in Chapter five and Chapter six, we employed a number of process mining algorithms, as well as epistemic network analysis, to provide a comparative methodological view. In two of the studies (Chapter three and Chapter four), we analysed and compared groups of learners that had been previously clustered in a study undertaken by Jovanović et al. (2017). In one study (Chapter five), we extracted the top and bottom deciles of learners, based on assessment performance. In three of the studies, we included basic statistical analyses to explore its limitations, but also to assess it value in complementing our process analyses.

To address research question three (RQ3), we deployed micro-level process analysis as means of framing our research in a theoretical model of SRL, forcing the articulation of raw trace data into SRL sequences. This pre-processing method was designed by Greene and Azevedo (2009) and used mainly in think-aloud studies until Siadaty et al. (2016) deployed it using the trace data generated from the experimental Learn-B knowledge system (as opposed to an authentic LMS). We developed an approach that can transform raw learner data from authentic LMS settings into SRL micro-processes, using a combination of regular expressions and an SRL pattern library. We termed the process, "Trace-SRL", and deployed it in the studies reported on in Chapter four, Chapter five, and Chapter six.

To address research question four (RQ4), we deployed two types of methodological comparisons. In the study reported on in Chapter five, we deployed the Trace-SRL framework on a common dataset, and then analysed the resultant data using: i) simple frequency measures; ii) epistemic network analysis (Shaffer et al., 2016); iii) frequency and time-based process mining, using the BupaR tool (Janssenswillen et al., 2019); and iv) stochastic process mining, using the first order Markov models generated from the pMineR tool (Gatta, Lenkowicz, et al., 2017). This allowed us to articulate outcomes individually from each method, but, more importantly, combine the outcomes in a qualitative exercise, which provided a richer set of outcomes. In the study reported on in Chapter six, using another common trace-dataset, we compared the outcomes from four process mining algorithms: i) Inductive Miner; ii) Heuristics Miner; iii) Fuzzy Miner; and iv) pMineR. We also conceptualised a combination of the metrics from two of these algorithms to provide an improved interpretation of temporal and sequential relations of SRL processes.

1.3 Thesis structure and overview

To address the four research questions, we organized the thesis into five individual chapters, as shown in Table 1. Each chapter focuses on one or more research questions and includes one peer-reviewed publication that constitutes the core of the chapter. We also provided a short overview and summary to each included publication to describe how the publication fits into the overall structure and the topic of the thesis, and contributes to its research goals.

1.3.1 Overview of chapter two: "Temporally focused Self-regulated Learning" (RQ1)

The study of SRL is now firmly established within the learning analytics community. This is motivated, in part, by the notion that students who display a mastery of SRL tend to perform better than their passive counterparts. The articulation and measurement of the temporal and sequential dimensions of SRL has gained traction in recent years, yet, despite this increased focus, there has been limited attempts to provide a cohesive analysis of this critical research area.

Research contributions:

- We presented a systematic literature review of studies that report on data-driven, temporally focused SRL analyses.
- We highlighted the key challenges that face researchers that seek to explore temporally focused SRL.
- We categorised these challenges to form a cohesive framework of considerations for future and ongoing research in this area.

Research output:

1. Saint, J., Fan, Y., Gašević, D., & Pardo, A. (2021). Temporally focused Self-regulated Learning: A Systematic Review of Literature: A journal article, submitted to the Educational Psychology Review, and currently under review. This is a systematic review of literature of studies that explore temporally focused SRL.

1.3.2 Overview of chapter three: "Exploration of Temporality and Probability from Trace Data" (RQ2)

In order to capture the temporal and sequential dynamics of learning strategy, researchers need to seek methods beyond the paradigm of count-based, variable-centric statistical analyses. The LA community has started to explore the insights provided by learner event logs from online and blended settings. The use of process mining is increasing in popularity, although its deployment and interpretation is subject to much variation depending on the algorithm and metrics used, as articulated in the systematic review of literature incorporated in Chapter two. In this chapter, we demonstrated the benefits of using stochastic process mining as a means of unlocking insights into optimal and less optimal learner behaviours.

Research contributions:

- We presented a novel combination of unsupervised and process mining methods to unlock insights into learning strategies in blended learning settings.
- We demonstrated that rich insights into learner engagement can be derived from a probability-focused process mining method, using first order Markov models.
- We demonstrated that this richness can be increased by the direct comparison of the transition metrics derived using this method (i.e., transition probabilities), and brings a more dimensional view than is possible with statistical measures alone.
- We demonstrated interpretable differences between higher and lower performing student groups.

Research output:

1. Saint, J., Gašević, D., & Pardo, A. (2018). Detecting Learning Strategies Through Process Mining. In V. Pammer-Schindler, M. Pérez-Sanagustín, H. Drachsler, R. Elferink, & M. Scheffel (Eds.), *Lifelong Technology-Enhanced Learning* (pp. 385–398). Springer International Publishing. https://doi.org/10.1007/978-3-319-98572-5_29: A full conference paper that was presented at the 2018 ECTEL conference. *The supplementary material for this paper can be found in Appendix A.*

1.3.3 Overview of chapter four: "Embedding Trace data in SRL" (RQ2, RQ3)

Researchers who deal with learner trace data are faced with a number of challenges in providing a coherent and consistent view of what the trace data say about the learner engagement. The framing of this engagement in the context of recognised theories of learning, in particular self-regulated learning, add another dimension to the challenge. In this chapter, we outlined and deployed a framework of methods that comprises: 1) the strategic clustering of learner types; 2) the use of micro-level processing to transform raw trace data into SRL processes; and 3) the use of a novel process mining algorithm to explore the generated SRL processes. The aim of this framework is to facilitate the analysis and articulation of SRL through the lenses of sequence and temporality.

Research contributions:

- We presented a novel framework for transforming authentic trace data into SRL processes, that is, *Trace-SRL*.
- We demonstrated that the temporal and sequential dynamics of SRL can be successfully interpreted from probabilistic process analytics.
- Our results showed that more successful students regularly engage in a higher number of optimal SRL behaviors than their less successful counterparts.

Research output:

1. Saint, J., Whitelock-Wainwright, A., Gašević, D., & Pardo, A. (2020). Trace-SRL: A Framework for Analysis of Microlevel Processes of Self-Regulated Learning From Trace Data [Conference Name: IEEE Transactions on Learning Technologies]. *IEEE Transactions on Learning Technologies*, *13*(4), 861–877. https://doi.org/10.1109/TLT.2020.3027496: A journal article that was published in IEEE Transactions on Learning Technologies in 2020. *The supplementary material for this paper can be found in Appendix B*.

1.3.4 Overview of chapter five: "Comparing Discovery Algorithms" (RQ2, RQ3, RQ4)

This chapter begins our exploration into the use of multiple analytic methods to explore SRL. Building on the methodological and theoretical work undertaken in the previous studies, we employed the *Trace-SRL* micro-level process method to provide the SRL process data that we subsequently explored using: i) simple frequency measures; ii) epistemic network analysis; iii) time-focused process mining; and iv) stochastic process mining. Moreover, we explored the possibility of consolidating the outcomes from these methods.

Research contributions:

- We further tested the *Trace-SRL* framework conceived in the previous chapter.
- We demonstrated, through the use of a common dataset, how the ontological limitations of frequency-based methods can be overcome by the use of temporally focused methods.
- Building on the previous point, we demonstrated how the use of multiple, temporally focused analytic methods can provide rich insights into the dynamics of SRL.
- We found that high performing learners employed more optimal SRL behaviours than their low performing counterparts, in context of the dynamic relations between SRL processes.

Research output:

1. Saint, J., Gašević, D., Matcha, W., Ahmad Uzir, N., & Pardo, A. (2020). Combining analytic

methods to unlock sequential and temporal patterns of self-regulated learning. *Proceedings of the Tenth International Conference on Learning Analytics & Knowledge*, 402–411. https://doi.org/10.1145/3375462.3375487: A full conference paper that was presented at the 2020 LAK conference.

1.3.5 Overview of chapter six: "Comparing and Combining Process Mining Metrics" (RQ2, RQ3, RQ4)

This chapter completes our exploration into the use of multiple analytic methods to explore SRL. More specifically, we explored the insights derived from the use of four process mining algorithms in the analysis of a common dataset derived from the *Trace-SRL* framework conceived in Chapter four. We explored the data using: i) Heuristics Miner, ii) Inductive Miner, iii) Fuzzy Miner, and iv) pMineR.

Research contributions:

- We provided evidence of the utility of the *Trace-SRL* framework on data from a new LMS source.
- We systematically demonstrated that Fuzzy Miner and pMineR offered better insights into SRL than the other two algorithms.
- We determined that a combination of metrics produced by several algorithms improved interpretation of temporal and sequential relations between SRL processes.

Research output:

1. Saint, J., Fan, Y., Singh, S., Gasevic, D., & Pardo, A. (2021). Using process mining to analyse self-regulated learning: A systematic analysis of four algorithms. *LAK21: 11th International Learning Analytics and Knowledge Conference*, 333–343. https://doi.org/10.1145/3448139.3448171: A full conference paper that was presented at the 2021 LAK conference. *The supplementary material for this paper can be found in Appendix C.*

1.3.6 Overview of chapter seven: "Conclusions and Future Directions"

In the final chapter, we examine the impact of the present work

2 Temporally focused Self-regulated Learning

> The events in our lives happen in a sequence in time, but in their significance to ourselves they find their own order...it is the continuous thread of revelation.
>
> — Eudora Welty, *One Writer's Beginnings*

2.1 Introduction

THERE is a sense that traditional, monologic learning provisions, such as large face-to-face lectures, have a lesser place in modern education, and that more authentic learning experiences are found in mobilising students to more actively manage their own knowledge-building (Paris & Paris, 2001; Zimmerman, 1986). As such, the study of SRL is now firmly established and has a prominent place within the learning analytics community (Winne, 2017). This is motivated by the notion that students who seek to take active control of their learning tend to perform better than their passive counterparts (Pintrich & de Groot, 1990; Zimmerman, 1989). As such, the exploration of how students engage with self-regulatory activities is of key importance to researchers who seek to inform and improve the design and deployment of learning resources. Within this empirical context, two broad conceptions exist: i) SRL as a characteristic or a trait of a learner; and ii) SRL as an ongoing cyclical process in which learners engage over time (Winne & Perry, 2000). It is the latter conception that drives this chapter and, indeed, the entire thesis.

The concept of learning as a sequence of events unfolding over time is one which has inspired researchers, such as Reimann (2009) and Molenaar (2014), to explore the conceptual and methodological challenges around its measurement in temporal contexts. Reimann (2009), in particular, highlighted the ontological limitations of commonly used, variable-centric analyses. Knight et al. (2017) and Chen et al. (2018) contemplated these challenges, but also the opportunities for the development of temporally focused LA, in their collective curation of ten empirical studies. It is in the thematic overlap between SRL and temporality that this chapter is conceived. The ongoing interest in SRL is demonstrated clearly by the number of studies to which it is dedicated and also by the number of literature reviews it has generated. We are unaware of any significant temporally focused reviews of literature and certainly none that focus on SRL as it manifests through the dimensions of sequence and time. As such, we present a systematic literature review to investigate research question one (RQ1), that is, *To what extent has Learning Analytics research addressed the notion of self-regulated learning as a process that unfolds over time?*

2.1.1 Chapter overview

The main objective of this chapter is to review the corpus of research into data-driven, temporally-aligned SRL, focusing on methodological aspects, such as data collection, data transformation, analytics platforms, as well as conceptual aspects, such as the extent to which theoretical models of (self-regulated) learning is deployed. Ultimately, we seek to summarise the key study findings and identify a clear path to furthering research in this area.

This review is underpinned by a semi-iterative process of keyword searching of seven journal databases, which resulted in the inclusion of 53 papers, after further filtering based on manuscript type, temporal focus, and SRL linkage. Based largely on a codification framework (outlined in the paper), we explored the following research questions:

1. What types of data sources/instruments are used in temporal data analysis of SRL and related dimensions?
2. What theoretical models of SRL do researchers use to inform interpretive decisions?
3. What types of temporal analysis/discovery methods are used?
4. What type of phenomena or processes are modelled and what type of insights do they provide?
5. To what extent does temporal analysis inform current models of SRL?

This allowed us to provide a comprehensive overview of research into data-driven temporally focused SRL. It should be noted that although the studies reported on in the remaining chapters of this thesis (3 to 6) make sole use of trace-data collection, we did not seek to impose this methodological restriction on our review of literature. This would have unnecessarily narrowed the scope of our systematic research, and eliminated a sizable number of critically important studies from the resultant corpus.

The outcomes of our analysis can be broadly categorised into the following:

- *Methodological Considerations*, pertaining to decisions around the method of data collection, data pre-processing/transformation, and the analytic method(s) used to explore and visualise the key learner behaviours. Also pertinent are decisions around combining these methods, be they data collection, data exploration and visualisation, or both.
- *Theoretical Considerations*, pertaining to the extent to which models of SRL are deployed to underpin the research presented, and how robustly (if at all) they inform the methodological

decisions discussed above. As above, key decisions around using a single model, a consolidation of elements of a model, or related dimensions thereof, are relevant here.

- *Validity Considerations*, following on from the previous point, to what extent does the combination of methodological and theoretical decisions highlighted above lead to a sense of validity in the findings, and to what extent can some sort of triangulation mechanism be deployed to support validity.
- *Temporal Considerations*, pertaining to the conceptualisation and analysis of the temporal and sequential dimensions of SRL and how the outcomes of these analyses can be of benefit to researchers of SRL.

2.2 Publication: Temporally focused Self-regulated Learning: a Systematic Review of Literature

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

> Saint, J., Fan, Y., Gašević, D., & Pardo, A. (2021). Temporally focused Self-regulated Learning: A Systematic Review of Literature

Temporally focused Self-regulated Learning: a Systematic Review of Literature

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ABSTRACT

We present a systematic literature review of into data-driven self-regulated learning (SRL) that emphasises the methodological importance of temporality and sequence, as opposed to conventional statistical analysis. Researchers seem unanimous in the view of the importance of SRL in modern online and blended educational settings; this is borne out by number of reviews of literature on the subject. There has, as yet been no systematic treatment of SRL in the context of its conceptualisation as a phenomenon that unfolds in sequences over time. To address this limitation, this review explores the corpus of work (n=53) in which SRL and its related dimensions are analysed through the lenses of temporality, sequence and order. The results show that, in the pursuit of validity and impact, key decisions need to be addressed in regard to theoretical grounding, data collection, and analytic methods. Based on these outcomes, we propose a framework of directives and questions to aid researchers who want to push forward the field.

1. Introduction

The evolution of digital technology has benefited the education sector in many ways, providing its stakeholders—students, teachers, academic managers and others—with a rich set of tools to aid the capture, delivery, and construction of knowledge. Online and blended environments provide learners with sophisticated educational resources. In this context, the shared responsibility of learning has seen a shift from teacher to student. In truth, the focus on student-driven, constructivist learning predates digitally facilitated mass education (Schunk and Greene, 2018). Nonetheless, the affordances of technology have focused educational research on the meta-cognitive, cognitive and motivational attributes of students who take more active control of their own learning. The modelling of these attributes, and the learning behaviours they inform, is articulated in the area of self-regulated learning (SRL) and its derivations: co-regulated learning (CoRL) and socially-shared regulation of learning (SSRL) (Hadwin et al., 2017). Educational researchers have long been convinced of the value of self-regulation (Zimmerman, 1986; Winne and Hadwin, 1998; Pintrich, 2000), which has given rise to the generation and development of several models of SRL (Panadero, 2017).

In applying the models of SRL, researchers are faced with methodological decisions around data collection, processing, and analysis. These decisions are increasingly informed by the notion that SRL, and learning in general, is a dynamic and recursive process that unfolds in steps over time (Butler and Winne, 1995). This notion is gaining increased traction as researchers seek to articulate learning in the context of sequence and time. Given this context, Reimann (2009) argues that temporality should not only encompass time-on-task, frequency and duration, but also the order of learning events. Molenaar (2014) builds on this theme and, citing Bannert et al. (2014), establishes a link between successful SRL and the cyclical ordering of strategies as they are played out over time. Arguably, this mode of sequential dynamics could not be articulated using traditional count-based statistical methods. Nonetheless, as Molenaar (2014) additionally states, although this temporal view of learning is conceptually innate, its operationalisation in empirical settings entails a shift beyond the traditional quantitative research paradigm.

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In an effort to explore this shift beyond variable-centric statistical constructs, a body of research has grown which encompasses event and discourse-based analytical methods, such as process mining (PM), Markov modelling, epistemic network analysis (ENA), lag sequential analysis (LSA), and other temporally focused discovery techniques. To that end, this systematic review of literature seeks to provide an overview and analysis of the corpus of research that addresses SRL in the context of temporality and sequence.

2. Background

2.1. Self-Regulated Learning and Related Dimensions

Since Zimmerman first posited the potential of SRL (Zimmerman, 1986), the development of models of learning within this context has gathered at pace and evolved to form a comprehensive ecosystem of research. The concept of SRL is predicated on that notion that learners with a specific learning goal, have agency over their path to that goal, given a set of external and internal conditions. Such goals may be micro or macro in scale—the completion of a multiple choice test, or the authoring of a dissertation—and, as such, the ultimate completion of the task may be a single SRL cycle, or an ongoing sequence of cycles and sub-cycles. In this sense, SRL is viewed as an ongoing process which unfolds and develops over time (Winne and Perry, 2000; Azevedo et al., 2010). The major SRL theorists—Zimmerman (2000), Pintrich (2000), Winne and Hadwin (1998), and Boekaerts (1996)—have all developed multiple versions of their models through iterations of empirical testing. As Panadero (2017) highlighted, these models are defined by thematic variations of the same fundamental cyclic framework of SRL: i) a preparatory phase; ii) a performance phase; and iii) an appraisal phase. The latest iteration of Zimmerman's model (2000) is a clear manifestation of the basic three-part cycle, comprising phases: i) forethought; ii) performance; and iii) self-reflection. Whilst cognitive and strategic elements are implicit in the model, the phase sub-processes focus on aspects of motivation, judgement and reflection. Pintrich (2000) posited a similar cycle but in four phases: i) forethought, planning and activation; ii) monitoring; iii) control; and iv) reaction and reflection. Panadero's alignment of these phases with the fundamental SRL cycle (Panadero, 2017) is, perhaps, a little simplistic, but it serves to underpin the common topology of all the models. Boekaerts (2011) articulated a similar three-part phasic cycle, but in the context of two strands, termed "dual processing": i) (meta)cognitive elements which inform learning intention and growth; and ii) affective and emotional elements which inform the learner's sense of self and well-being. There is a clear emphasis on the importance of both processes as defined elements, but also as interlinked drivers (Boekaerts, 2011). The Winne and Hadwin (1998) model provided a sophisticated take on the cycle, with a strong focus on meta-cognition in learning tactics. As opposed to Zimmerman (2000), Winne's phases are less rigidly aligned to a mono-directional cycle, being positioned in a more fluid recursive structure, known as COPES: i) Conditions; ii) Operations; iii) Products; iv) Evaluations; and v) Standards. These facets are linked through internal and external pathways of feedback. The choice of model is determined by the trajectory of the study in which the model is embedded—or more possibly, the trajectory of the study is determined by the choice of model.

In truth, the extent to which these models are applied tends to vary, due to an assortment of drivers and constraints. The relative novelty of the methods that fall inside the scope of this review mean that strict adherence to theoretical models of learning is not always the primary focus. It would, therefore, be remiss to eliminate studies which at least acknowledge the measure of certain dimensions of learning that could fall under the umbrella of SRL. Hence, this review encapsulates studies that recognise the importance of SRL *or* its related dimensions, such as learning tactics and strategies.

2.2. Analysing Process, Sequence and Temporality

The definition of SRL as a cyclical process that unfolds over time is well-established (Butler and Winne, 1995; Molenaar, 2014). In acknowledging this dimension of SRL, researchers are bound to address the methodological demands of process, sequence, and temporality. Quantitative learning analytics (LA) research is largely characterised by the use of statistical models for data interrogation and discovery. Descriptive, inferential, and predictive analytic methods occupy an empirical space supported by years of applied experimentation. As such, it is an obvious choice for educational researchers who seek to position their outcomes on a bedrock of validity. Many studies use statistical analysis to significant effect, and have genuinely enriched the LA community. Studies by, for example, Taub and Azevedo (2016), Siadaty et al. (2016a), Paans et al. (2019), and Greene et al. (2019) all provided critical insights into SRL—and temporality in some cases—using empirically solid statistical methods. Despite their value, a body of opinion suggests use of statistical methods can impose ontological limitations on temporally focused studies (Reimann, 2009; Knight et al., 2017; Chen et al., 2018a). Constructs formerly measured in terms of relative frequency are now conceptualized as sequences of events that unfold in temporal space (Molenaar, 2014). In this context, the assertion by Reimann (2009) that a variable-centered view, as typified by statistical analysis, is not as dimensionally rich as an event-based view, is particularly apposite. As such, for those who do position learning in the context of sequence and temporality, the choice of method requires a shift beyond the empirical safety of frequency-based statistical analysis.

Indeed, Molenaar (2014) recognised the importance of this paradigmatic shift, identifying these key aspects of temporal analysis: i) a common understanding of different temporal dimensions and how this can inform the research narrative; ii) an understanding of appropriate temporally focused methods; iii) an articulation of guidelines for the segmentation of time; and iv) the design of a bridge between engagement data—typically micro in grain—and learning model constructs, which tend to be defined at macro level. Building on this manifesto, Knight et al. (2017) and Chen et al. (2018a) curated two groups of studies which sought to further the cause of temporal analysis. Chen et al. (2018a) identify temporal analysis as: i) the frequency and lengths of engagement events; and ii) the sequential order of engagement events. This shift in perspective has prompted the exploration of analytic techniques such as, for example, process mining (PM), sequence mining (SM), graph theory, and epistemic network analysis (ENA). Such methods have the promise to unlock temporally dynamic insights undetectable in frequency measures. This review seeks to capture the scope of temporally and sequentially focused analyses of SRL and its related dimensions of learning.

2.3. Related Reviews of Literature

In data-driven educational research, the empirical corpus of SRL dwarfs that of temporal analysis, notwithstanding the thematic overlap previously discussed. This is reflected in the number of published systematic literature reviews. Devolder et al. (2012) explored the use of scaffolding in computer-based learning environments (CBLEs), deploying an integrated model of SRL to assess its utilisation. Whilst not a meta-analysis in the strictest sense, it did provide a qualitative summation of the efficacy of scaffolding in SRL. Broadbent and Poon (2015) produced a correlative meta-analysis, based on nine SRL strategies, to assess the relationship of these strategies with academic outcomes; they noted a positive correlation in all but three of the defined strategies. Brydges et al. (2015) explored the use of SRL in medical simulation-based training, in the context of controlled interventions. They found that assisted SRL was not prevalent in many of the studies in this area. Roth et al. (2016) focused on studies employing self-report measures, touching on an important methodological choice for SRL researchers. Van Laer and Elen (2017) focused on SRL in blended learning environments, identifying seven key attributes that were seen as significant in the context of effective SRL. Garcia et al. (2018) and Araka et al. (2020) both explored SRL with a specific focus on e-learning tools and platforms. Garcia et al. assessed the emerging use of these tools in relation to the taxonomy of SRL strategies first presented by Zimmerman and Pons (1986), defining a granular comparison in context of the specific software used. Araka et al. provided a more categorised view of e-learning tools and also the methods used. Lee et al. (2019) provided a specific treatment of SRL in massive open online courses (MOOCs), positing that effective SRL arguably plays a greater role in enhancing learning in pure online settings (as opposed to face-to-face or blended). Wong et al. (2019) assessed SRL in MOOCs in context of support and scaffolding mechanisms, such as prompts, feedback, and other integrated support systems. They concluded that factors—such as prior knowledge, gender, culture, and cognitive ability—play a key role in the conceptualisation of SRL support systems. Pérez-Álvarez et al. (2018) provided a more specific review of tool use in MOOCs, concluding that interactive visualisations and social comparison mechanisms positively effect learner engagement. They also posited a lack of tools that recognise SRL strategy deployment. Cerón et al. (2021), however, systematically analysed SRL strategy in their review of SRL in MOOCs, concluding that goal setting, *help seeking*, *time management*, self-evaluation, and strategic planning, were the most prominent SRL strategies. Matcha et al. (2020) analysed the consideration, or otherwise, of SRL in the design of learning analytics dashboards (LADs). They established that SRL is poorly supported in many LADs and therefore meta-cognitive gains are severely limited. Viberg et al. (2020) explored the importance of specific phases of Zimmerman's model (2002), as realised in SRL studies. Cuyvers et al. (2020) focused on SRL in professional settings, which they termed self-regulation of professional learning (SRpL). They recognised the value of using SRL models from educational settings as a theoretical bases, but that simple transference of such models ignores key facets of workplace learning. Most of these reviews focused on improving our understanding of the theoretical perspective of SRL, such as how learners use tools, and how to provide scaffolding, but focused less on the measurement and interpretation SRL in its temporal context.

The articles cited in the previous section on temporal analysis—Reimann (2009), Reimann et al. (2014), Molenaar (2014), Knight et al. (2017), and Chen et al. (2018a)—combine to elicit a rallying call to the educational research communities to explore the empirical landscape beyond the conventions of variable-centric statistical analysis. There are, nonetheless, no systematic reviews of literature which discreetly cover temporal analysis of SRL (at the time of writing). Our systematic review of literature seeks to respond to the increasing interest in SRL in digital settings and to answer the rallying call of Reimann (2009), Molenaar (2014), Knight et al. (2017), and Chen et al. (2018a). As such, we present a systematic review of literature that analyses the findings of studies that explore SRL through the lenses of temporality and sequence to provide insights into the dynamics of SRL.

More specifically, this review sought to answer the following research questions:

1. What types of data sources/instruments are used in temporal data analysis of SRL and related dimensions?
2. What theoretical models of SRL do researchers use to inform interpretive decisions based on temporal analysis of learner data?
3. What types of temporal analysis/discovery methods are used in the research of SRL?
4. What type of phenomena or processes are modelled and what type of insights do they provide?
5. To what extent does temporal analysis inform the modelling of SRL?

3. Methodology

3.1. Search Strategy and Criteria

We used the guiding principles of the PRISMA framework (Moher et al., 2009) to inform the structure of this review. To capture the relevant literature for this study, we targeted seven journal databases using variations of the following keyword string: *(self-regulate* learning) AND (process OR sequence* OR sequential OR temporal*) AND (Analytic* OR Mining)*. The flow of the search over time can be seen in Figure 1 . We conducted four searches over three years in order to keep the the corpus refreshed. The first passes of each search produced 1105, 248, 205, and 118 papers, going from the earliest search on the 31st May 2019 to latest on the 25th May 2021. After each of these search events, we imposed exclusion criteria on the resultant papers to remove short papers, studies which relied heavily or solely on traditional statistical methods, studies with weak connections to SRL, and those that did not actually report on an empirical study. The 72 remaining papers were further reduced in a final exclusion process; in this final pass, we removed duplicates and borderline studies, giving the final total of 53 papers.

3.2. Coding System

To answer the research questions 1 to 4, we mapped them to a set of coding categories, as can be seen in table 1. In conceiving the coding categories, we considered how the various dimensions aligned to the broad process of analysis for the types of studies in our target sample. **RQ1** relates to the capture and curation of the study data. **RQ2** relates to the theoretical underpinning of the analyses. **RQ3** relates to the discovery and visualisation methods. **RQ4** relates to the nature and the outcomes of the captured phenomena. The mechanics of **RQ5**, which relates to the temporal nature of the analyses, could not be coded in any meaningful, without merely reflecting the methodological characteristics represented.

To support **RQ1**, seven codes were employed: **Participant make-up** relates to the educational setting in which the learners operated. Only one study operated exclusively in professional settings (Siadaty et al., 2016b) but it should be noted that a number of studies —MOOCs in particular— could be undertaken by professionals as well as students. **Setting authenticity** indicates whether the study setting was authentic, such as a conventional HE environment, or experimental, such as the learning lab utilised by Malmberg et al. (2021). **System** relates the central (generally digital) system used to support the delivery of the teaching and, in many cases, the collection of the study data. Whilst it is often both the delivery mechanism and a source for the study data collection, this is not always the case. Some papers, for example Bannert et al. (2014), employed an LMS but did not extract learner data from it, instead choosing a think-aloud method. In this context, the categorisation of **System authenticity** requires a nuanced view. The **Data collection method** category can be broadly viewed in terms of digital trace data or self-report data (or combinations thereof). Multi-modal/multi-channel methods are also considered. The **Data transformation** category describes any method used to configure or re-characterise the raw data into a form appropriate for the needs of study, such as the micro-level processing method developed by Greene and Azevedo (2009) to translate learner utterances (captured using think-aloud) into recognised of SRL processes. The **Sample size** category is self-explanatory.

To support **RQ2**, two codes were employed: **SRL designation** indicates whether the study positions SRL as a key theoretical element, or focuses on certain dimensions (such as tactics or strategies). Leading on from this is the **Underpinning Model of SRL** category, that indicates which of the major SRL models, discussed in section 2.1, were used in the study (if at all). This category also requires a nuanced view. Some studies aligned to a single model of

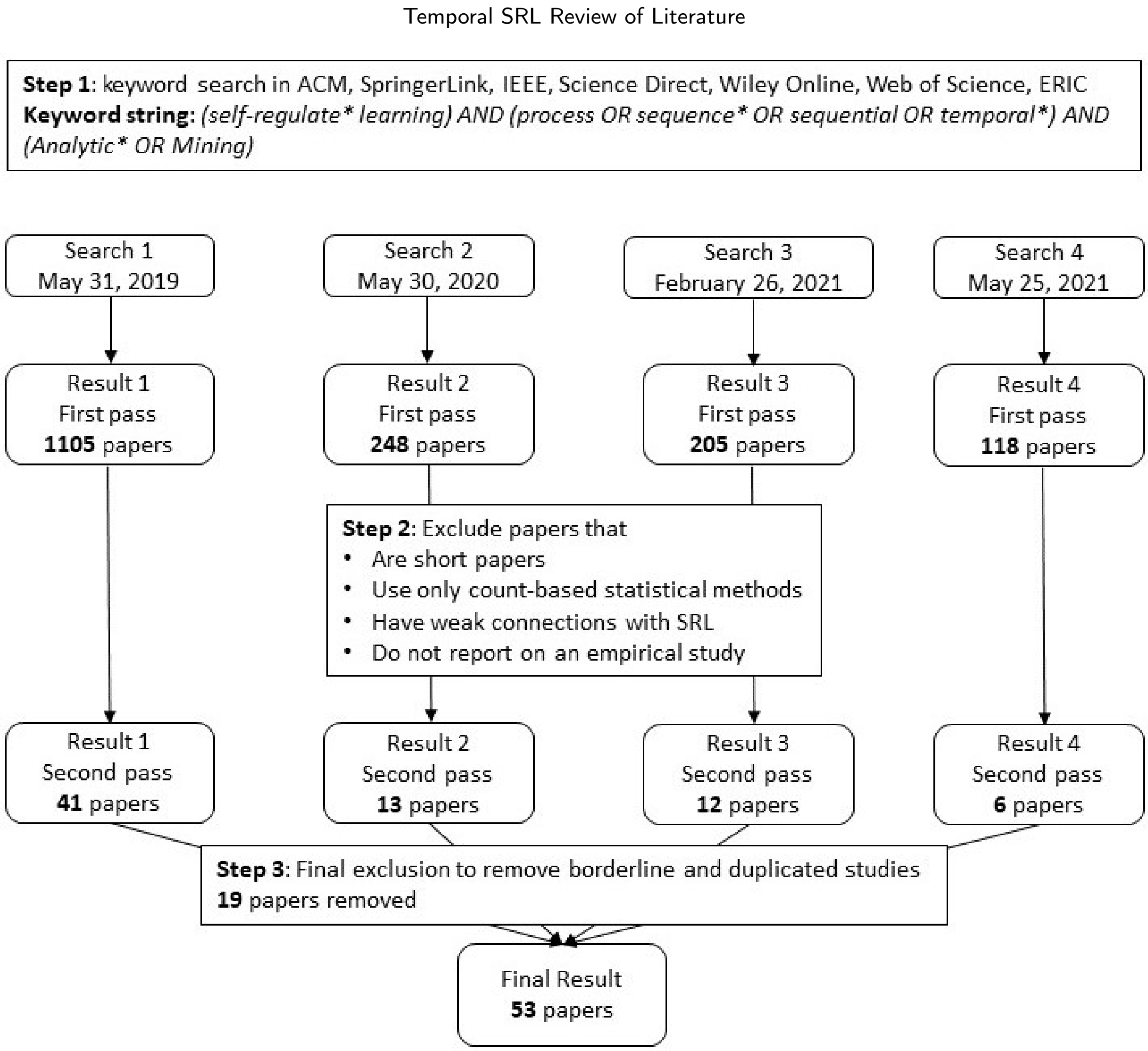

Figure 1: Systematic Literature Review Methodology

SRL, some utilised certain dimensions of SRL, and some combined dimensions from multiple models. In addition, some studies used SRL frameworks to transform data and visualise SRL constructs, whilst others use it to categorise learner group mastery of SRL (normally through questionnaire data). For others, SRL is more of a theoretical context than a framework.

We employed a single code for **RQ3**, namely Discovery/Representation/Visualisation. This a key category as it relates to the method deployed in analysing and visualising the analytical outcomes, and has key implications for the nature and temporality of the phenomena that are modelled in the studies. It should be noted that a section of the studies presented multiple methods for discovery and visualisation. In this review, we report on the methods that are relevant to our scope. To clarify, a study may use Markov models and t-tests to measure some phenomena; in this case, we focus on the Markov models as they relate more specifically to sequence, process, and temporality. This, however, should be viewed as a general approach and not a strict rule.

To support **RQ4**, three codes were employed to characterise these phenomena. **Event type** relates to the core learning event(s) which drive the studies. It is important to note that whilst this may relate to the specific learner actions, such as *page access* or *quiz attempt*, more often this relates to the transformed view of these phenomena, such as learner action sequences. This is key in studies where SRL models are used as theoretical frameworks to inform the design of these transformations and therefore the event descriptions. The **Comparison Criteria** category indicates the

Table 1
Codification by Research Question (1 to 4)

RQ1: What types of data sources/instruments are used in temporal data analysis of SRL?	
Coding	Categories
Participant make-up	K-12, Undergraduate, Postgraduate, MOOC, Professional.
Setting authenticity	Authentic, Experimental, Hybrid
System	LMS, MOOC, OELE, Multi-channel.
System authenticity	Authentic, Experimental, Hybrid
Data collection method	Trace data, Questionnaire, Think-aloud, Digital self-report, Multi-modal.
Data transformation	Micro-level process analysis, Verbal protocol, Trace protocol, Tactic extraction
Sample Size	5 to 7887 (maybe some supporting stats here)
RQ2: What theoretical models of SRL are used?	
Coding	Categories
SRL designation	SRL, Dimensions of SRL
Underpinning Model of SRL	Winne & Hadwin, Zimmerman, Pintrich, Combined.
RQ3: What types of temporal analysis/discovery methods are used.	
Coding	Categories
Discovery / Representation / Visualisation	Process Mining, Epistemic Network Analysis, Transition Diagrams.
RQ4: What type of phenomena or processes are modelled; what type of insights do they provide?	
Coding	Categories
Event Type	SRL phase, SRL process, Learner action, Conversation turn, Video action.
Comparison Criteria	High/Low performance, Unsupervised clusters, Control/Experiment
Learning Outcomes / Assessment measures	Quizzes, Tests, Exams, Projects

way the sample is grouped for comparative analysis, for example, high vs low assessment performers. The **Learning Outcomes/Assessment measures** category indicates what types learning outcomes were assessed. In some cases, this category directly informs the **Comparison criteria** category, and in others it is less relevant.

RQ5 is not subject to codification in this context.

3.3. Presentation of Outcomes

The outcomes of the review are presented in the Results section (4) aligned to the five research questions. These outcomes are further discussed in section 5 through four perspectives: i) *methodological*, informed by the findings of RQ1 and RQ3; ii) *theoretical*, informed by the findings of RQ2; iii) *validity-focused*, informed by the findings of RQ1 and RQ4; and iv) *temporal*, informed by the findings of RQ5. In order to leverage impactful outcomes from this research, the insights from the four perspectives are used to frame a set of questions that we believe researchers should consider and explicitly document in their ongoing study in this area (see section 6). We hope that this inspires a greater clarity of study design and narrative for such studies.

4. Results

We present the results of the review according to the five research questions. Figure 2 shows the general increasing trend in the number of studies in this area. Appendix A provides a summary of the studies included in this review, and some of their key characteristics.

4.1. RQ1: Data Sources and Instruments

4.1.1. Participant Settings

In our sample (see Table 2), the most common educational setting was higher education (HE), with K-12 studies making up the second largest group. One study pooled data from professional settings (Siadaty et al., 2016b) and was

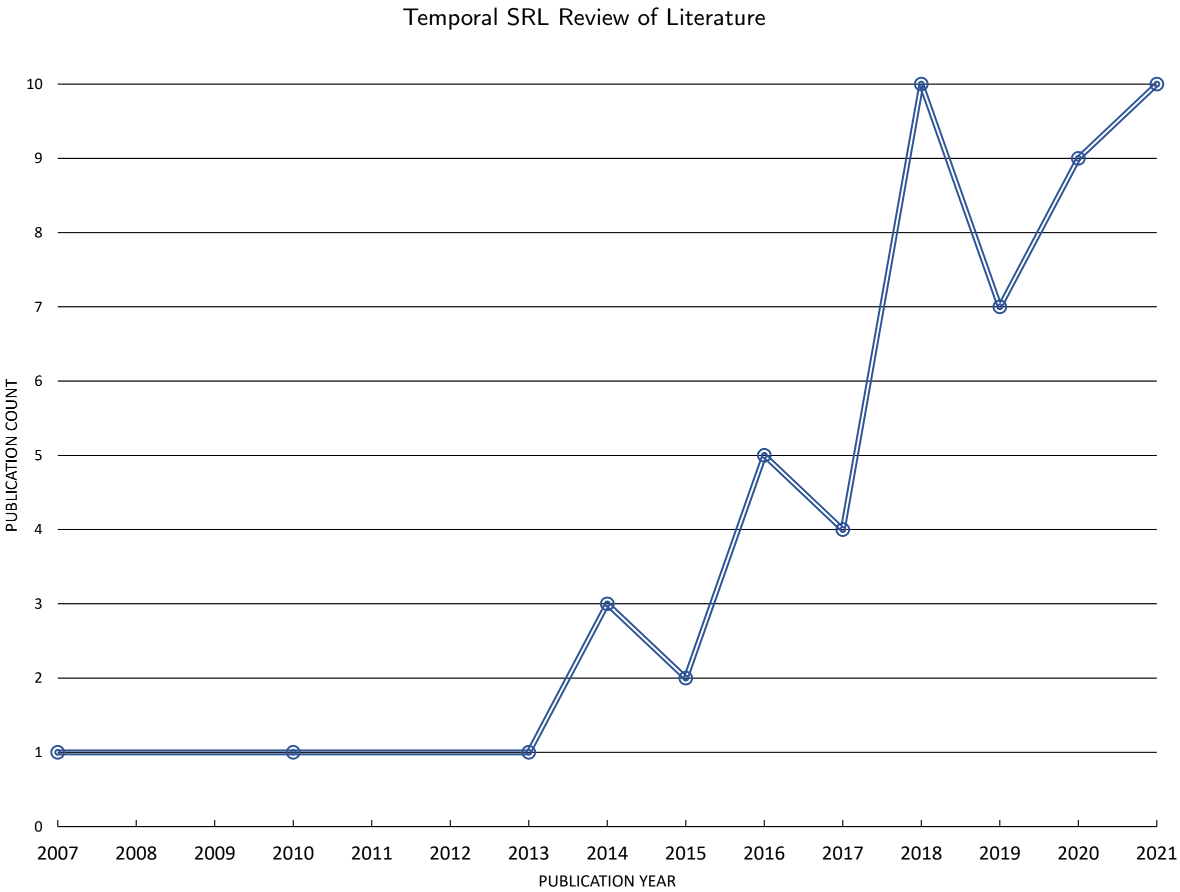

Figure 2: Study counts by publication year

included as it represents a singular and significant contribution to the scope of this review. The majority of studies took place in authentic settings (e.g., in a classroom or online). In the cases of laboratory settings, there were three types of study: i) think-aloud; ii) observed/video-captured studies undertaken in classroom-like laboratories; and iii) multi-modal studies also undertaken in classroom-like laboratories.

The dominance of HE in our study sample is to be expected; educational researchers are generally affiliated to HE institutions and, as such, have ready access to many potential sources of learner data. Within this context, the decision to use undergraduate or postgraduate learners may be driven by considerations of sample size or course design. It also raises the question of the relative mastery of SRL we can expect to measure in context of educational level, and how this can inform learning design in general, as highlighted by Pardo and Mirriahi (2017). The work undertaken in the K-12 studies is no less critical in this context. The studies built on the work undertaken by Biswas et al. (2010) —based on 'Betty's Brain'—highlight the importance of early development of the cognitive and meta-cognitive skills necessary for effective SRL. In addressing the challenges of training K-12 students in SRL, Molenaar et al. (2013) explore the importance of scaffolding at this level. It is clear that a section of students arrive in HE ill-equipped to manage SRL strategies, as evinced in studies by, for example, Bannert et al. (2014) and Saint et al. (2020b). In these studies, groups of students were characterised by optimal and sub-optimal patterns of SRL in relation to performance. The lesson from this may be that sub-optimal self-regulated learners in HE are just ill-equipped, but under-trained, as highlighted in the research on learning regulation and meta-cognitive judgement undertaken by McCabe (2011), Bjork et al. (2013), and Bjork and Bjork (2020).

Sample sizes in MOOC-based studies ranged from 368 to 8,788, notwithstanding the nuances of retention and completion. Institutional studies, which accounted for the majority, have a sample range of 4 to 1,135, a mean of 158, and a median of 71. The methods generally employed in these contexts do not rely on conventional statistical

Table 2
Participant Settings

Coding	Categories	F	RF	Examples
Participant make-up	Undergraduate	38	72%	Cerezo et al. (2020); Bannert et al. (2014)
	K-12	11	21%	Biswas et al. (2010); Molenaar et al. (2013)
	Postgraduate	3	6%	Malmberg et al. (2017); Cheng and Zhang (2020)
	Professional	1	2%	Siadaty et al. (2016b)
Authenticity	Authentic	45	85%	Saint et al. (2018); Maldonado-Mahauad et al. (2018a)
	Experimental	8	15%	Engelmann and Bannert (2021); Sobocinski et al. (2017)
Sample Size	0-100	26	49%	
	100-1000	18	34%	
	1000-10000	7	13%	
	Not stated	2	4%	

Table 3
Systems Utilised

Coding	Categories	F	RF	Examples
System	LMS	28	53%	Järvelä et al. (2016); Bogarín et al. (2018); Ahmad Uzir et al. (2020a)
	MOOC	7	13%	Kizilcec et al. (2017); Fan et al. (2021b)
	OELE	4	8%	Kinnebrew et al. (2014); Paquette et al. (2021)
	Simulation /Modelling	3	6%	Li et al. (2020); Sedrakyan et al. (2016)
	Multimodal	3	6%	Järvelä et al. (2016); Sobocinski et al. (2020)
	Various	8	14%	Davis and Hadwin (2021); Rodríguez et al. (2018)
Authenticity	Authentic	37	70%	Mirriahi et al. (2016); Saint et al. (2020a)
	Experimental	10	19%	Nguyen et al. (2021); Heirweg et al. (2020)
	Hybrid	6	11%	Malmberg et al. (2014); Järvelä et al. (2016)

assumptions such as sample size or normality. This frees temporally focused researchers to explore the dynamics of sample groups of all sizes. The largest non-MOOC study (Matcha et al., 2019a) provided critical insights into learners' strategies and tactics across three years of data, providing insight into the effect of increased feedback provision over the time period. In contrast, Siebert-Evenstone et al. (2017) focused on fine-grained discourse analysis with a sample of 5 students. It highlights the promise of a more nuanced approach to the study of SRL which is afforded by small sample sizes, but forces a discussion on inferential weight.

4.1.2. Systems

In most cases, the systems discussed in the studies are both learning platforms and the sources for data collection. As can be seen in Table 3, most studies use LMSs, MOOC platforms, open-ended learning environments (OELEs) and related systems in this context. There are studies where the LMS has the sole purpose of delivering learning; in the Bannert et al. (2014) study, although a digital platform was deployed to stimulate and support the students' learning, no data were actually collected from it, the data collection method being synchronous think-aloud sessions. In some cases, there is no central digital system for learning, as the study data were collected through observation, for example, Malmberg et al. (2017). It is interesting to note that despite the general prevalence of MOOC studies in the broader field of LA, our sample showed a relatively small number; many of the MOOC studies initially searched, tended to use statistical rather than event-based temporal/sequential methods.

Of the systems used, the majority can be termed authentic. This group is dominated by LMSs. It is prudent to highlight the specialised nature of some LMSs. For example, the nStudy web application (Beaudoin and Winne, 2009), used in the Järvelä et al. (2016) study, was designed to satisfy the demands of SRL research and authentic deployment, as was the web tool (Learn-B) used in the Siadaty et al. (2016b) study. These systems succeed through comprehensive engineering of mechanisms that stimulate learner engagement with cognitive and meta-cognitive activities. As such, the studies that used these systems provided rich results. Siadaty's Learn-B system, however, exists only in the research scope of her studies, so cannot be viewed as anything other than experimental. nStudy still enjoys a presence in SRL circles, but is specially engineered to elicit SRL trace-data and is categorised as hybrid rather than authentic. Clear challenges exist in recreating similar outcomes in more authentic systems.

That MOOCs have some prominence in our sample is understandable, as researchers contemplate the promise of capturing learning patterns that are overtly positioned in online settings, as opposed to the partial or diluted picture that may come from a conventional LMS. This positioning has afforded researchers the opportunities to explore, for example, the linkage between learning design and SRL (Fan et al., 2021a). Several studies made use of OELEs, in particular the 'Betty's Brain' system for K-12 learners (Biswas et al., 2010), which provided a unique means of coaching and supporting its learners in active engagement with SRL.

Some systems are not subject to simple platform categorisation, as they extract data from specific and specialised areas of LMSs, or do not utilise a recognised LMS of any kind. The Sedrakyan et al. (2016) study, for example, used an enterprise modelling tool (JMermaid) to capture specialised problem solving behaviours, which were then analysed in the context of self-regulation. Such systems provide singular insights into self-regulation and planning, due to the applied, problem-based nature of their design.

4.1.3. Data collection methods

The choice of system informs, or is informed by the data collection method. The most common data collection methods in our sample were (digital) trace data and self-report data in its various forms (see Table 4). In this context, trace data are digital logs of learner actions undertaken in a LMS/MOOC/OELE type setting. Self-report data collection encompasses think-aloud, questionnaire, interview, or any scenario where the learner is asked to reflect on an aspect of their learning. This reflection maybe synchronous, that is, collected at the same time (or very shortly before or after) the learning event happens, or asynchronous, such as questionnaires captured before or after the event. Think-aloud data capture (e.g., Bannert et al. (2014)) is a common example of synchronous capture, although digital self-report mechanisms, such as the S-REG tool used in the Sobocinski et al. (2017) study, are also used. Asynchronous capture is exemplified in the Kizilcec et al. (2017) study, where pre-questionnaires were administered to learners in order to determine groupings of SRL mastery.

The decision to use trace data, self-report data, or a combination of the two, is important. Ericsson and Simon (1980), Ericsson and Simon (1984), and Greene et al. (2011) provide compelling arguments in favour of self-report as a method of capture. Self-report measures provide researchers with the means of capturing nuances of SRL that cannot be extracted from trace data alone. This is demonstrated by the studies in our sample (e.g., (Bannert et al., 2014; Sonnenberg and Bannert, 2016)). Self-report data collection allows researchers to extract truly rich articulations of SRL. In some cases, where learning behaviours were recorded (e.g., Nguyen et al. (2021)) or think-aloud data capture was employed (e.g., Heirweg et al. (2020)), no central digital system was actually used. The veracity of self-report has been called into question; Winne and Jamieson-Noel (2002), for example, explored the disparity between students' reporting of their own study tactics and their actual behaviours and found that students tended to demonstrate a positive bias in their perception of their achievements and of their use of study tactics.

The use of authentic LMS/MOOC trace data is attractive to researchers as it mitigates many of the concerns highlighted above; data are collected unobtrusively from digital learning platforms, without any extra cognitive demands on the learners. The downside is that, outside of specialised SRL platforms, like nStudy (Beaudoin and Winne, 2009) or Learn-B (Siadaty et al., 2012), the data captured require significant transformation and interpretation to provide meaningful insights. As such, the use of this method (or more accurately, the data transformation methods discussed in section 4.1.4) raises validity issues that some see as insurmountable without observational or self-report mechanisms to provide corroboration Rovers et al. (2019).

Of particular importance to the exploration of SRL are the studies which pool data from multiple sources to analyse the same phenomena, categorised here as *multi-channel*. For example, in the Järvelä et al. (2016) study, temporal/sequential analyses of chat discussions and trace data were matched to identify evidence of socially shared regulation in postgraduate students. This triangulation has important implications for the cross-validation of SRL analyses of trace data. The Järvelä et al. (2021) study is one of three studies that attempt to triangulate multi-modal data (e.g., heart-rate, electrodermal, facial expressions) as a means of understanding SRL. These studies are large in ambition and

Table 4
Data Collection and Transformation Methods

Coding	Categories	F	RF	Examples
Data collection method	Trace data	35	66%	Bogarín et al. (2018); Boroujeni and Dillenbourg (2019)
	Questionnaire	11	21%	Kizilcec et al. (2017); Mahzoon et al. (2018)
	Think-aloud	5	9%	Bannert et al. (2014); Sonnenberg and Bannert (2016)
	Digital self-report	3	6%	Davis and Hadwin (2021)
	Observation / Recordings	6	11%	Malmberg et al. (2017); Munshi et al. (2018)
	*Multi-Channel	7	13%	Sobocinski et al. (2020); Malmberg et al. (2021)
	**Combined	27	51%	Malmberg et al. (2014); Dorodchi et al. (2018)
Data transformation	Verbal protocol	20	38%	Molenaar et al. (2013); Siebert-Evenstone et al. (2017)
	Trace protocol	15	28%	Cerezo et al. (2020); Lim et al. (2021)
	**Combined Trace Verbal	5	9%	Li et al. (2020); Cheng and Zhang (2020)
	Micro-level process analysis	8	15%	Siadaty et al. (2016b); Saint et al. (2020b)
	Tactic extraction	2	4%	Matcha et al. (2019a); Fan et al. (2021b)
	None	3	6%	

*These studies combine multiple data sources/channels about the same observed phenomenon.
**These studies combine multiple data sources/channels about observed phenomenon.

their results provide key insights into understanding regulatory behaviours that are not detectable from standard LMS or MOOC data. There is an obvious trade-off with regard to the level of resources and skills required to orchestrate the experiments and triangulate the data.

4.1.4. Data Transformation

In most studies, the data were transformed or categorised prior to the main discovery and analysis process. In many cases, some form of pre-defined or data-informed qualitative coding took place (see Table 4). For trace data transformation, a section of the studies, including Siadaty et al. (2016b) and Saint et al. (2020b), employed a formalised method of SRL transformation called micro-level process analysis (Cleary, 2011), using regular expression (REGEX) scripts. For self-report transformation, such as those based on the Bannert framework (Bannert, 2007), researchers employed specific verbal protocols Chi (1997) to transform the raw data—respondent utterances—into learning/SRL events. This type of coding is also necessary for asynchronous verbal capture instruments which analyse discourse, typically from discussion boards, such as the study by Huang and Lajoie (2021). This phase, often termed pre-processing, is critical, particularly when considering the empirical demands of conceptualising models of SRL (discussed in section 4.2)

4.2. RQ2: Models of SRL

In regard to embedding analyses in models of learning, our sample breaks down broadly into these model categories: i) Recognised models of SRL, which are dominated by Zimmerman (2000) and Winne and Hadwin (1998); ii) SRL in conjunction with, or as part of a model of socially shared regulation of learning (SSRL) and/or co-regulated learning (CoRL); and iii) related dimensions of SRL, referring to studies which do not present SRL as a key element but touch on related elements, such as cognition, meta-cognition, and strategy. Within the first two model categories, we added two subcategories to the model descriptions (see Table 5). The term *Consolidated* refers to instances where dimensions of multiple SRL models were employed in unified frameworks. The term *Dimensions* refers to instances where SRL was presented as a key element of the study, but does not draw on all elements of a single or consolidated model.

4.2.1. Recognised SRL Models

Of the studies underpinned by Zimmerman (2000), most used trace data as a primary data source. In this context, it may be seen that Zimmerman's model is more easily adapted to trace-data interrogations. In all cases, the major constructs of the model were adapted in the form of a coding framework of learner actions sequences into SRL processes.

Table 5
SRL Model Categories

Model Category	Model Description	F	RF	Examples
SRL		**36**	**68%**	
	Zimmerman	9	17%	Molenaar et al. (2013); Saint et al. (2020b)
	Winne and Hadwin	4	8%	Bakhtiar and Hadwin (2020); Malmberg et al. (2021)
	Bannert	4	8%	Bannert et al. (2014); Engelmann and Bannert (2021)
	Pintrich	1	2%	Biswas et al. (2010)
	Consolidated	10	19%	Kizilcec et al. (2017); Paquette et al. (2021)
	Dimensions	7	13%	Munshi et al. (2018); Fan et al. (2021a)
SRL, CoRL, SSRL		**8**	**15%**	
	Winne and Hadwin	3	6%	Malmberg et al. (2017); Bakhtiar and Hadwin (2020)
	Consolidated	5	9%	Su et al. (2018); Sobocinski et al. (2020)
Related Dimensions		**9**	**17%**	Mahzoon et al. (2018); Boroujeni and Dillenbourg (2019)

As such, the codings can be viewed as a model-informed framework, where the major constructs of the model align to the three fundamental SRL phases, named here: i) planning; ii) enactment; and iii) reflection. The study by Siadaty et al. (2016b) was the first to use the micro-level process technique to a transform trace data (albeit semi-experimental) into SRL patterns and this technique was built on in the Saint et al. (2020b) study, using authentic LMS trace data. The Winne and Hadwin (1998) model of SRL informs a number of studies in our sample. The Bakhtiar and Hadwin (2020) study, for example, explored a broader set of elements of the Winne and Hadwin model, such as external and cognitive conditions, as well as affective and behavioural elements. As already stated, it is more viable to articulate a nuanced view of SRL when using self-report or discourse-based data as a source, as also demonstrated by Malmberg et al. (2021). With regard to the studies that use the Bannert (2007) coding, it is defined as a theoretical framework of self-regulated hypermedia. It is a coding scheme based on a distillation of SRL elements. Indeed, Bannert et al. do not present this framework as an SRL model, but more as a means of demonstrating how PM can be used to test theoretical models: "This analysis is rather illustrative than informative for SRL research because theoretical assumptions on the micro-level would be needed for a proper analysis which are not provided by SRL models at the moment" (2014, p. 181). Despite this caveat, the framework has many structural elements of recognised models of SRL, and is thus categorised as such in this review.

4.2.2. Consolidated Models

The MOOC study by Kizilcec et al. (2017) is significant in that it highlights a key methodological choice with regard to analysing SRL; whether to use a single SRL model in its entirety, and risk polling data to measure inappropriate constructs, or to construct a contextually relevant framework from disparate, though empirically robust, SRL sources. Kizilcec et al. chose the latter and from this derived a set of six strategies/measures—goal-setting, strategic planning, self-evaluation, task strategy, elaboration, and help-seeking—from various SRL authorities, such as Zimmerman (2000), Pintrich (2000), Schunk (2005), Effeney et al. (2013), and Niemi et al. (2003), amongst others. Kizilcec's framework, it should be noted, was not used to transform trace data, but to inform the design of pre-study questionnaires used to segment learner groups. The trace data analysed were atomic learner actions, not SRL processes. This method was employed by several studies in our sample (e.g., Cheng and Zhang (2020)).

4.2.3. SRL, CoRL, SSRL

A section of studies recognised that key models of SRL may not fully represent the machinations of learning in group-based collaborative settings. The Malmberg et al. (2015) study focused on socially shared regulation of learning (SSRL) and presented a coding scheme based on empirical conceptions of SSRL explored by Hadwin et al. (2011) and Järvelä et al. (2015). Using a consolidated framework of SSRL, the authors were able to more clearly recognise

Table 6
Summary and Comparison of the Main Analytic Discovery Methods

	Process Mining	ENA	Transition and Sequence Analysis	Other methods
Proportions	53%	13%	26%	25%
Methods	Fuzzy Miner Classic Fuzzy Miner Modern FOMM Heuristics Miner Inductive Miner ProDiGen	ENA	Sequential diagrams Transition graphs	Sankey diagrams CORDTRA diagrams Dotted Chart HMM Temporal Heatmaps Bespoke
Package /Toolkit	ProM, BupaR Disco, Celonis pMineR	rENA Web-based ENA tool	Various	Various
Key features	Frequency, time Correlation Transition probability	Frequency Co-occurrence Node positions	Frequency Co-occurrence Transition metrics	Time series Hidden States
Examples	Bannert et al. (2014) Saint et al. (2020b) Bogarín et al. (2018)	Matcha et al. (2019b) Fan et al. (2021a) Saint et al. (2020a)	Molenaar et al. (2013) Mirriahi et al. (2016) Siadaty et al. (2016b)	Chen et al. (2018b) Lim et al. (2021) Dorodchi et al. (2018)
Advantages	Multiple metrics, Configurable, Multiple platforms, Interpretable, Copes with messy data	Static nodal positions, Difference plots, dENA	Aspects of PM and ENA	Customised, Novel, State-of-the-art
Limitations	Metrics can be deceptive	No directional association, demotion of less frequent activities	Usurped by PM and ENA	Not familiar, hard to recreate analyses

how students addressed technological and time-management issues in the context of shared regulation, for example, (Malmberg et al., 2015).

4.2.4. Dimensions of SRL

In some studies, SRL informs the analyses in explicit or implicit ways, but does not impose specific SRL model demands. The Chen et al. (2018b) study demonstrated a variety of novel visualisations relating to frequency, sequence, and temporality, and although SRL is not front and centre, its potential to facilitate SRL is highlighted. The Sedrakyan et al. (2016) study proposed that self-regulative learning patterns could be found in activities such as testing and validation in relation to domain modelling tasks. It does not, however, go as far as identifying a model, or even a generic SRL framework. The Siebert-Evenstone et al. (2017) study does not attempt to present SRL in any form, but nonetheless presents findings that could inform SSRL research. The co-temporality and categorisation of discussions on collaboration, technical constraints, and reasoning, have definite synergies with SRL theory. The Dorodchi et al. (2018) study explicitly adapted the seminal model of experiential learning developed by Kolb (2015) as a course model in their study; the adaptation has echoes of the SRL cycle, with components such as pre, post, and in-class activities, punctuated by periods of reflection.

4.3. RQ3: Discovery Methods

Half of the studies in our sample used PM in some form (see Table 6), which reflects the growing popularity of this group of methods outside of the business sector in which it was first conceived and operationalised. A quarter of the studies used variations on transition graphs and sequence-oriented models. ENA (Shaffer et al., 2016) is gaining popularity and was used in the more recent studies in our sample. A small number of studies used hidden Markov models. Around a tenth of the studies employed uncommon or novel methods, not found in other studies. Several studies used multiple discovery methods to explore a potentially richer view of SRL and its related dimensions.

4.3.1. Processing Mining

PM seeks to provide insights into the sequential nature of activities within a given process space. This is achieved through PM discovery algorithms, which allow for the identification of arrangements of activities in a given operational space (Günther and Rozinat, 2012). This is visualised in the form of process maps. In our sample, the Fuzzy Miner PM algorithm (Günther and van der Aalst, 2007) was used more than any other. In its original form, Fuzzy Miner provided two fundamental metrics named *significance* and *correlation*. These measures should not be confused with the recognised statistical measures with which they share names. *Significance* is described as a measure of importance of an event class in a log, or of the importance of a relationship between pairs of event classes in terms of precedence. *Importance* is generally measured in terms of frequency, and so we can interpret this quite intuitively. The *correlation* metric, which measures the closeness in relation between two events, is more abstract and complex in its conception, taking into account factors such as overlap of data attributes, and the similarity of event names (Günther and van der Aalst, 2007). The Bannert et al. (2014) study and the Sonnenberg and Bannert (2016) both used classic Fuzzy Miner (Günther and van der Aalst, 2007), to examine SRL patterns from think-aloud data. In using PM, these studies promised a novel way of viewing patterns of SRL not seen before at the time, and provided useful visual insights into contrasting levels of SRL across performance groups. Fuzzy Miner gained greater popularity in its later incarnation in commercial tools such as Fluxicon Disco and Celonis, where, crucially, the classic metrics were dropped in favour of more intuitive measures, such a frequency and time. The majority of Fuzzy Miner-based studies in our sample use the modern platforms. A number of studies used the BupaR processing mining tool to produce almost identical outcomes to the modern Fuzzy platforms; we have categorised them as part of the modern *Fuzzy Miner Modern* algorithms in Table 6. The Maldonado-Mahauad et al. (2018a) study employed frequency metrics to analyse how students' interactions with video content reflected SRL mastery, while the Saint et al. (2020a) study used time (median time-on-task and between-activity lag in minutes) to explore SRL behaviours in high and low performance groups. In the studies that used PM based on first-order Markov models (FOMMs) (Gatta et al., 2017), probability is the primary metric used to articulate transition behavior between learner activities. Matcha et al. (2019a), for example, used this method to explore the dynamics of learning tactics in and the likelihood of transition between them in a given learning session. The Kinnebrew et al. (2013) and Cheng and Zhang (2020) studies both used hidden Markov models to explore SRL process transitions in contrasting groups of students. Several studies used the Heuristics Miner (Weijters et al., 2006) as their primary discovery method. Two of the studies (Bogarín et al., 2018; Cerezo et al., 2020) used Inductive Miner, which employs frequency and time metrics, but places an emphasis on sequential, rather than temporal association. In these studies, LMS learning paths, termed sub units, were modelled. The specific design of these sub units aligned well with sequential demands of Inductive Miner to provide useful insights into learner actions categorised as SRL processes.

4.3.2. Epistemic Network Analysis

ENA is an analytical technique which utilises epistemic frames theory to analyse log/trace data in individual and collaborative settings to provide insights into co-existence of learning behaviours in time (Shaffer, 2004). ENA categorises features of individual and group learning (e.g., action, communication, and cognition), which it then uses to create nodes in an epistemic network. This method was explored by Siebert-Evenstone et al. (2017), who used ENA to explore cotemporality in the context of discourse analysis. In truth, ENA was originally designed to capture learning as it is expressed in conversation turns, and in collaborative scenarios, but has been extensively used to analyse activity-based learning. It was used to analyse co-temporality in SRL and related strategies in the studies by Matcha et al. (2019b), Ahmad Uzir et al. (2020a), and Saint et al. (2020a).

4.3.3. Transition and Sequence Analysis

The discovery methods in this section reflect certain elements of more recognised methods (e.g., PM or ENA), and in some cases can be seen as prototypical. The study reported by Molenaar et al. (2013) used sequential diagrams to explore sub-metacognitve events in K-12 students. This technique has echoes with the probabilistic process mining techniques in that it provides a likelihood of movement from one process to the next, in terms of relative percentage frequencies; effectively transition probabilities. The Mirriahi et al. (2016) study used transition graphs, which reflect elements of ENA and PM, albeit in a cruder form. The Siadaty et al. (2016b) also used a similar, if more sophisticated, method to articulate, in a network space, the associations between intervention events and SRL activities.

4.3.4. Novel methods

The Järvelä et al. (2016) study is largely frequency-based but provided some interesting temporal insights in the form of micro-level sequence diagrams, which provide the reader with contrasting SRL sequences of higher and lower performers. The Mahzoon et al. (2018) and Dorodchi et al. (2018) studies both used a sequence-based analysis method that generated term-long "signatures" that exemplified succeeding and failing students. The Chen et al. (2018b) study employed a set of novel visualisations not found elsewhere, to mine sequential patterns and non-linear learner events, linked to academic performance. The Lim et al. (2021) study used Sankey diagrams (Kennedy and Sankey, 1898) to articulate key associations between tactics and temporal study modes.

4.4. RQ4: Phenomena Insights

The largest portion of learner events modelled in our sample can be categorised as SRL processes (see Table 7). In most cases, some form of SRL-informed data transformation or coding was enacted to derive these processes (see section 4.1.4). This allowed for a direct interpretation pattern or sequences of SRL events in whatever discovery method was used. For the cases categorised as learner actions, whilst some data cleansing/transformation may have been applied, the modelled event was generally a context-specific learner action, such as *read* or *watch video*. In these cases, insights were extracted through an SRL-informed interpretation of the learner actions, or an SRL-informed questionnaire was used to identify learner clusters. Learning tactics were modelled to derive learning strategies in one particular study group. The comparison criteria deployed are varied but the most commonly used is assessment performance. The next most common method is by tactic or strategy clusters; a number of studies combined performance and clustering. Several studies used the classic control-treatment method, mostly in connection to metacogntive support (e.g., with prompts or without). The assessment outcomes were dominated by assignments and task or project-based work. A smaller section of the studies employed pre and post knowledge transfer tests, although the lines were blurred in regard to whether these tests link to learning outcomes, experimental outcomes, or both.

We have identified five groups of studies that are typified by recurring authors, data sources, and methods. The importance of such research groups is that they make use of common instruments, data, or methods, yet provide differing perspectives and insights.

4.4.1. Bannert and Sonnenberg

The studies by Bannert et al. (2014), Sonnenberg and Bannert (2015), Sonnenberg and Bannert (2016), and Engelmann and Bannert (2021) all made use of the same self-report data source and the same SRL coding framework. Their collective strength is that they avoided unnecessary inquiry duplication and provided a multi-dimensional view of common sets of learning behaviours. These views are derived from the use of differing modes of discovery in combination with differing comparative criteria. The original Bannert et al. (2014) study employed a novel—as it was at the time—use of the Fuzzy Miner PM algorithm to explore SRL engagement in higher and lower performing students in differing levels of granular coarseness. In this way, the researchers were able to attach meaning to the contrasting ways in which the learner groups manifested SRL. The PM visualisations provided a means of observing the occurrences of SRL elements and how strongly or weakly they connected in a sequential and temporal space. The three subsequent Sonnenberg and Bannert studies shifted the focus from high and low-performers to the effect of meta-cognitive prompting, utilising the control/experiment method to isolate their effect. Fuzzy Miner and Heuristics Miner were variously used, as well as dotted chart analyses. These visualisations, in combination with non-temporal statistical metrics, were used effectively to identify the impact of the prompts on behaviour sequences in the context of SRL, for example, “In contrast to the model of the students in the experimental group, ANALYZE is only weakly connected with SEARCH, and therefore, it is quite isolated” (Sonnenberg and Bannert, 2015, p. 92). This typifies the narrative affordances provided by event-based process analyses that are not accessible through statistical measures alone. It should be noted that, in all these studies, statistical measures do have an important place as a complementary set of metrics.

4.4.2. Järvelä, Malmberg and Molenaar

The studies by Molenaar et al. (2013), Malmberg et al. (2014), Malmberg et al. (2015), Järvelä et al. (2016), Sobocinski et al. (2017), and Malmberg et al. (2017), provided a focus on group learning, collaboration, and social self-regulated learning. The data collection methods used were various—self-report, video-capture, trace-data, assessment codification—but all of these studies demonstrated a genuine attempt to embed analyses in constructs of SRL through codified translation of data into SRL processes or phases. This strong alignment to SRL (and its collaborative

Table 7
Modeled Phenomena

Coding	Categories	F	RF	Examples
Event Type	SRL processes	22	42%	Malmberg et al. (2015); Saint et al. (2020a)
	Learner actions	16	30%	Biswas et al. (2010); Maldonado-Mahauad et al. (2018a)
	Learning tactics	6	11%	Matcha et al. (2019a); Fan et al. (2021b)
	SRL processes/phases, Physiological	3	6%	Sobocinski et al. (2020); Järvelä et al. (2021)
	Various	8	15%	Mahzoon et al. (2018); Boroujeni and Dillenbourg (2019)
Comparison Criteria	Performance High/(Medium)/Low	17	32%	Bannert et al. (2014); Cheng and Zhang (2020)
	Tactic/Strategy Clusters	11	21%	Mirriahi et al. (2016); Ahmad Uzir et al. (2020a)
	Control/Experiment	6	11%	Kinnebrew et al. (2014); Lim et al. (2021)
	SRL self-perception	5	9%	Kizilcec et al. (2017); Li et al. (2020)
	By student	2	4%	Siebert-Evenstone et al. (2017); Järvelä et al. (2021)
	At-risk/Not at-risk	2	4%	Mahzoon et al. (2018); Dorodchi et al. (2018)
	Various	8	15%	Sonnenberg and Bannert (2016); Nguyen et al. (2021)
	None	2	4%	Siadaty et al. (2016b); Chen et al. (2018b)
Learning Outcomes	Assignments	21	40%	Saint et al. (2018); Cerezo et al. (2020)
	Task/project-based	12	23%	Sedrakyan et al. (2016); Huang and Lajoie (2021)
	Pre-post/transfer test	9	17%	Biswas et al. (2010); Munshi et al. (2018)
	n/a	6	11%	Hadwin et al. (2007); Malmberg et al. (2017)
	Various	5	9%	Malmberg et al. (2015); Heirweg et al. (2020)

variations) is a constant across the group but there are novel variations in comparison criteria; in fact, almost all the identified criteria—Performance, Clustering, Control/Experiment, amongst others—are represented. The Molenaar et al. (2013) study provided insights, gleaned from discourse analysis, into the effects of meta-cognitive prompts in online settings. The prompts devised were overtly designed using SRL constructs and so helped articulate the analyses in a strong theoretical context. The Malmberg et al. (2015) study relies on codified self-report data drawn from SSRL prompt mechanisms within the LMS. The resultant SSRL constructs were aligned into pairs to represent focus and function in a transitional sense. High and low performing groups were compared using PM. As with other comparative PM SRL studies, the findings reflected a more cohesive sense of learning management in the higher performers. The later studies undertaken in this group, Sobocinski et al. (2020), Järvelä et al. (2021), Malmberg et al. (2021), demonstrate even greater levels of innovation by triangulating observational data with multi-modal physiological data to provide rich insights into collaborative SRL.

4.4.3. Gašević and Pardo

The group of studies by Saint et al. (2018), Matcha et al. (2019a), Ahmad Uzir et al. (2019), Saint et al. (2020b), Saint et al. (2020a), Ahmad Uzir et al. (2020a), Ahmad Uzir et al. (2020b), Fan et al. (2021b), Fan et al. (2021a), and Saint et al. (2021), is underpinned by a commitment to the analysis of trace-data. A section of the studies pooled data from the same LMS source, albeit from differing cohorts/time periods; the remainder were pooled from MOOC and Moodle data sources. The Saint et al. (2018) study explored the use of a novel FOMM PM algorithm to articulate and compare patterns of learning across a set of student tactic clusters. The contrasting patterns of learning tactics and time management were explored though the lens of process and probabilistic sequence, using first order Markov models. The Matcha et al. (2019a) study presented a sophisticated clustering method to identify tactic patterns across different learner strategy groups, further overlaid with analyses of feedback provision and assessment performance. The Ahmad Uzir et al. (2020b) study used a similar clustering technique but provided a more specific focus on time management strategies. In these studies, SRL-informed insights were provided without binding to a specific model of

SRL. The Saint et al. (2020b) and Fan et al. (2021b) studies, for example, did employ a specific SRL coding framework, first explored by Siadaty et al. (2016b), in order to embed the analyses in a model of SRL. In summary, three event types were explored by this group, time-management actions, tactics, and SRL processes, using tactic/strategy clusters and (associated assessment metrics) as comparison criteria. The Fan et al. (2021b) study uniquely combined tactic extraction and SRL processing to explore the intersection between the two concepts.

4.4.4. Kizilcec and Maldonado-Mahauad

The studies by Kizilcec et al. (2017), Maldonado-Mahauad et al. (2018a), and Maldonado-Mahauad et al. (2018b) all employed a consolidated SRL framework to measure learner behaviours. In these studies, questionnaires were used to poll strategies based on instrument constructs such as goal-setting, help-seeking, self-evaluation, and other elements well-known to SRL researchers (Kizilcec et al., 2017). The survey scores were then used to categorise and triangulate subsequent MOOC trace-data findings. In these cases, the final visualisations related directly to trace-data interaction events, for example, 'video-lecture play', 'assessment pass', and 'assessment review', which were not direct manifestations of SRL in and of themselves. However, the sequential-temporal visualisations of these interactions provided a means of clustering learners and, critically, assigning different interaction sequences to specific SRL constructs. Cheng and Zhang (2020) made use of the Kizilcec et al. method in the studies they documented in relation to writing and reading comprehension. They, however, made use of hidden Markov models to visualise sequence and temporality, as opposed to the various PM methods used by Kizilcec and colleagues.

4.4.5. Biswas and Kinnebrew

Four studies, Biswas et al. (2010), Kinnebrew et al. (2014) Munshi et al. (2018) Paquette et al. (2021), explored SRL and temporality in K-12 students by harnessing data from a common open-ended computer-based learning environment, 'Betty's Brain' (Biswas et al., 2005). As such the comparison criteria and learning outcomes are closely linked via the control/experiment pre/post test experimental design, and the event types are also equivalent. Much variety is found in methodological choices around data analysis and visualisation. In the Biswas et al. (2010) study, groups were delineated by feedback provision. The LBT (learning by teaching) group were provided corrective feedback and the SRL group were provided with more strategic guidance, on request. The control group (ICS) did not have Betty. In this case, delineation is by experimental control, as opposed to performance or unsupervised clustering. The Paquette et al. (2021) study used ENA to explore the coherence (or otherwise) in the problem solving actions of low and high performers, in the context of SRL. In this group, a common platform has inspired a varied and novel set of studies that have significant implications on the introduction of SRL in early learners.

4.5. Research Group Mobilisation

Most researchers are, in some way, part of one or more research groups (see section 4.4), and these groupings provide an interesting lens through which to view the phenomena modelled in temporally focused research of SRL. The Bannert and Sonnenberg group all pooled from the same data source(s) and modelled the same types of SRL events and the learning outcomes and comparison criteria were geared towards the experimental. Beyond these constants, there is a diversity of discovery methods and differing emphases on meta-cognitive support, providing very useful insights which can be used to inform LMS support systems. The Järvelä, Molenaar and Malmberg group are characterised by a strong adherence to SRL theory, which see them consistently model SRL process events. This constant allowed for a rich diversity of comparative criteria and innovative analyses of assessment work. The group is also typified by a broad selection of discovery methods which provide key SRL insights. The Gašević and Pardo group, typified by LMS and MOOC trace data collection, was able to analyse SRL and tactic-oriented event data, and provided strong methodological emphases on process mining and ENA, and combinations thereof. The Kizilcec and Maldonado-Mahauad group provided unique insights with the combination of trace data and SRL questionnaires (which they then used to categorise learners). The Biswas and Kinnebrew group modelled exactly the same 'Betty's Brain' events but employed novel and varied discovery algorithms and powerful experimental comparative methods across the group to provide varied insights from similar data. Beyond the categories outlined in Table 7, the studies in our sample are typified by a number of moving parts, as outlined in Table 1. In building on current studies, thought should be given to which parts to fix and which to change in order to push forward the collective aims of the research group.

4.6. RQ5 Temporal Analysis and SRL

The studies in our sample bear witness to the increasing focus on temporal dynamics in SRL. The conception of SRL as a process that unfolds over time (as opposed to a learner characteristic) reveals a synergy between the research disciplines of SRL and temporal analysis. There is therefore an increase in the number of studies that recognise that conventional statistical measures are obviously valuable but are part of a paradigm that suffers from ontological shortcomings in the light of temporally informed models of SRL. Molenaar (2014) issued a manifesto for the research of temporally focused learning analytics, to which Chen et al. (2018a) provided a response. These two rallying calls inform the treatment of results in this section.

4.6.1. Learning constructs of SRL in relation to time

As discussed in section 4.2, the way SRL constructs are modelled is subject to a certain amount of nuance, and the same could be said of their temporal dynamics. Chen et al. (2018a) conceptualised two broad temporal features: i) The *passage of time* relates to duration or frequency, for example, time spent on a learning task or frequency/mean/median of engagement with learning tasks over a defined period, demonstrated at a weekly level in the study by Ahmad Uzir et al. (2020b); and ii) Temporality as a representation of how events or states are ordered and the nature of their relationship in terms of sequence. SRL temporal engagement can be defined in absolute terms of frequency of engagement but the order and sequence of engagement is lost in this conception (Reimann, 2009). In the studies included in this review, temporal currency is not only duration, as in time-on-task or time-between-task, but frequency of transition between learning events (e.g., Maldonado-Mahauad et al. (2018a)), and the probability of transition between SRL events (e.g., Saint et al. (2020b)), or non-directional temporal co-occurrence (e.g., Paquette et al. (2021)). The usage of one or more of these temporal dimensions in SRL studies demands a justification as a way of demonstrating an awareness of what they can and cannot bring to the analysis of SRL. Capturing events in a temporal context can be challenging if we accept that learners may gain access to an artifact, but may not engage with it. They may, for example, have opened a page and then moved onto something else. Are periods of inactivity really inactive? As such, the management of (or the acceptance of) temporal nuances such as this require thought.

4.6.2. Bridging the gap between micro data and macro theory

The coding schemes used by, for example, Bannert et al. (2014), Siadaty et al. (2016b), Saint et al. (2020b), and Fan et al. (2021b), are clear examples of an attempt to bridge the gap between the micro-level source data and the theoretical macro-level constructs of SRL. As such they represent positive moves to strengthen the theoretical basis for such studies. These transformations (see section 4.1.4), which essentially coarsen the grain of the raw data, seek to embed analyses in theoretical models of SRL (see section 4.2). If deployed optimally, the coding frameworks serve the purpose of bridging the gap between theoretical models of learning and raw learner actions. With regard to the broader issue of validity, these efforts are not always sufficient. From a temporal perspective, in bridging this gap, the question of event and time segmentation is raised.

4.6.3. Segmenting time units

In our studies, there are examples of broad and narrow temporal segmentation. The studies by Mahzoon et al. (2018) and Dorodchi et al. (2018) employ segmentation at both semester level to inform *between semester* sequence modelling, and at weekly level to inform *within semester* modelling. Weekly segmentation is used in several studies on the understandable premise of weekly learning cycles, as commonly built into syllabus design. The Matcha et al. (2019a) study, for example, plotted tactic engagement frequency and how it changed from week to week over the course of a single semester. The Sobocinski et al. (2020) study employs finer segmentation, plotting sequences of group regulation across various segments ranging from around 10 to 30 minutes. In the studies which employed macro/micro transformations (e.g., Saint et al. (2020b), Fan et al. (2021b), see section 4.6.2), segmentation is key for researchers who seek to analyse learning patterns within designated learning sessions, which are variable in length but delineated by periods of inactivity. The Fan et al. (2021b) study, for example, employed a two-step segmentation process to segment days and then learning sessions; a gap of 45 minutes or more between activities triggered the start of a new learning session.

4.6.4. Analysing theorised learning constructs in a temporal sense

In a sense, this question is a methodological extension of section 4.6.1 and brings to bear much of the discussions in section 4.3. The Bannert et al. (2014) study is seminal in many ways, and represents one of the earliest attempts to capture SRL using PM as a means to capture temporal order of individual regulation activities. This emphasises a position that temporality in the context of order and sequence. Order matters because learning is a cumulative sequence of experiences Reimann (2009). In the Saint et al. (2020b) study, for example, PM was used to analyse probabilistic temporal dimensions from SRL-coded trace data, that is, looking at the likelihood of transition between SRL processes.

In this study, the limitations of frequency measures were explored, as was their value as complementary analyses for the more temporally focused insights. While PM methods emphasise sequence and order, the epistemic network analysis method does not, focusing more on temporal co-existence. The Nguyen et al. (2021) study, for example, explored how shared regulation events (such as *Reflection*, *Collaboration*, and *Monitoring*) occurred together. The authors were able to detect that instances of closer cotemporality of certain conversational events indicated strong regulatory behavior. The Sobocinski et al. (2020) study produced a fascinating set of timeline-style graphs that show temporal transitions between SRL processes and instances of on-track, adaptive and maladaptive learning therein. In the Munshi et al. (2018) study (Betty's Brain) posited that affect has some impact on SRL deployment. The temporal orderings of cognitive activities and transitions (e.g., Hint →Read) were extracted and observed against affective states (e.g., boredom, delight). In this context, the cognitive activities were viewed as "temporal antecedents" for affective states. In summary, the ontological intersection between SRL and temporality provides a rich source of insights, if care is given to model usage and methodological selection.

5. Discussion

5.1. Methodological Considerations

Clearly, there is a movement in the SRL community to use temporal and sequence-based discovery methods to analyse and articulate SRL. Most of the studies in our sample make effective use of such methods in an effort to move beyond the ontological limitations of conventional statistical analysis, or to complement its strengths. To build effectively on this work, researchers should not only be aware of the methods available, but also of the strengths and limitations of these methods in the context of SRL. For example, the PM platforms encompass a variety of discovery algorithms which provide metrics in recognised scales, such as frequency, time and probability, as well as proprietary scales. As such, the choice of metric is key. For example, absolute measures, such as frequency of transition between SRL activities, could provide key insights, but may prove prohibitive for researchers to interpret while retaining a sense of relative scale. Conversely, using relative scales, such as probability, removes the absolute view and may produce deceptive results (Saint et al., 2021). The use of time as a metric is attractive to researchers exploring temporal aspects of SRL but should be approached with care. Time-on-task metrics, for example, could be skewed by idle time recorded as task engagement; a learner could open a page of content in an LMS, then switch focus to something else, undetected by the system, thus providing a false picture of engagement in the data (Kovanovic et al., 2016). ENA provides insights that PM cannot, such as a sense of how learning activities exist thematically in relation to each other, and their co-existence in temporal terms. In its original form, however, ENA was unable to articulate a sense of directional sequence between learning activities. This limitation, however, has been recognised, and a new version of the ENA, dENA (Fogel et al., 2021), has been developed in which transition sequence is represented in a measurable and visual way. This has very promising implications for future research on SRL and the modelling of its temporal and sequential aspects. Factors such as these should be considered as part of an explicit assessment of methods in the context of the study aims. This assessment should provide an informed view of the chosen method and its capabilities, hopefully leading to a more authentic analytic narrative.

In order to inform such decisions, the Matcha et al. (2019b) study provided a systematic comparison of the efficacy of PM, ENA, and sequence analysis in specific context. Whilst such competitive comparisons are useful, we argue that more value can be gained in combining methods, thus avoiding methodological compromise. A section of researchers in our sample agree, and have employed multiple discovery methods in their studies. For example, Saint et al. (2020a) combined ENA and PM to examine the sequential and temporal nature of SRL behaviours and identified behaviours that differentiate between learners across performance levels. Ahmad Uzir et al. (2020b) and Fan et al. (2021a) also used ENA and PM to provide rich insights into learner tactic usage. In both these studies, a combined interpretation from the methods provided readers with a view of tactics commonly associated in time (from ENA), and also their association in terms of temporal sequence (from process mining). As suggested by these studies, when applied jointly, ENA together with other methods can provide a richer description of SRL activities than using a single method. Methodological combinations, such as these ones, can provide a more profound understanding of the learning phenomena at play. They also provide the promise of analytic triangulation or cross-validation. The decision to use multiple methods is not without its challenges, not least in terms of the skills and resources needed to deploy the methods, but also to provide a coherent interpretation of the results. An informed assessment of the costs and benefits of a combined project should be considered. If researchers are armed with an informed view of the discovery method landscape, they will be able to make a better choice as to: i) the choice of single or multiple methods, and; ii) the choice of the tool(s) to deploy. This should mitigate the temptation to bend the study outcomes to fit the chosen method, as opposed to aligning the correct method(s) with the study aims.

5.2. Theoretical Considerations

The usage of SRL models is subject to nuance. In some cases, a clear model was chosen and applied in a way which directly affected how the study data were transformed and presented, using a clearly articulated framework. The Siadaty et al. (2016b) study is an example of this but this type of SRL-informed, codification was also demonstrated by Bannert et al. (2014) and Saint et al. (2020b). We argue that this type of applied coding, deployed as micro-level process analysis in many cases, represents an explicit attempt to embed analyses in theoretical models of SRL. It does not necessarily guarantee empirically robust SRL insights as there are dependencies on the quality of the model used and of the veracity of the data transformation and interpretation, but its structure is clear and explicit. The Kizilcec et al.(2017) study used an SRL framework to identify different groups of learners, as captured in an SRL self-perception survey, as opposed to the actual transformation of data. Some studies more accurately use SRL as a theoretical context, as opposed to an embedded framework. This is demonstrated in the study by Matcha et al. (2019a), for example, where certain dimension of SRL (tactics and strategies) were analysed.

The Kizilcec et al. (2017) study is also worthy of note for the way SRL is theorised, that is, as a consolidation of strategies from around six different sources. Other studies used less models in the consolidation process (e.g., Kinnebrew et al. (2014)), and the Heirweg et al. (2020) study does not even explicitly state the source models, consolidating as it does, from general SRL theory. The promise of consolidating SRL constructs, or mapping them onto other pedagogic models (e.g., Mirriahi et al. (2016)) is an intriguing one. We should, however, sound a note of caution; the appropriation of SRL strategies from different models to measure specific constructs is a choice that raises questions of construct validity. The dilemma faced in these types of research settings is whether to bend your data capture and analyses to fit an established model, retaining some form of construct validity, or formulate a framework that is a better fit for your data and/or study context. It also forces a conversation on the extent to which the repeated use of a framework (preferably by different authors) induces a sense of validity in and of itself. In some studies, the use of one complete model may invalidate elements of the study, as the data will not fit without unreasonable leaps of logic and assumption. In authentic trace data studies, for example, while lower-level activities, such as reading or video viewing, may be easy to capture, challenges exist around measuring higher level metacognitive SRL constructs such as reflection or evaluation. In these cases, questions may be asked about the appropriateness of the model and its deployment in the context of the aims of the research.

There is an argument that while the major SRL models provide differing focuses, they all share commonalities at a fundamental level. Heirweg et al. (2020) note that there is a general agreement that SRL consists of metacognitive, cognitive, and motivational dimensions. In regard to the cyclical and temporal nature of SRL, Panadero (2017) highlights the three common fundamental phases of SRL—preparatory, performance, and appraisal—and explicitly maps the major model elements into these phases, in tabular form. This is important, as it hints at a way in which common SRL model elements can be viewed. With these commonalities established, researchers can more clearly focus on the unique nuances that each model brings, and more readily align them to study scope. It is clear, however, that the measurement of higher constructs of SRL is challenging in authentic trace data studies, and easier to capture in self-report studies, so the choice of model should reflect that. It would be fruitless, for example, to choose a model which emphasises motivation or affective states in a scenario where only event-based trace data is a available.

Given the fact that model choice and usage is subject to nuance, it is incumbent on researchers to provide as much conceptual and methodological clarity as possible. It is common for studies to compromise clarity in favour of breadth of context. The Sobocinski et al. (2017) study, for example, used the Zimmerman SRL model and, whilst the model is discussed, this discussion is intermingled with discussion on conceptual aspects of other models. In itself, this is a useful treatment of SRL, but the reader has to work hard to determine the Zimmerman model is the primary model of choice. This contrasts with the later Sobocinski et al. (2020) study in which the model choice is made explicit early on the theoretical framework section, providing clear signposting for the reader. The Rodríguez et al. (2018) study is clear in its theoretical focus on the SRL and provides a comprehensive theoretical treatment on the subject, signalling the Zimmerman (2000) and Pintrich (2000) models for particular focus. The method and results section, however, abandon any explicit linkage with SRL, in favour of a more atomic interpretation of video interactions. This disconnect weakens the impact of the paper, somewhat. The desire to provide a rich context is admirable, but should be tempered to ensure clarity and narrative cohesion.

5.3. Validity

Validity is fundamentally dependent on the empirical evidence (Messick, 1987; Winne, 2020). An important approach to gauging reliability and validity is to triangulate the measurement between different data channels, which uses several different processes or instruments to record data about the same event or pattern (Winne, 2020). Although triangulation across measurement protocols is infrequent, there are some notable examples in our sample. The Sobocinski et al. (2020) study derived a set timeline-style graphs that show how physiological state changes occurred temporally in terms of changes in learning regulation. Järvelä and Bannert (2021) also presented a similarly impressive set of multidimensional timeline diagrams based on a triangulated multimodal study. In these cases, SRL phenomena were measured from concurrent sources, providing a more robust analysis.

In many of the studies in our sample, the central LMS/MOOC/OELE system is a learning platform and a source for study data. In this context, the decision to use an authentic, experimental, or hybrid LMS has fundamental implications for measurement of SRL. Authentic LMSs generate authentic LMS data, providing researchers with some small weapon in the battle for validity. The use of such data, however, necessitates a level of pre-processing or transformation into more recognisable SRL (or related) processes, which introduces its own questions around validity. Additionally, whilst model-driven transformations of this kind are valuable for observational studies, they pose challenges for researchers who seek to provide educators with timely, in situ classroom insights. The Boroujeni and Dillenbourg (2019) study was important in this respect as it presented an unsupervised discovery method that required no theoretical framing, and only the collection of action sequences as input. The authors suggest that it could be used to analyse interaction patterns in various online learning environments. Semi-experimental systems, such as nStudy (used in the study by Järvelä et al. (2016)) and Learn-B (used in the study by Siadaty et al. (2016b)), potentially provide researchers with richer, SRL-aligned data, despite questions around the authenticity of such systems. The challenge here is to exploit the outcomes from these findings in authentic settings, which demands that researchers explore better instrumentation tools for SRL; ones that that can used across different educational contexts (van der Graaf et al., 2021).

A key aspect of our studies is the focus on comparison and comparative methods. Some studies enhance the validity of research by focusing on patterns that can reflect a certain degree of discrimination. For example, Munshi et al. (2018) focused on the contrasting affective states of high and low performing students; they were able to enrich the comparative dimension of their research by observing differences in response from receiving feedback from the virtual agents, or not. A similar type of multi-level comparison was employed by Lim et al. (2021), who extracted strategy patterns from two different undergraduate courses, mediated also by the provision, or otherwise, of online feedback. These examples demonstrate how the robustness of validity can be increased through sophisticated comparative criteria. The scope of our review, by its very definition, encompasses studies that did not rely on variable-centric statistical measures. As such, interpretation of the observed phenomena cannot be validated in isolation in the same way as such studies. Therefore, there is much value in comparing sample groups, for example, high vs low performing learners or student clusters who used different learning tactics. It is in these comparisons that real insights can be found. Conversely, a critical validity question is, did the delineations genuinely reflect differing behaviours or did the researchers (knowingly or unknowingly) implant meaning based on those delineations? For example, if we group learners by assessment marks (high vs low) and observe different learning patterns, are we observing patterns which genuinely reflect better or worse learning, or are we projecting desired outcomes into these patterns of learning. In other words, whilst comparison is of key importance, researchers must retain analytical objectivity, and resist the urge to project meaning into group behaviour that is not really there.

In a push toward confirmatory research in SRL and temporal analysis, we must be wary of dampening innovation and novelty in pursuit of inferential solidity. Key studies in our group did not rely on large sample sizes (e.g., Siebert-Evenstone et al. (2017); Bakhtiar and Hadwin (2020)) but nonetheless extracted nuanced insights not detectable in larger samples. This is not to dissuade using large samples, but to entertain a narrative where sample size is not inherently critical. Large sample sizes, such as those found in MOOC-based studies, provide insight on a broader scale. This scale, in combination with the promise of data free of the context of offline interactions, makes MOOC analysis a compelling option for SRL researchers. It also brings its own set of challenges; MOOC learners' motivations and goals can be subject to significant diversification; it would be wrong to assume that all engage from start to finish, or that they align their learning goals with the design of the course. As such, the broader scale of analysis dilutes nuance, with important implications for research validity. One suggestion to improve the interpretation of SRL related dimensions, is to focus on specific sub-groups of MOOC learners (Chen et al., 2020).

Finally, we argue that although multi-method analysis can provide rich insights, even greater empirical gains can be made in employing *multi-channel* analysis in which the same SRL phenomena are analysed, based on data collection from different data sources, providing the opportunity for validation through triangulation; the Järvelä et al. (2016) study, for example, triangulated chat discussions and trace data to identify evidence of socially shared regulation. Notwithstanding the demands on resources and skills that such experimental projects demand, the potential of true ontological triangulation and a movement towards some sort of grounding of truth, or the generation of a set of credible proxies, is a compelling one.

5.4. Temporal SRL

This question builds on the previous ones but invites a discussion on the specific implications of temporal analysis for SRL research, and its ongoing impact. The analytical outcomes of the studies included in the review are determined not just by the endpoint discovery algorithms, but by the broader design of the study. The use of think-aloud protocols (e.g., Bannert et al. (2014)) provided the affordance of clearly articulated SRL processes at both meta-cognitive and cognitive levels, as well as motivational and affective phenomena. The obvious advantage here is that a complete picture of SRL can be gleaned, providing nuance which is also timestamped. Whist the experimental nature of the method hinders its immediate impact, its strength lies in its exploratory richness. Similar richness of insights can be gleaned from observed/recorded discourse analysis (e.g., Nguyen et al. (2021)), which removes the responsibility of articulation from the learner but shifts it to the researcher. Trace data studies provide insights from authentic learning platforms and whilst the nuance of self-report cannot be matched, robust SRL coding can unearth key insights. The Saint et al. (2020b) study, for example, identified optimal and sub-optimal patterns of SRL in terms of temporal likelihood (i.e., the relative likelihood of moving from one SRL process to another), identifying cohesive and less-cohesive patterns of SRL, in the context temporal order.

It is clear that the studies that employ PM seek to articulate a sense of temporal movement between SRL processes, or between learner actions and tactics that indicate a sense of self-regulation. The studies that employ ENA provide a different perspective, which seemingly goes against notions of SRL as sequential and cyclical process. Nonetheless, positioning SRL processes in network space allows for the identification of SRL behaviours that are likely to happen in close temporal proximity, as well as providing a qualitative view of SRL constructs in a network space. The Paquette et al. study, for example, was able to articulate intricate behaviours, for example, "When assessing their solution, they showed stronger connections between quiz taking, quiz result views, and coherent responses to those results (readings and adding or revising a link)" (2021, p. 197). Several studies (e.g., Saint et al. (2020a)) used multiple methods (ENA and process mining) to elicit a more multi-dimensional view of SRL. A key lesson can be learnt from this; certain analytic methods (e.g., ENA) relegate less-frequent processes in visual terms, and some cases (Fuzzy Miner) remove them entirely from analysis or merge them with other less frequent processes. This is problematic for SRL research where meta-cognitive activities, such as *planning* or *reflection*, happen less frequently by definition, but are critically important in the analysis of SRL. In studies that use first order Markov models, where likelihood, not frequency, is not measured, such meta-cognitive activities retain prominence. Conversely, their presence may distort the absolute view of SRL engagement. In this context, researchers must be aware of the nuances of temporal analysis and how it can be impacted by the distortions in metrics and associated visualisations.

Most studies make assumptions that learners can only engage in one activity at a time. While this may be true at an atomic level (e.g., a learner cannot read two books at the same time; read and write at the same time), it becomes more complex when we aggregate learner actions to a learning construct, such as an SRL process. For example, the activity of *reading*, a lower cognition activity, may simultaneously be part of a higher cognition activity, such as *planning* or *reflection* (Kim et al., 2020). We face the possibility of simultaneous engagement in lower and higher cognition processes, and overarching meta-cognition. In this context, the segmentation and categorisation of units of learning in temporal space is critical future research on possible simultaneous engagement into different SRL processes.

6. Future Work and Recommendations

The studies in this review were realised in an exploratory period of temporally focused SRL research, and some can be seen as genuine state-of-the-art demonstrations of what can be achieved when combining novel methods with strong theoretical underpinnings of SRL. It is, however, telling that many of the analytic methods originated in more general business settings, specifically the process mining algorithms that dominate our sample. Great steps could be made in the development of analytic methods designed in data-driven educational research. There are a number of novel methods in our review which seek to achieve this, but only epistemic network analysis has evolved as a recognised technique to be used in educational settings. It is very encouraging that this technique is being developed further to encompass temporal sequence as well as association (Fogel et al., 2021), and we argue that this should inspire other researchers to develop algorithms with educational research as a main focus, in addition to using platforms born of commerce and business.

Whilst temporally focused SRL still needs more exploratory studies, the move towards more impactful research relies on building on the lessons learnt thus far, and providing a clear articulation, in such studies, of the empirical scope and trajectory. In conducting our review, we perceived that many of the studies would benefit from an increase in conceptual and methodological clarity. We argue that this clarity should be viewed through the lenses of: i) method, ii) theory, iii) validity, and iv) temporality. To that end, we present a framework of questions for researchers to address before embarking on temporally focused research into SRL:

Methodological Considerations

1. Are we aiming for exploration or experimentation, or impact and confirmation?
2. Are we using trace data or self-report?
3. Are we using a combination of data collection methods to analyse related phenomena?
4. Are we using combination of data collection methods to analyse and triangulate the same phenomena, i.e., multi-channel?
5. Have we fully assessed the strengths of the proposed analytic discovery algorithm?
6. Can we easily make use of combining the insights of multiple data analysis algorithms or metrics?
7. Does the discovery algorithm lend itself to ready comparison of multiple models?

Theoretical Considerations

8. Are we using an SRL model more as context rather than an actual method framework?
9. Are we using a single SRL model or framework explicitly in our method?
10. Are we using a combination or consolidation of models?
11. Are we using a model/framework to categorise actual learner actions/verbal utterances, or just to categorise learners into groups?

Validity Considerations

12. How robust is our theoretical model of SRL?
13. Are we using an SRL coding framework to interpret/transform raw data?
14. How robust is the coding framework in context of our chosen model of SRL?
15. To what extent can we triangulate our analyses?
16. To what extent can we transfer our findings to new settings?

Temporal Considerations

17. Are we conceptualising temporality as frequency/duration or in terms of order and sequence, or both?
18. How do we clearly articulate our conceptualisation of temporality to the reader?
19. How do we clearly articulate this conceptualisation in its underpinning of SRL?
20. How are we segmenting units of time in our study?
21. Can we justify our choice of discovery method in the temporal context of our study?

We would further advise that once the parameters of the chosen model of SRL have been established, to avoid lengthy treatises on multiple models of SRL that are not going to be used in the study. If researchers collectively clarify their position in papers on SRL, the community can more readily join up its research and push it forward.

References

Ahmad Uzir, N., Gašević, D., Jovanović, J., Matcha, W., Lim, L.A., Fudge, A., 2020a. Analytics of time management and learning strategies for effective online learning in blended environments, in: Proceedings of the Tenth International Conference on Learning Analytics & Knowledge, Association for Computing Machinery, Frankfurt, Germany. pp. 392–401. URL: https://doi.org/10.1145/3375462.3375493, doi:10.1145/3375462.3375493.

Ahmad Uzir, N., Gašević, D., Matcha, W., Jovanović, J., Pardo, A., 2020b. Analytics of time management strategies in a flipped classroom. Journal of Computer Assisted Learning 36, 70–88. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/jcal.12392, doi:10.1111/jcal.12392. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/jcal.12392.

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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: Scheffel, M., Broisin, J., Pammer-Schindler, V., Ioannou, A., Schneider, J. (Eds.), Transforming Learning with Meaningful Technologies, Springer International Publishing. pp. 555–569.

Araka, E., Maina, E., Gitonga, R., Oboko, R., 2020. Research trends in measurement and intervention tools for self-regulated learning for e-learning environments—systematic review (2008–2018). Research and Practice in Technology Enhanced Learning 15, 6. URL: https://doi.org/10.1186/s41039-020-00129-5, doi:10.1186/s41039-020-00129-5.

Azevedo, R., Moos, D.C., Johnson, A.M., Chauncey, A.D., 2010. Measuring Cognitive and Metacognitive Regulatory Processes During Hypermedia Learning: Issues and Challenges. Educational Psychologist 45, 210–223. URL: https://doi.org/10.1080/00461520.2010.515934, doi:10.1080/00461520.2010.515934. publisher: Routledge _eprint: https://doi.org/10.1080/00461520.2010.515934.

Bakhtiar, A., Hadwin, A., 2020. Dynamic Interplay between Modes of Regulation During Motivationally Challenging Episodes in Collaboration. Frontline Learning Research 8, 1–34. URL: https://journals.sfu.ca/flr/index.php/journal/article/view/561, doi:10.14786/flr.v8i2.561. number: 2.

Bannert, M., 2007. Metakognition beim Lernen mit Hypermedien. Erfassung, Beschreibung und Vermittlung wirksamer metakognitiver Strategien und Regulationsaktivitäten. Pädagogische Psychologie und Entwicklungspsychologie. 61, Waxmann, Münster u.a. ISSN: 1430-2977 Type: gedruckt.

Bannert, M., Reimann, P., Sonnenberg, C., 2014. Process mining techniques for analysing patterns and strategies in students' self-regulated learning. Metacognition and Learning 9, 161–185. URL: https://doi.org/10.1007/s11409-013-9107-6, doi:10.1007/s11409-013-9107-6.

Beaudoin, L., Winne, P., 2009. nStudy: An Internet Tool to Support Learning, Collaboration and Researching Learning Strategies , 1–28.

Biswas, G., Jeong, H., Kinnebrew, J.S., Sulcer, B., Roscoe, R., 2010. Measuring self-regulated learning skills through social interactions in a teachable agent environment. Research and Practice in Technology Enhanced Learning 05, 123–152. URL: https://www.worldscientific.com/doi/abs/10.1142/S1793206810000839, doi:10.1142/S1793206810000839. publisher: World Scientific Publishing Co.

Biswas, G., Leelawong, K., Schwartz, D., Vye, N., 2005. Learning by teaching: A new agent paradigm for educational software. Applied Artificial Intelligence 19, 363–392. doi:10.1080/08839510590910200. place: United Kingdom Publisher: Taylor & Francis.

Bjork, R.A., Bjork, E.L., 2020. Desirable Difficulties in Theory and Practice. Journal of Applied Research in Memory and Cognition 9, 475–479. URL: https://www.sciencedirect.com/science/article/pii/S2211368120300899, doi:10.1016/j.jarmac.2020.09.003.

Bjork, R.A., Dunlosky, J., Kornell, N., 2013. Self-Regulated Learning: Beliefs, Techniques, and Illusions. Annual Review of Psychology 64, 417–444. URL: https://doi.org/10.1146/annurev-psych-113011-143823, doi:10.1146/annurev-psych-113011-143823. _eprint: https://doi.org/10.1146/annurev-psych-113011-143823.

Boekaerts, M., 1996. Coping with stress in childhood and adolescence, in: Handbook of coping: Theory, research, applications. John Wiley & Sons, Oxford, England, pp. 452–484.

Boekaerts, M., 2011. Emotions, Emotion Regulation, and Self-Regulation of Learning. Routledge Handbooks Online. URL: https://www.routledgehandbooks.com/doi/10.4324/9780203839010.ch26, doi:10.4324/9780203839010.ch26.

Bogarín, A., Cerezo, R., Romero, C., 2018. Discovering learning processes using Inductive Miner: A case study with Learning Management Systems (LMSs). Psicothema , 322–329URL: https://doi.org/10.7334/psicothema2018.116, doi:10.7334/psicothema2018.116.

Boroujeni, M.S., Dillenbourg, P., 2019. Discovery and Temporal Analysis of MOOC Study Patterns. Journal of Learning Analytics 6, 16–33. URL: https://learning-analytics.info/journals/index.php/JLA/article/view/6105.

Broadbent, J., Poon, W.L., 2015. Self-regulated learning strategies & academic achievement in online higher education learning environments: A systematic review. The Internet and Higher Education 27, 1–13. URL: http://www.sciencedirect.com/science/article/pii/S1096751615000251, doi:10.1016/j.iheduc.2015.04.007.

Brydges, R., Manzone, J., Shanks, D., Hatala, R., Hamstra, S.J., Zendejas, B., Cook, D.A., 2015. Self-regulated learning in simulation-based training: a systematic review and meta-analysis. Medical Education 49, 368–378. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/medu.12649, doi:10.1111/medu.12649. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/medu.12649.

Butler, D.L., Winne, P.H., 1995. Feedback and Self-Regulated Learning: A Theoretical Synthesis. Review of Educational Research 65, 245–281. URL: https://www.jstor.org/stable/1170684, doi:10.2307/1170684. publisher: [Sage Publications, Inc., American Educational Research Association].

Cerezo, R., Bogarín, A., Esteban, M., Romero, C., 2020. Process mining for self-regulated learning assessment in e-learning. Journal of Computing in Higher Education 32, 74–88. URL: https://doi.org/10.1007/s12528-019-09225-y, doi:10.1007/s12528-019-09225-y.

Cerón, J., Baldiris, S., Quintero, J., García, R.R., Saldarriaga, G.L.V., Graf, S., Valentin, L.D.L.F., 2021. Self-Regulated Learning in Massive Online Open Courses: A State-of-the-Art Review. IEEE Access 9, 511–528. doi:10.1109/ACCESS.2020.3045913. conference Name: IEEE Access.

Chen, B., Fan, Y., Zhang, G., Liu, M., Wang, Q., 2020. Teachers' networked professional learning with MOOCs. PLOS ONE 15, e0235170. URL: https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0235170, doi:10.1371/journal.pone.0235170. publisher: Public Library of Science.

Chen, B., Knight, S., Wise, A.F., 2018a. Critical Issues in Designing and Implementing Temporal Analytics. Journal of Learning Analytics 5, 1–9. URL: https://epress.lib.uts.edu.au/journals/index.php/JLA/article/view/5940, doi:10.18608/jla.2018.53.1. number: 1.

Chen, Q., Yue, X., Plantaz, X., Chen, Y., Shi, C., Pong, T., Qu, H., 2018b. ViSeq: Visual Analytics of Learning Sequence in Massive Open Online Courses. IEEE Transactions on Visualization and Computer Graphics , 1–1doi:10.1109/TVCG.2018.2872961.

Cheng, H.N.H., Zhang, X., 2020. Modeling the Self-Regulated Learning Behaviors of Graduate Students in Online Academic Reading and Writing Environments, in: Pinkwart, N., Liu, S. (Eds.), Artificial Intelligence Supported Educational Technologies. Springer International Publishing, Cham. Advances in Analytics for Learning and Teaching, pp. 227–244. URL: https://doi.org/10.1007/978-3-030-41099-5_13, doi:10.1007/978-3-030-41099-5_13.

Chi, M.T., 1997. Quantifying Qualitative Analyses of Verbal Data: A Practical Guide. Journal of the Learning Sciences 6, 271–315. URL:

http://www.tandfonline.com/doi/abs/10.1207/s15327809jls0603_1, doi:10.1207/s15327809jls0603_1.

Cleary, T.J., 2011. Emergence of self-regulated learning microanalysis: Historical overview, essential features, and implications for research and practice, in: Handbook of self-regulation of learning and performance. Routledge/Taylor & Francis Group, New York, NY, US. Educational psychology handbook series, pp. 329–345.

Cuyvers, K., Van den Bossche, P., Donche, V., 2020. Self-Regulation of Professional Learning in the Workplace: a State of the Art and Future Perspectives. Vocations and Learning 13, 281–312. URL: https://doi.org/10.1007/s12186-019-09236-x, doi:10.1007/s12186-019-09236-x.

Davis, S.K., Hadwin, A.F., 2021. Exploring differences in psychological well-being and self-regulated learning in university student success. Frontline Learning Research 9, 30–43. URL: https://journals.sfu.ca/flr/index.php/journal/article/view/581, doi:10.14786/flr.v9i1.581. number: 1.

Devolder, A., Braak, J.v., Tondeur, J., 2012. Supporting self-regulated learning in computer-based learning environments: systematic review of effects of scaffolding in the domain of science education. Journal of Computer Assisted Learning 28, 557–573. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/j.1365-2729.2011.00476.x, doi:10.1111/j.1365-2729.2011.00476.x. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1365-2729.2011.00476.x.

Dorodchi, M., Benedict, A., Desai, D., Mahzoon, M.J., MacNeil, S., Dehbozorgi, N., 2018. Design and Implementation of an Activity-Based Introductory Computer Science Course (CS1) with Periodic Reflections Validated by Learning Analytics, in: 2018 IEEE Frontiers in Education Conference (FIE), pp. 1–8. doi:10.1109/FIE.2018.8659196.

Effeney, G., Carroll, A., Bahr, N., 2013. Self-regulated learning: Key strategies and their sources in a sample of adolescent males1. Australian Journal of Educational and Developmental Psychology 13, 58–74.

Engelmann, K., Bannert, M., 2021. Analyzing temporal data for understanding the learning process induced by metacognitive prompts. Learning and Instruction 72, 1–11. URL: https://www.sciencedirect.com/science/article/pii/S0959475218307163, doi:10.1016/j.learninstruc.2019.05.002.

Ericsson, K.A., Simon, H.A., 1980. Verbal reports as data. Psychological Review 87, 215–251. doi:10.1037/0033-295X.87.3.215. place: US Publisher: American Psychological Association.

Ericsson, K.A., Simon, H.A., 1984. Protocol analysis: Verbal reports as data. Protocol analysis: Verbal reports as data, The MIT Press, Cambridge, MA, US. Pages: 426.

Fan, Y., Matcha, W., Uzir, N.A., Wang, Q., Gašević, D., 2021a. Learning Analytics to Reveal Links Between Learning Design and Self-Regulated Learning. International Journal of Artificial Intelligence in Education URL: https://doi.org/10.1007/s40593-021-00249-z, doi:10.1007/s40593-021-00249-z.

Fan, Y., Saint, J., Singh, S., Jovanovic, J., Gašević, D., 2021b. A learning analytic approach to unveiling self-regulatory processes in learning tactics, in: LAK21: 11th International Learning Analytics and Knowledge Conference, Association for Computing Machinery, New York, NY, USA. pp. 184–195. URL: https://doi.org/10.1145/3448139.3448211, doi:10.1145/3448139.3448211.

Fogel, A., Swiecki, Z., Marquart, C., Cai, Z., Wang, Y., Brohinsky, J., Siebert-Evenstone, A., Eagan, B., Ruis, A.R., Shaffer, D.W., 2021. Directed Epistemic Network Analysis, in: Ruis, A.R., Lee, S.B. (Eds.), Advances in Quantitative Ethnography, Springer International Publishing, Cham. pp. 122–136. doi:10.1007/978-3-030-67788-6_9.

Garcia, R., Falkner, K., Vivian, R., 2018. Systematic literature review: Self-Regulated Learning strategies using e-learning tools for Computer Science. Computers & Education 123, 150–163. URL: http://www.sciencedirect.com/science/article/pii/S0360131518301064, doi:10.1016/j.compedu.2018.05.006.

Gatta, R., Lenkowicz, J., Vallati, M., Stefanini, A., Dinapoli, N., Bari, B.D., Sacchi, L., 2017. pMineR: Processes Mining in Medicine. URL: https://CRAN.R-project.org/package=pMineR.

van der Graaf, J., Lim, L., Fan, Y., Kilgour, J., Moore, J., Bannert, M., Gasevic, D., Molenaar, I., 2021. Do Instrumentation Tools Capture Self-Regulated Learning?, in: LAK21: 11th International Learning Analytics and Knowledge Conference, ACM, Irvine CA USA. pp. 438–448. URL: https://dl.acm.org/doi/10.1145/3448139.3448181, doi:10.1145/3448139.3448181.

Greene, J.A., Azevedo, R., 2009. A macro-level analysis of SRL processes and their relations to the acquisition of a sophisticated mental model of a complex system. Contemporary Educational Psychology 34, 18–29. URL: http://www.sciencedirect.com/science/article/pii/S0361476X08000465, doi:10.1016/j.cedpsych.2008.05.006.

Greene, J.A., Plumley, R.D., Urban, C.J., Bernacki, M.L., Gates, K.M., Hogan, K.A., Demetriou, C., Panter, A.T., 2019. Modeling temporal self-regulatory processing in a higher education biology course. Learning and Instruction , 101201URL: http://www.sciencedirect.com/science/article/pii/S0959475218304407, doi:10.1016/j.learninstruc.2019.04.002.

Greene, J.A., Robertson, J., Costa, L.J.C., 2011. Assessing self-regulated learning using think-aloud methods, in: Handbook of self-regulation of learning and performance. Routledge/Taylor & Francis Group, New York, NY, US. Educational psychology handbook series, pp. 313–328.

Günther, C.W., van der Aalst, W.M.P., 2007. Fuzzy Mining – Adaptive Process Simplification Based on Multi-perspective Metrics, in: Alonso, G., Dadam, P., Rosemann, M. (Eds.), Business Process Management, Springer, Berlin, Heidelberg. pp. 328–343. doi:10.1007/978-3-540-75183-0_24.

Günther, C.W., Rozinat, A., 2012. Disco: discover your processes, in: Proceedings of the Demonstration Track of the 10th International Conference on Business Process Management (BPM 2012), CEUR-WS.org. pp. 40–44. URL: https://research.tue.nl/en/publications/disco-discover-your-processes.

Hadwin, A., Järvelä, S., Miller, M., 2017. Self-regulation, co-regulation and shared regulation in collaborative learning environments., in: Schunk, D., Greene, J. (Eds.), Handbook of self-regulation of learning and performance. 2 ed.. Routledge/Taylor & Francis Group, New York, NY, US. Educational psychology handbook series, pp. 83–106.

Hadwin, A.F., Järvelä, S., Miller, M., 2011. Self-regulated, co-regulated, and socially shared regulation of learning, in: Handbook of self-regulation of learning and performance. Routledge/Taylor & Francis Group, New York, NY, US. Educational psychology handbook series, pp. 65–84.

Hadwin, A.F., Nesbit, J.C., Jamieson-Noel, D., Code, J., Winne, P.H., 2007. Examining trace data to explore self-regulated learning. Metacognition and Learning 2, 107–124. URL: https://doi.org/10.1007/s11409-007-9016-7, doi:10.1007/s11409-007-9016-7.

Heirweg, S., De Smul, M., Merchie, E., Devos, G., Van Keer, H., 2020. Mine the process: investigating the cyclical nature of upper primary school students' self-regulated learning. Instructional Science 48, 337–369. URL: https://doi.org/10.1007/s11251-020-09519-0, doi:10.1007/s11251-020-09519-0.

Huang, L., Lajoie, S.P., 2021. Process analysis of teachers' self-regulated learning patterns in technological pedagogical content knowledge development. Computers & Education 166, 104169. URL: https://www.sciencedirect.com/science/article/pii/S0360131521000464, doi:10.1016/j.compedu.2021.104169.

Järvelä, S., Bannert, M., 2021. Temporal and adaptive processes of regulated learning - What can multimodal data tell? Learning and Instruction 72, 101268. URL: https://www.sciencedirect.com/science/article/pii/S0959475219307388, doi:10.1016/j.learninstruc.2019.101268.

Järvelä, S., Kirschner, P.A., Panadero, E., Malmberg, J., Phielix, C., Jaspers, J., Koivuniemi, M., Järvenoja, H., 2015. Enhancing socially shared regulation in collaborative learning groups: designing for CSCL regulation tools. Educational Technology Research and Development 63, 125–142. URL: https://doi.org/10.1007/s11423-014-9358-1, doi:10.1007/s11423-014-9358-1.

Järvelä, S., Malmberg, J., Haataja, E., Sobocinski, M., Kirschner, P.A., 2021. What multimodal data can tell us about the students' regulation of their learning process? Learning and Instruction 72, 101203. URL: https://www.sciencedirect.com/science/article/pii/S095947521830416X, doi:10.1016/j.learninstruc.2019.04.004.

Järvelä, S., Malmberg, J., Koivuniemi, M., 2016. Recognizing socially shared regulation by using the temporal sequences of online chat and logs in CSCL. Learning and Instruction 42, 1–11. URL: http://www.sciencedirect.com/science/article/pii/S0959475215300384, doi:10.1016/j.learninstruc.2015.10.006.

Kennedy, A.B.W., Sankey, H.R., 1898. The thermal efficiency of steam engines. report of the committee appointed to the council upon the subject of the definition of a standard or standards of thermal efficiency for steam engines: with an introductory note. (including appendixes and plate at back of volume). Minutes of the Proceedings of the Institution of Civil Engineers 134, 278–312. URL: https://www.icevirtuallibrary.com/doi/10.1680/imotp.1898.19100, doi:10.1680/imotp.1898.19100. publisher: ICE Publishing.

Kim, Y.e., Brady, A.C., Wolters, C.A., 2020. College students' regulation of cognition, motivation, behavior, and context: Distinct or overlapping processes? Learning and Individual Differences 80, 101872. URL: https://www.sciencedirect.com/science/article/pii/S1041608020300522, doi:10.1016/j.lindif.2020.101872.

Kinnebrew, J.S., Biswas, G., Sulcer, B., Taylor, R.S., 2013. Investigating Self-Regulated Learning in Teachable Agent Environments, in: Azevedo, R., Aleven, V. (Eds.), International Handbook of Metacognition and Learning Technologies. Springer New York, New York, NY. Springer International Handbooks of Education, pp. 451–470. URL: https://doi.org/10.1007/978-1-4419-5546-3_29, doi:10.1007/978-1-4419-5546-3_29.

Kinnebrew, J.S., Segedy, J.R., Biswas, G., 2014. Analyzing the temporal evolution of students' behaviors in open-ended learning environments. Metacognition and Learning 9, 187–215. URL: https://doi.org/10.1007/s11409-014-9112-4, doi:10.1007/s11409-014-9112-4.

Kizilcec, R.F., Pérez-Sanagustín, M., Maldonado, J.J., 2017. Self-regulated learning strategies predict learner behavior and goal attainment in Massive Open Online Courses. Computers & Education 104, 18–33. URL: http://www.sciencedirect.com/science/article/pii/S0360131516301798, doi:10.1016/j.compedu.2016.10.001.

Knight, S., Wise, A.F., Chen, B., 2017. Time for Change: Why Learning Analytics Needs Temporal Analysis. Journal of Learning Analytics 4, 7–17. URL: https://epress.lib.uts.edu.au/journals/index.php/JLA/article/view/5847, doi:10.18608/jla.2017.43.2. number: 3.

Kolb, D.A., 2015. Experiential learning: experience as the source of learning and development. Second edition ed., Pearson Education, Inc, Upper Saddle River, New Jersey.

Kovanovic, V., Gašević, D., Dawson, S., Joksimovic, S., Baker, R., 2016. Does Time-on-task Estimation Matter? Implications on Validity of Learning Analytics Findings. Journal of Learning Analytics 2, 81–110. URL: https://epress.lib.uts.edu.au/journals/index.php/JLA/article/view/4501, doi:10.18608/jla.2015.23.6. number: 3.

Lee, D., Watson, S.L., Watson, W.R., 2019. Systematic Literature Review on Self-Regulated Learning in Massive Open Online Courses. Australasian Journal of Educational Technology 35, 28–41. doi:10.14742/ajet.3749. publisher: Australasian Society for Computers in Learning in Tertiary Education.

Li, S., Du, H., Xing, W., Zheng, J., Chen, G., Xie, C., 2020. Examining temporal dynamics of self-regulated learning behaviors in STEM learning: A network approach. Computers & Education 158, 103987. URL: https://www.sciencedirect.com/science/article/pii/S0360131520301858, doi:10.1016/j.compedu.2020.103987.

Lim, L.A., Gasevic, D., Matcha, W., Ahmad Uzir, N., Dawson, S., 2021. Impact of learning analytics feedback on self-regulated learning: Triangulating behavioural logs with students’ recall, in: LAK21: 11th International Learning Analytics and Knowledge Conference, Association for Computing Machinery, New York, NY, USA. pp. 364–374. URL: https://doi.org/10.1145/3448139.3448174, doi:10.1145/3448139.3448174.

Mahzoon, M.J., Maher, M.L., Eltayeby, O., Dou, W., Grace, K., 2018. A Sequence Data Model for Analyzing Temporal Patterns of Student Data. Journal of Learning Analytics 5, 55–74–55–74. URL: https://learning-analytics.info/journals/index.php/JLA/article/view/5428, doi:10.18608/jla.2018.51.5.

Maldonado-Mahauad, J., Pérez-Sanagustín, M., Kizilcec, R.F., Morales, N., Munoz-Gama, J., 2018a. Mining theory-based patterns from Big data: Identifying self-regulated learning strategies in Massive Open Online Courses. Computers in Human Behavior 80, 179–196. URL: http://www.sciencedirect.com/science/article/pii/S0747563217306477, doi:10.1016/j.chb.2017.11.011.

Maldonado-Mahauad, J., Pérez-Sanagustín, M., Moreno-Marcos, P.M., Alario-Hoyos, C., Muñoz-Merino, P.J., Delgado-Kloos, C., 2018b. Predicting Learners' Success in a Self-paced MOOC Through Sequence Patterns of Self-regulated Learning, in: Pammer-Schindler, V., Pérez-Sanagustín, M., Drachsler, H., Elferink, R., Scheffel, M. (Eds.), Lifelong Technology-Enhanced Learning, Springer International Publishing, Cham. pp. 355–369. doi:10.1007/978-3-319-98572-5_27.

Temporal SRL Review of Literature

Malmberg, J., Fincham, O., Pijeira-Díaz, H.J., Järvelä, S., Gašević, D., 2021. Revealing the hidden structure of physiological states during metacognitive monitoring in collaborative learning. Journal of Computer Assisted Learning n/a, 1–14. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/jcal.12529, doi:https://doi.org/10.1111/jcal.12529. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/jcal.12529.

Malmberg, J., Järvelä, S., Järvenoja, H., 2017. Capturing temporal and sequential patterns of self-, co-, and socially shared regulation in the context of collaborative learning. Contemporary Educational Psychology 49, 160–174. URL: http://www.sciencedirect.com/science/article/pii/S0361476X17300115.

Malmberg, J., Järvelä, S., Järvenoja, H., Panadero, E., 2015. Promoting socially shared regulation of learning in CSCL: Progress of socially shared regulation among high- and low-performing groups. Computers in Human Behavior 52, 562–572. URL: http://www.sciencedirect.com/science/article/pii/S0747563215002848, doi:10.1016/j.chb.2015.03.082.

Malmberg, J., Järvelä, S., Kirschner, P.A., 2014. Elementary school students' strategic learning: does task-type matter? Metacognition and Learning 9, 113–136. URL: https://doi.org/10.1007/s11409-013-9108-5, doi:10.1007/s11409-013-9108-5.

Matcha, W., Gašević, D., Ahmad Uzir, N., Jovanović, J., Pardo, A., 2019a. Analytics of Learning Strategies: Associations with Academic Performance and Feedback, in: Proceedings of the 9th International Conference on Learning Analytics and Knowledge, Association for Computing Machinery, Tempe, AZ, USA. pp. 461–470. URL: https://doi.org/10.1145/3303772.3303787, doi:10.1145/3303772.3303787.

Matcha, W., Gašević, D., Ahmad Uzir, N., Jovanović, J., Pardo, A., Maldonado-Mahauad, J., Pérez-Sanagustín, M., 2019b. Detection of Learning Strategies: A Comparison of Process, Sequence and Network Analytic Approaches, in: Scheffel, M., Broisin, J., Pammer-Schindler, V., Ioannou, A., Schneider, J. (Eds.), Transforming Learning with Meaningful Technologies, Springer International Publishing, Cham. pp. 525–540. doi:10.1007/978-3-030-29736-7_39.

Matcha, W., Uzir, N.A., Gašević, D., Pardo, A., 2020. A Systematic Review of Empirical Studies on Learning Analytics Dashboards: A Self-Regulated Learning Perspective. IEEE Transactions on Learning Technologies 13, 226–245. doi:10.1109/TLT.2019.2916802. conference Name: IEEE Transactions on Learning Technologies.

McCabe, J., 2011. Metacognitive awareness of learning strategies in undergraduates. Memory & Cognition 39, 462–476. doi:10.3758/s13421-010-0035-2.

Messick, S., 1987. Validity. ETS Research Report Series 1987, i–208. URL: https://onlinelibrary.wiley.com/doi/abs/10.1002/j.2330-8516.1987.tb00244.x, doi:10.1002/j.2330-8516.1987.tb00244.x. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/j.2330-8516.1987.tb00244.x.

Mirriahi, N., Liaqat, D., Dawson, S., Gašević, D., 2016. Uncovering student learning profiles with a video annotation tool: reflective learning with and without instructional norms. Educational Technology Research and Development 64, 1083–1106. URL: https://doi.org/10.1007/s11423-016-9449-2, doi:10.1007/s11423-016-9449-2.

Moher, D., Liberati, A., Tetzlaff, J., Altman, D.G., 2009. Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. BMJ 339, b2535. URL: https://www.bmj.com/content/339/bmj.b2535, doi:10.1136/bmj.b2535. publisher: British Medical Journal Publishing Group Section: Research Methods & Reporting.

Molenaar, I., 2014. Advances in temporal analysis in learning and instruction. Frontline Learning Research 2, 15–24. URL: https://journals.sfu.ca/flr/index.php/journal/article/view/118, doi:10.14786/flr.v2i4.118. number: 4.

Molenaar, I., van Boxtel, C., Sleegers, P., 2013. Dynamic Computerized Scaffolding of Metacognitive Activities in Small Groups, in: Azevedo, R., Aleven, V. (Eds.), International Handbook of Metacognition and Learning Technologies. Springer New York, New York, NY. Springer International Handbooks of Education, pp. 561–574. URL: https://doi.org/10.1007/978-1-4419-5546-3_36, doi:10.1007/978-1-4419-5546-3_36.

Munshi, A., Rajendran, R., Ocumpaugh, J., Biswas, G., Baker, R.S., Paquette, L., 2018. Modeling Learners' Cognitive and Affective States to Scaffold SRL in Open-Ended Learning Environments, in: Proceedings of the 26th Conference on User Modeling, Adaptation and Personalization, ACM, New York, NY, USA. pp. 131–138. URL: http://doi.acm.org/10.1145/3209219.3209241, doi:10.1145/3209219.3209241. event-place: Singapore, Singapore.

Nguyen, H., Lim, K.Y., Wu, L.L., Fischer, C., Warschauer, M., 2021. "We're looking good": Social exchange and regulation temporality in collaborative design. Learning and Instruction 74, 101443. URL: https://www.sciencedirect.com/science/article/pii/S0959475221000025, doi:10.1016/j.learninstruc.2021.101443.

Niemi, H., Nevgi, A., Virtanen, P., 2003. Towards self-regulation in web-based learning. Journal of Educational Media 28, 49–71. URL: https://doi.org/10.1080/1358165032000156437, doi:10.1080/1358165032000156437. publisher: Routledge _eprint: https://doi.org/10.1080/1358165032000156437.

Paans, C., Molenaar, I., Segers, E., Verhoeven, L., 2019. Temporal variation in children's self-regulated hypermedia learning. Computers in Human Behavior 96, 246–258. URL: http://www.sciencedirect.com/science/article/pii/S0747563218301584, doi:10.1016/j.chb.2018.04.002.

Panadero, E., 2017. A Review of Self-regulated Learning: Six Models and Four Directions for Research. Frontiers in Psychology 8, 1–28. URL: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5408091/, doi:10.3389/fpsyg.2017.00422.

Paquette, L., Grant, T., Zhang, Y., Biswas, G., Baker, R., 2021. Using Epistemic Networks to Analyze Self-regulated Learning in an Open-Ended Problem-Solving Environment, in: Ruis, A.R., Lee, S.B. (Eds.), Advances in Quantitative Ethnography, Springer International Publishing, Cham. pp. 185–201. doi:10.1007/978-3-030-67788-6_13.

Pardo, A., Mirriahi, N., 2017. Design, Deployment and Evaluation of a Flipped Learning First-Year Engineering Course, in: Reidsema, C., Kavanagh, L., Hadgraft, R., Smith, N. (Eds.), The Flipped Classroom: Practice and Practices in Higher Education. Springer, Singapore, pp. 177–191. URL: https://doi.org/10.1007/978-981-10-3413-8_11, doi:10.1007/978-981-10-3413-8_11.

Pintrich, P.R., 2000. Chapter 14 - The Role of Goal Orientation in Self-Regulated Learning, in: Boekaerts, M., Pintrich, P.R., Zeidner, M. (Eds.), Handbook of Self-Regulation. Academic Press, San Diego, pp. 451–502.

Pérez-Álvarez, R., Maldonado-Mahauad, J., Pérez-Sanagustín, M., 2018. Tools to Support Self-Regulated Learning in Online Environments:

Literature Review, in: Pammer-Schindler, V., Pérez-Sanagustín, M., Drachsler, H., Elferink, R., Scheffel, M. (Eds.), Lifelong Technology-Enhanced Learning, Springer International Publishing, Cham. pp. 16–30. doi:10.1007/978-3-319-98572-5_2.

Reimann, P., 2009. Time is precious: Variable- and event-centred approaches to process analysis in CSCL research. International Journal of Computer-Supported Collaborative Learning 4, 239–257. URL: https://doi.org/10.1007/s11412-009-9070-z, doi:10.1007/s11412-009-9070-z.

Reimann, P., Markauskaite, L., Bannert, M., 2014. e-Research and learning theory: What do sequence and process mining methods contribute? British Journal of Educational Technology 45, 528–540. URL: http://onlinelibrary.wiley.com/doi/abs/10.1111/bjet.12146, doi:10.1111/bjet.12146.

Rodríguez, M.C., Nistal, M.L., Fonte, F.A.M., Penín, M.L., Molina, M.M., 2018. Exploring the application of process mining to support self-regulated learning: An initial analysis with video lectures, in: 2018 IEEE Global Engineering Education Conference (EDUCON), pp. 1766–1774. doi:10.1109/EDUCON.2018.8363448.

Roth, A., Ogrin, S., Schmitz, B., 2016. Assessing self-regulated learning in higher education: a systematic literature review of self-report instruments. Educational Assessment, Evaluation and Accountability 28, 225–250. URL: https://doi.org/10.1007/s11092-015-9229-2, doi:10.1007/s11092-015-9229-2.

Rovers, S.F.E., Clarebout, G., Savelberg, H.H.C.M., de Bruin, A.B.H., van Merriënboer, J.J.G., 2019. Granularity matters: comparing different ways of measuring self-regulated learning. Metacognition and Learning 14, 1–19. URL: https://doi.org/10.1007/s11409-019-09188-6, doi:10.1007/s11409-019-09188-6.

Saint, J., Fan, Y., Singh, S., Gasevic, D., Pardo, A., 2021. Using process mining to analyse self-regulated learning: a systematic analysis of four algorithms, in: LAK21: 11th International Learning Analytics and Knowledge Conference, Association for Computing Machinery, New York, NY, USA. pp. 333–343. URL: https://doi.org/10.1145/3448139.3448171, doi:10.1145/3448139.3448171.

Saint, J., Gašević, D., Matcha, W., Uzir, N.A., Pardo, A., 2020a. Combining analytic methods to unlock sequential and temporal patterns of self-regulated learning, in: Proceedings of the Tenth International Conference on Learning Analytics & Knowledge, Association for Computing Machinery, Frankfurt, Germany. pp. 402–411. URL: https://doi.org/10.1145/3375462.3375487, doi:10.1145/3375462.3375487.

Saint, J., Gašević, D., Pardo, A., 2018. Detecting Learning Strategies Through Process Mining, in: Pammer-Schindler, V., Pérez-Sanagustín, M., Drachsler, H., Elferink, R., Scheffel, M. (Eds.), Lifelong Technology-Enhanced Learning, Springer International Publishing, Cham. pp. 385–398. doi:10.1007/978-3-319-98572-5_29.

Saint, J., Whitelock-Wainwright, A., Gašević, D., Pardo, A., 2020b. Trace-SRL: A Framework for Analysis of Microlevel Processes of Self-Regulated Learning From Trace Data. IEEE Transactions on Learning Technologies 13, 861–877. doi:10.1109/TLT.2020.3027496. conference Name: IEEE Transactions on Learning Technologies.

Schunk, D.H., 2005. Self-Regulated Learning: The Educational Legacy of Paul R. Pintrich. Educational Psychologist 40, 85–94. URL: https://doi.org/10.1207/s15326985ep4002_3, doi:10.1207/s15326985ep4002_3. publisher: Routledge _eprint: https://doi.org/10.1207/s15326985ep4002_3.

Schunk, D.H., Greene, J.A., 2018. Historical, contemporary, and future perspectives on self-regulated learning and performance, in: Handbook of self-regulation of learning and performance, 2nd ed. Routledge/Taylor & Francis Group, New York, NY, US. Educational psychology handbook series, pp. 1–15.

Sedrakyan, G., De Weerdt, J., Snoeck, M., 2016. Process-mining enabled feedback: "Tell me what I did wrong" vs. "tell me how to do it right". Computers in Human Behavior 57, 352–376. URL: http://www.sciencedirect.com/science/article/pii/S0747563215303113, doi:10.1016/j.chb.2015.12.040.

Shaffer, D.W., 2004. Epistemic Frames and Islands of Expertise: Learning from Infusion Experiences, in: Proceedings of the 6th International Conference on Learning Sciences, International Society of the Learning Sciences. pp. 473–480. Event-place: Santa Monica, California.

Shaffer, D.W., Collier, W., Ruis, A.R., 2016. A Tutorial on Epistemic Network Analysis: Analyzing the Structure of Connections in Cognitive, Social, and Interaction Data. Journal of Learning Analytics 3, 9–45. URL: https://eric.ed.gov/?id=EJ1126800.

Siadaty, M., Gašević, D., Hatala, M., 2016a. Associations between technological scaffolding and micro-level processes of self-regulated learning: A workplace study. Computers in Human Behavior 55, 1007–1019. URL: http://www.sciencedirect.com/science/article/pii/S0747563215302132, doi:10.1016/j.chb.2015.10.035.

Siadaty, M., Gašević, D., Hatala, M., 2016b. Measuring the impact of technological scaffolding interventions on micro-level processes of self-regulated workplace learning. Computers in Human Behavior 59, 469–482. URL: http://www.sciencedirect.com/science/article/pii/S0747563216300772, doi:10.1016/j.chb.2016.02.025.

Siadaty, M., Gašević, D., Jovanović, J., Milikić, N., Jeremić, Z., Ali, L., Giljanović, A., Hatala, M., 2012. Learn-B: A Social Analytics-enabled Tool for Self-regulated Workplace Learning, in: Proceedings of the 2Nd International Conference on Learning Analytics and Knowledge, ACM, New York, NY, USA. pp. 115–119. URL: http://doi.acm.org/10.1145/2330601.2330632, doi:10.1145/2330601.2330632. event-place: Vancouver, British Columbia, Canada.

Siebert-Evenstone, A.L., Irgens, G.A., Collier, W., Swiecki, Z., Ruis, A.R., Shaffer, D.W., 2017. In Search of Conversational Grain Size: Modeling Semantic Structure using Moving Stanza Windows. Journal of Learning Analytics 4, 123–139–123–139. URL: https://learning-analytics.info/journals/index.php/JLA/article/view/5416, doi:10.18608/jla.2017.43.7.

Sobocinski, M., Järvelä, S., Malmberg, J., Dindar, M., Isosalo, A., Noponen, K., 2020. How does monitoring set the stage for adaptive regulation or maladaptive behavior in collaborative learning? Metacognition and Learning 15, 99–127. URL: https://doi.org/10.1007/s11409-020-09224-w, doi:10.1007/s11409-020-09224-w.

Sobocinski, M., Malmberg, J., Järvelä, S., 2017. Exploring temporal sequences of regulatory phases and associated interactions in low- and high-challenge collaborative learning sessions. Metacognition and Learning 12, 275–294. URL: https://doi.org/10.1007/s11409-016-9167-5, doi:10.1007/s11409-016-9167-5.

Sonnenberg, C., Bannert, M., 2015. Discovering the Effects of Metacognitive Prompts on the Sequential Structure of SRL-Processes Using Process Mining Techniques. Journal of Learning Analytics 2, 72–100. URL: https://epress.lib.uts.edu.au/journals/index.php/JLA/

article/view/4090, doi:10.18608/jla.2015.21.5. number: 1.

Sonnenberg, C., Bannert, M., 2016. Evaluating the Impact of Instructional Support Using Data Mining and Process Mining: A Micro-Level Analysis of the Effectiveness of Metacognitive Prompts. JEDM | Journal of Educational Data Mining 8, 51–83. URL: https://jedm.educationaldatamining.org/index.php/JEDM/article/view/JEDM2016-8-2-3, doi:10.5281/zenodo.3554597. number: 2.

Su, Y., Li, Y., Hu, H., Rosé, C.P., 2018. Exploring college English language learners' self and social regulation of learning during wiki-supported collaborative reading activities. International Journal of Computer-Supported Collaborative Learning 13, 35–60. URL: https://doi.org/10.1007/s11412-018-9269-y, doi:10.1007/s11412-018-9269-y.

Taub, M., Azevedo, R., 2016. Using Eye-Tracking to Determine the Impact of Prior Knowledge on Self-Regulated Learning with an Adaptive Hypermedia-Learning Environment, in: Micarelli, A., Stamper, J., Panourgia, K. (Eds.), Intelligent Tutoring Systems, Springer International Publishing. pp. 34–47.

Van Laer, S., Elen, J., 2017. In search of attributes that support self-regulation in blended learning environments. Education and Information Technologies 22, 1395–1454. URL: https://doi.org/10.1007/s10639-016-9505-x, doi:10.1007/s10639-016-9505-x.

Viberg, O., Khalil, M., Baars, M., 2020. Self-regulated learning and learning analytics in online learning environments: a review of empirical research, in: Proceedings of the Tenth International Conference on Learning Analytics & Knowledge, Association for Computing Machinery, Frankfurt, Germany. pp. 524–533. URL: https://doi.org/10.1145/3375462.3375483, doi:10.1145/3375462.3375483.

Weijters, A.J.M.M., W. M.P. Aalst, V.D., Medeiros, A.K.A.D., 2006. Process mining with the HeuristicsMiner algorithm. Technische Universiteit Eindhoven. URL: https://research.tue.nl/en/publications/process-mining-with-the-heuristicsminer-algorithm.

Winne, P.H., 2020. Construct and consequential validity for learning analytics based on trace data. Computers in Human Behavior 112, 106457. URL: https://www.sciencedirect.com/science/article/pii/S0747563220302090, doi:10.1016/j.chb.2020.106457.

Winne, P.H., Hadwin, A.F., 1998. Studying as self-regulated learning, in: Metacognition in educational theory and practice. Lawrence Erlbaum Associates Publishers, Mahwah, NJ, US. The educational psychology series, pp. 277–304.

Winne, P.H., Jamieson-Noel, D., 2002. Exploring students' calibration of self reports about study tactics and achievement. Contemporary Educational Psychology 27, 551–572. URL: http://www.sciencedirect.com/science/article/pii/S0361476X02000061, doi:10.1016/S0361-476X(02)00006-1.

Winne, P.H., Perry, N.E., 2000. Chapter 16 - Measuring Self-Regulated Learning, in: Boekaerts, M., Pintrich, P.R., Zeidner, M. (Eds.), Handbook of Self-Regulation. Academic Press, San Diego, pp. 531–566. URL: http://www.sciencedirect.com/science/article/pii/B9780121098902500457, doi:10.1016/B978-012109890-2/50045-7.

Wong, J., Baars, M., Davis, D., Zee, T.V.D., Houben, G.J., Paas, F., 2019. Supporting Self-Regulated Learning in Online Learning Environments and MOOCs: A Systematic Review. International Journal of Human–Computer Interaction 35, 356–373. URL: https://doi.org/10.1080/10447318.2018.1543084, doi:10.1080/10447318.2018.1543084. publisher: Taylor & Francis _eprint: https://doi.org/10.1080/10447318.2018.1543084.

Zimmerman, B.J., 1986. Becoming a self-regulated learner: Which are the key subprocesses? Contemporary Educational Psychology 11, 307–313. URL: http://www.sciencedirect.com/science/article/pii/0361476X86900275, doi:10.1016/0361-476X(86)90027-5.

Zimmerman, B.J., 2000. Chapter 2 - Attaining Self-Regulation: A Social Cognitive Perspective, in: Boekaerts, M., Pintrich, P.R., Zeidner, M. (Eds.), Handbook of Self-Regulation. Academic Press, San Diego, pp. 13–39. URL: http://www.sciencedirect.com/science/article/pii/B9780121098902500317.

Zimmerman, B.J., 2002. Becoming a Self-Regulated Learner: An Overview. Theory Into Practice 41, 64–70. URL: http://www.tandfonline.com/doi/abs/10.1207/s15430421tip4102_2, doi:10.1207/s15430421tip4102_2.

Zimmerman, B.J., Pons, M.M., 1986. Development of a Structured Interview for Assessing Student Use of Self-Regulated Learning Strategies:. American Educational Research Journal URL: https://journals.sagepub.com/doi/10.3102/00028312023004614, doi:10.3102/00028312023004614. publisher: SAGE Publications.

A. Appendix: Study Characteristics

Year	Author(s)	Sytem	Data Collection	SRL Model	Analytic Method
2007	Hadwin, Allyson F.; Nesbit, John C.; Jamieson-Noel, Dianne; Code, Jillianne; Winne, Philip H	LMS (Specialised)	Trace data, Questionnaire	Specific Dimensions	Transition/Sequence
2010	Biswas, Gautam; Jeong, Hogyeong; Kinnebrew, John S.; Sulcer, Brian; Roscoe, Rod	OELE	Trace data	Pintrich	HMM
2013	Molenaar, Inge; van Boxtel, Carla; Sleegers, Peter	LMS	Various	Zimmerman	Transition/Sequence
2014	Malmberg, Jonna; Järvelä, Sanna; Kirschner, Paul A.	LMS (Specialised)	Trace data and various	Winne and Hadwin	Transition/Sequence
2014	Bannert, Maria; Reimann, Peter; Sonnenberg, Christoph	LMS (Bespoke)	Think-aloud	Bannert	PM
2014	Kinnebrew, John S.; Segedy, James R.; Biswas, Gautam	OELE	Trace data	Consolidated	Novel
2015	Malmberg, Jonna; Järvelä, Sanna; Järvenoja, Hanna; Panadero, Ernesto	LMS (Specialised)	Digital self report and various	Consolidated	PM
2015	Sonnenberg, Christoph; Bannert, Maria	LMS (Bespoke)	Think-aloud	Bannert	PM
2016	Sedrakyan, Gayane; De Weerdt, Jochen; Snoeck, Monique	Simulation/Modelling Environment	Trace data	Related Dimensions	PM and various
2016	Sonnenberg, Christoph; Bannert, Maria	LMS (Bespoke)	Think-aloud	Bannert	PM and various
2016	Järvelä, 0Sanna; Malmberg, Jonna; Koivuniemi, Marika	LMS (Specialised)	Multi-channel	Winne and Hadwin	Transition/Sequence
2016	Siadaty, Melody; Gašević, Dragan; Hatala, Marek	LMS (Specialised)	Trace data, Questionnaire	Zimmerman	Transition/Sequence
2016	Mirriahi, Negin; Liaqat, Daniyal; Dawson, Shane; Gašević, Dragan	Video tool	Trace data	Related Dimensions	Transition/Sequence
2017	Kizilcec, René F.; Pérez-Sanagustín, Mar; Maldonado, Jorge J.	MOOC	Trace data, Questionnaire	Consolidated	Transition/Sequence
2017	Sobocinski, Márta; Malmberg, Jonna; Järvelä, Sanna	Narrative Capture Tool	Multi-channel	Zimmerman	PM
2017	Siebert-Evenstone, Amanda Lee; Irgens, Golnaz Arastoopour; Collier, Wesley; Swiecki, Zachari; Ruis, Andrew R.; Shaffer, Dav	Simulation/Modelling Environment	Discussion Logs	Related Dimensions	ENA
2017	Malmberg, Jonna; Järvelä, Sanna; Järvenoja, Hanna	Various	Various	Winne and Hadwin	Transition/Sequence
2018	Maldonado-Mahauad, Jorge; Pérez-Sanagustín, Mar; Moreno-Marcos, Pedro Manuel; Alario-Hoyos, Carlos; Muñoz-Merino,	MOOC	Trace data, Questionnaire	Consolidated	PM
2018	Maldonado-Mahauad, Jorge; Pérez-Sanagustín, Mar; Kizilcec, René F.; Morales, Nicolás; Munoz-Gama, Jorge	MOOC	Trace data, Questionnaire	Consolidated	PM
2018	Bogarín, Alejandro; Cerezo, Rebeca; Romero, Cristóbal	LMS	Trace data	Consolidated	PM
2018	Saint, John; Gašević, Dragan; Pardo, Abelardo	LMS (Bespoke)	Trace data	Specific Dimensions	PM
2018	Su, You; Li, Yanyan; Hu, Hening; Rosé, Carolyn P.	LMS	Discussion Logs	Consolidated	Transition/Sequence
2018	Munshi, Anabil; Rajendran, Ramkumar; Ocumpaugh, Jaclyn; Biswas, Gautam; Baker, Ryan S.; Paquette, Luc	OELE	Multi-channel	Specific Dimensions	Transition/Sequence
2018	Rodríguez, M. C.; Nistal, M. L.; Fonte, F. A. M.; Penín, M. L.; Molina, M. M.	Video tool	Trace data	Specific Dimensions	PM
2018	Chen, Q.; Yue, X.; Plantaz, X.; Chen, Y.; Shi, C.; Pong, T.; Qu, H.	MOOC	Trace data and various	Related Dimensions	Novel
2018	Mahzoon, Mohammad Javad; Maher, Mary Lou; Eltayeby, Omar; Dou, Wenwen; Grace, Kazjon	LMS	Trace data, Questionnaire	Related Dimensions	Novel
2018	Dorodchi, M.; Benedict, A.; Desai, D.; Mahzoon, M. J.; MacNeil, S.; Dehbozorgi, N.	LMS	Trace data and various	Related Dimensions	Novel
2019	Cerezo, Rebeca; Bogarín, Alejandro; Esteban, María; Romero, Cristóbal	LMS	Trace data	Zimmerman	PM
2019	Ahmad Uzir, Nora'ayu; Gašević, Dragan; Matcha, Wannisa; Jovanović, Jelena; Pardo, Abelardo; Lim, Lisa-Angelique; Gentili,	LMS (Bespoke)	Trace data	Specific Dimensions	PM
2019	Matcha, Wannisa; Gašević, Dragan; Ahmad Uzir, Nora'ayu; Jovanović, Jelena; Pardo, Abelardo; Maldonado-Mahauad, Jorge	MOOC	Trace data	Related Dimensions	PM and various
2019	Engelmann, Katharina; Bannert, Maria	LMS (Bespoke)	Think-aloud	Bannert	PM
2019	Matcha, Wannisa; Gašević, Dragan; Uzir, Nora'Ayu Ahmad; Jovanović, Jelena; Pardo, Abelardo	LMS (Bespoke)	Trace data	Specific Dimensions	PM
2019	Hadwin, Allyson F.; Davis, Sarah K.; Bakhtiar, Aishah; Winne, Philip H	LMS	Various	Winne and Hadwin	PM
2019	Boroujeni, Mina Shirvani; Dillenbourg, Pierre	MOOC	Trace data	Related Dimensions	Transition/Sequence
2020	Cheng, Hercy N. H.; Zhang, Xiaotong	LMS (Bespoke)	Trace data, Questionnaire	Consolidated	HMM
2020	Li, Shan; Du, Hanxiang; Xing, Wanli; Zheng, Juan; Chen, Guanhua; Xie, Charles	Simulation/Modelling Environment	Trace data, Questionnaire	Consolidated	Transition/Sequence
2020	Ahmad Uzir, Nora'ayu; Gašević, Dragan; Jovanović, Jelena; Matcha, Wannisa; Lim, Lisa-Angelique; Fudge, Anthea	LMS (Bespoke)	Trace data	Specific Dimensions	PM and various
2020	Ahmad Uzir, Nora'ayu; Gašević, Dragan; Matcha, Wannisa; Jovanović, Jelena; Pardo, Abelardo	LMS (Bespoke)	Trace data	Related Dimensions	PM
2020	Bakhtiar, Aishah; Hadwin, Allyson	Narrative Capture Tool	Multi-channel	Winne and Hadwin	Novel
2020	Heirweg, Sofie; De Smul, Mona; Merchie, Emmelien; Devos, Geert; Van Keer, Hilde	n/a	Think-aloud	Consolidated	PM
2020	Sobocinski, Márta; Järvelä, Sanna; Malmberg, Jonna; Dindar, Muhterem; Isosalo, Antti; Noponen, Kai	Multimodal	Multi-channel	Consolidated	Novel
2020	Saint, John; Gašević, Dragan; Matcha, Wannisa; Uzir, Nora'Ayu Ahmad; Pardo, Abelardo	LMS (Bespoke)	Trace data	Zimmerman	PM and various
2020	Saint, John; Whitelock-Wainwright, Alexander; Gašević, Dragan; Pardo, Abelardo	LMS (Bespoke)	Trace data	Zimmerman	PM
2021	Lim, Lisa-Angelique	LMS (Bespoke)	Trace data and various	Zimmerman	Novel
2021	Nguyen, Ha; Lim, Kyu Yon; Wu, Liang Li; Fischer, Christian; Warschauer, Mark	n/a	Discussion Logs	Consolidated	ENA and various
2021	Malmberg, Jonna; Fincham, Oliver; Pijeira-Díaz, Héctor J.; Järvelä, Sanna; Gašević, Dragan	Multimodal	Multi-channel	Winne and Hadwin	HMM
2021	Saint, John; Fan, Yizhou; Singh, Shaveen; Gašević, Dragan; Pardo, Abelardo	LMS	Trace data	Zimmerman	PM
2021	Fan, Yizhou; Saint, John; Singh, Shaveen; Jovanovic, Jelena; Gašević, Dragan	LMS	Trace data	Zimmerman	PM
2021	Huang, Lingyun; Lajoie, Susanne P.	LMS (Specialised)	Trace data and various	Consolidated	PM
2021	Fan, Yizhou; Matcha, Wannisa; Uzir, Nora'ayu Ahmad; Wang, Qiong; Gašević, Dragan	MOOC	Trace data	Specific Dimensions	PM and various
2021	Davis, Sarah K.; Hadwin, Allyson F.	Narrative Capture Tool	Digital self report and various	Winne and Hadwin	PM
2021	Järvelä, Sanna; Malmberg, Jonna; Haataja, Eetu; Sobocinski, Marta; Kirschner, Paul A.	Multimodal	Multi-channel	Consolidated	Novel
2021	Paquette, Luc; Grant, Theodore; Zhang, Yingbin; Biswas, Gautam; Baker, Ryan	OELE	Trace data	Consolidated	ENA

2.3 Summary

The systematic literature review presented here provides insights into the landscape of temporally focused SRL, in answer to research question one (RQ1). Apart from providing a comprehensive articulation of the research landscape, it also provides the reader with a set of broad considerations for potential researchers to accommodate when embarking on projects in this area.

From a methodological viewpoint, it is clear that researchers are answering the call, initiated by Reimann (2009), to challenge ontological limitations of conventional statistical analysis. We are not suggesting that conventional statistical analysis should be abandoned, but that its positioning at the go-to analytical option should be questioned in scenarios where sequence and temporality are key. In fact we would suggest that its presence, alongside more temporally oriented methods, has unarguable analytic potency. This notwithstanding, we argue that the choice of analytic method should be approached with greater consideration than is generally articulated in the studies. This is not a criticism; many of the studies explored novel methods in the pursuit of richer insights, and future researchers can benefit from this exploration. In short, we encourage an explicit assessment of methods in the context of the study aims. We also argue that value can be gained in combining methods, thus avoiding methodological compromises inherent in choosing a single method. We explore this theme in an applied sense in the studies reported on in Chapter five and Chapter six.

From a theoretical viewpoint, we see that the usage of SRL models is subject to nuance. In some cases, a clear model is chosen and applied in a way which directly effects how the study data are transformed and presented and a framework is clearly articulated. The studies underpinned by the Greene and Azevedo (2009) micro-level process method (e.g., Siadaty et al. (2016)) are testament to its clarity. Other studies (e.g., Kizilcec et al. (2017)) employ SRL models to inform survey design as a means of assessing different groups of learners in context of their SRL mastery (or perception thereof). In many cases, SRL is presented more in a theoretical context as opposed to an applied framework. Key decisions arise around the use of a complete model of SRL, or some sort of consolidated SRL framework. There is an argument that while the major SRL models provide differing focuses, they all share temporal and cyclical commonalities as highlighted by Panadero (2017). As with methodological choices, there is much to consider, but an explicit appraisal of the choice and deployment of an SRL model should be undertaken and justified in the work. Our hope is that this will go some way to address the call, issued by Gašević et al. (2015), that all LA research should have a strong basis in theory.

Leading on from this, the subject of validity is arguably more difficult to tackle in this context as it is in settings where researchers can rely on conventional statistical constructs. Nonetheless, the way researchers approach validity can be informed by decisions over data collection and transformation methods, as well as that of comparative analyses. Indeed, the comparison of learner groups is central to many of our studies; the scope of our review encompasses studies that do not rely on variable-centric measures, so the interpretation of the observed phenomena cannot be easily validated in isolation. In undertaking a comparison, do the delineations genuinely reflect differing behaviours or did the researchers (knowingly or unknowingly) implant a biased meaning? We argue that researchers should retain analytical objectivity, and resist the urge to project meaning into group behaviour that is not really there. We argue that great empirical gains can be made in employing *multi-channel* analysis in which the same SRL phenomena are analysed, based on data collection from different data sources. The potential of true ontological triangulation, and a movement towards some sort of grounding of truth, is a compelling one.

From a temporal viewpoint, in our studies, there are examples of broad and narrow temporal segmentation; from semester-long periods to event sequences that can be counted in minutes, or even seconds. It is, however, important to maintain a broader perspective. Chen et al. (2018) conceptualised two broad temporal features: i) The *passage of time* relating to duration or frequency; and ii) a representation of how events are ordered and their relationship in terms of ongoing sequence. The latter emphasises temporality as order and sequence and, as Reimann (2009) states, order matters because learning is a cumulative sequence of experiences. This brings us back to the methodological considerations of our analytic discovery method; do we focus on directional association, as emphasised in process mining algorithms, or do we focus on temporal proximity, as emphasised in epistemic network analysis? The recent development of the dENa algorithm (Fogel et al., 2021), may prove to bridge the gap between these temporal perspectives. This notwithstanding, researchers must be aware of the nuances of temporal analysis, and how it can be impacted by the method-specific distortions inherent in each method.

In addressing these key elements, this chapter forces a conversation and provides a more cohesive framework for future research in this area. Critically, this chapter provides a context for the rest of the thesis, which proposes a novel combination of analytic methods to explore SRL through the lenses of temporality and sequence. This context is shaped by these factors:

- **Temporally focused analysis**. The studies in our systematic review of literature demonstrated the methodological importance of decisions made around discovery and analytic algorithms. In certain studies, entirely new techniques were developed to address specific dimensions of temporality and sequence (e.g., the sequence models developed by Mahzoon et al. (2018)); in others, techniques were appropriated from industrial and commercial analytic tools. Considerations of replicability led us to explore the use of various existent process analytic platforms, with a focus on probabilistic (or stochastic) process mining. At this stage, nobody had made extensive use of stochastic process mining to explore learner behaviour. We suggest that the use of such probabilistic metrics synergises with the Winne (2010) conceptualisation of SRL as a sequence of events, in which likely sequences be articulated across contrasting learner groups. We argue that use of a relative scale is helpful in the study of SRL, where high-level, meta-cognitive processes, such as *planning* or *reflection*, may not happen often, but are of key importance. The studies presented in the following chapters represent the only studies which combine this particular form of processing mining with a formal method of SRL data transformation. The process mining algorithm is first explored in the study in Chapter three, but in truth, this exploration, and a broader process analytic exploration underpins all studies reported on in the remaining chapters.

- **Employing systematic interpretations of algorithm metrics**. Leading on from the first point, we noted that the interpretation of process mining metrics was subject to some variation, with only the studies by Ahmad Uzhir and Matcha (e.g., Ahmad Uzir et al. (2020), Ahmad Uzir et al. (2019), and Matcha, Gašević, Ahmad Uzir, Jovanović, and Pardo (2019), Matcha, Gašević, Ahmad Uzir, Jovanović, Pardo, et al. (2019)) demonstrating a relative consistency of interpretation, albeit without embedding a model of SRL. Our own studies not only demonstrate robust analytical interpretations, but (in Chapter six) we issue a rallying call, echoed in our systematic review of literature, for a more considered choice and deployment of methods and metrics, going forward, which could apply to both SRL and SRL-based studies.

- **Embedding a recognised model of SRL**. We noted that this area was subject to the greatest variation and nuance of deployment. Whilst a reasonable number of self-report studies made use of SRL-informed frameworks to transform utterances into recognised SRL processes, only the Siadaty et al. (2016) study employed a similarly robust method, (micro-level processing (Greene & Azevedo, 2009)), in trace data settings, albeit in experimental settings. In the study reported on in Chapter four, we deploy a semi-automated method to frame authentic trace data in recognised SRL constructs; something which, as far as we are aware, had not been done before.

- **Consolidation of methods and metrics**. A number of studies proposed the use of multiple analytics methods to enrich analysis (Ahmad Uzir et al., 2020; Fan et al., 2021; Matcha, Gašević, Ahmad Uzir, Jovanović, Pardo, et al., 2019; Swiecki et al., 2019); none of them embed their analyses in true models of SRL or offer the promise of consolidating interpretations through algorithm metrics. In Chapter five and Chapter six, not only do we compare the relative strengths and limitations of multiple analytic methods through the analysis of common datasets, but demonstrate how outcomes from these methods, and the metrics they provide, can be consolidated to provide a multi-dimensional view of SRL.

3 Exploration of Temporality and Probability from Trace Data

It is the concept of likelihood that a real understanding of probability resides, and we must learn how to measure it.
— Anthony Stafford Beer, *Management Science*

3.1 Introduction

We established in Chapter two that the temporal aspect of learning has emerged as a key interest in the field of learning analytics. Although we can view the temporal nature of learning as it relates to the passage of time (i.e., duration of engagement with a learning event), we can also view it in the context of sequence and order (Chen et al., 2018). The conceptual and ontological challenges that exist around the measurement and analysis of the temporal associations, as highlighted by Reimann (2009), impose key methodological decisions for researchers in this field.

A number of valuable studies, such as Kinnebrew and Biswas (2012), Lust et al. (2013), Jovanović et al. (2017), and Fincham et al. (2019), used analytic techniques to capture various dimensions of learner actions and tactics from trace data but these techniques did not represent (nor did they seek to represent) the dynamics of temporal analysis that Reimann (2009) and Chen et al. (2018) articulate. In this context, *process mining* has a strong methodological presence. The studies by, for example, Bannert et al. (2014), Sonnenberg and Bannert (2015), and Malmberg et al. (2015), provided the promise of temporal analyses using process mining, but derived these analyses from self-report data collection methods. One major tenet of our thesis is use of authentic trace data as a collection source, in response to various concerns around the veracity of self-report data collection, as reported by Winne and Jamieson-Noel (2002), Zhou and Winne (2012), and Bjork et al. (2013). The study reported on in this chapter was a response to the rarity of trace data-based analyses that emphasised sequence and temporality. In addition, the promise of exploring this temporal dynamic through analyses of sequential likelihood, as afforded by the use of first order Markov models derived from stochastic process mining, was entirely unexplored.

To that end, this chapter investigates the utility of stochastic process mining in articulating the comparative temporal and sequential characteristics of different learner strategy groups, and assesses the outcomes in contrast to basic statistical measures. The study presented in this chapter serves to investigate research question two (RQ2), that is, *How effectively can we measure the temporal dynamics of learning strategies in delineated student groupings, using process analytic techniques?*

3.1.1 Chapter overview

This chapter reports on the findings of a study undertaken to explore the extent to which process mining algorithms can provide insights into learning strategies and tactic deployment, as derived from LMS log data. These techniques, which allow the identification of unique arrangements of activities in a temporal space, do not rely on conventional statistical measures; the phenomena captured are event based, and the relationships between them are articulated in associative metrics, such as time-lag or frequency of transition. The study makes use of a novel process mining algorithm, pMineR (Gatta, Lenkowicz, et al., 2017), in which the associative metric is probabilistic, using first-order Markov chains to generate the process models. In this context, temporal and sequential association are articulated in terms of likelihood of transition between activities. It is this "transition probability" that is central to the interpretation of the process models in this study.

The LMS activities captured were categorised in two ways: firstly by a combination sequence analysis and clustering which uncovered a set of five action types, specifically, *reading course materials*, *formative assessment*, *video viewing with associated formative assessment*, *reading course materials*, and *summative assessment*; secondly, time management attributes where added, based on the point, relative to the week of study, when the activity was undertaken, specifically, *ahead*, *preparing*, *revisiting*, and *catch-up*. The work undertaken by Jovanović et al. (2017) is important as it provided a set of student groups characterised by engagement strategy that we were able to further characterise using our process mining analyses, that is, *Active Agile*, *Efficient*, *Summative Gamblers*, *Active Cohesive*, and *Extreme Minimalists*.

The process mining algorithm used in this study—first order Markov modelling via the pMineR package—had not been used in LA research at the time of publication; it was created to explore process modelling in the medical sector. We recognised its potential as way of modelling learning engagement through probabilistic association and of characterising learner groups through a sense of likely movement, or transition, between action sequences. In Chapter two, we posited that group comparison is a powerful means of articulating learner behaviours. In this chapter, we characterised groups individually, but additionally were able to include pairwise comparisons of a selection of the student groups. This was facilitated by the affordances of the pMineR platform, which allowed the direct mapping of one process model onto another, highlighting key differences in behaviours as seen in transition probabilities. The resulting "compare" plots provided key insights for our study. As far as we are aware, no other process mining platforms provide this comparative mechanism although a similarly useful visual comparison is available using epistemic network analysis (see

Chapter five).

3.2 Publication: Detecting Learning Strategies Through Process Mining

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

> Saint, J., Gašević, D., & Pardo, A. (2018). Detecting Learning Strategies Through Process Mining. In V. Pammer-Schindler, M. Pérez-Sanagustín, H. Drachsler, R. Elferink, & M. Scheffel (Eds.), *Lifelong Technology-Enhanced Learning* (pp. 385–398). Springer International Publishing. https://doi.org/10.1007/978-3-319-98572-5_29

Detecting Learning Strategies Through Process Mining

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Abstract. The recent focus on learning analytics to analyse temporal dimensions of learning holds a strong promise to provide insights into latent constructs such as learning strategy, self-regulated learning, and metacognition. There is, however, a limited amount of research in temporally-focused process mining in educational settings. Building on a growing body of research around event-based data analysis, we explore the use of process mining techniques to identify strategic and tactical learner behaviours. We analyse trace data collected in online activities of a sample of nearly 300 computer engineering undergraduate students enrolled in a course that followed a flipped classroom pedagogy. Using a process mining approach based on first order Markov models in combination with unsupervised machine learning methods, we performed intra- and inter-strategy analysis. We found that certain temporal activity traits relate to performance in the summative assessments attached to the course, mediated by strategy type. Results show that more strategically minded activity, embodying learner self-regulation, generally proves to be more successful than less disciplined reactive behaviours.

Keywords: Learning analytics · Process mining · First order Markov models Temporal dynamics · Self-regulated learning

1 Introduction

Enhancing learning experience is one of the primary goals for many higher education institutions. Approaches such as flipped classrooms offer some promise of advancing student academic performance and satisfaction [1]. However, the emphasis on the self-directed use of technology to complete learning activities increases a need for students to have high skills for self-regulated learning. Poor choices of study tactics and strategies are often reported in the literature, through the collection of student self-reports. Although such approaches can offer some insights to the ways students study, they offer little information that can be used by educators to offer guidance to students in real-time.

The development of the field of learning analytics promises to provide insights into learning strategies by analysis of trace data about students' use of and interaction with online resources provided in learning management systems (LMS). Machine learning

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techniques have been used to explore trace data sequences to reveal distinct strategies and approaches to learning e.g., [2–4]. Nonetheless, a section of these studies uses statistical methods and focus more on engagement frequency/categorisation where the dimension of time (critical to this study) is not considered e.g., [5, 4]. Others recognise time as a dimension, but this is restricted to measurement of time on task, and not a reflection of true inter-process temporal dynamics e.g., [6]. Another section of studies provides key insights into learner engagement over time, as opposed to comparative, stochastic inter-strategy analyses e.g., [7].

This paper reports on the findings of a study that was set out to explore the extent to which process mining techniques can provide insights into learning strategies provided by current approaches based on machine learning methods. Specifically, the study used first-order Markov chains to complement the findings of an existing method, based on machine learning, to examine internal dynamics of learning strategies and perform inter-strategy comparison in terms of the temporal sequencing of individual activities can be performed. The results showed that proposed approach provides a genuine insight into inter and intra-tactic dynamics, providing a different dimension to the narrative around learning strategy presently reported in the literature. The study also provides a view of learning malformation as typified by movement through and between study actions.

We use first order Markov models (FOMMs) as an initial exploratory process-mining algorithm with a view to testing their viability as an interpretive tool for learning sciences. FOMMs are based on transition probabilities between sets of processes. It is proposed that this type of stochastic insight combines effectively with the process activity formulation described in the methodology section.

2 Background and Related Work

2.1 Learning Strategy

The utilisation of effective study strategies is an important factor of effective self-regulated learning (SRL), as is the awareness of the relationship between these strategies and the aspired outcomes [8]. As stated by Boekaerts, self-regulated learners are "…aware of what they know and feel about the domain of study, including which general cognitive and motivation strategies are (less) effective to attain the learning goals…." [9]. Accordingly, they are aware of the attributes of their own knowledge, motivations, beliefs, expectations, and cognitive behaviours, and seek to reapply ongoing task-oriented mediation, in keeping with their defined goals and standards [10]. However, the standards learners use for evaluation of the choices of their learning strategies and products of their learning can be suboptimal. Winne and Noel-Jamieson showed that learners generally overestimate their use of individual study tactics [11]. Bjork et al. [12] suggest that learners mostly use ineffective study strategies – e.g., reading and re-reading text instead of practising memory recall through self-testing. The challenge, therefore, is to determine an effective analytical method of capturing and measuring the choices of study strategies and tactics to enhance the effectiveness of learners' self-regulation. Study tactics and strategies are closely related concepts. Winne [13] characterises a set of tactics and strategies, as well as an overarching sense of metacognition employed in the learning process. In doing so, he identifies three key aspects of SRL. A tactic can be viewed as an if-then construct, e.g., *if* I read an article which confirms an aspect of my theory *then* I will add to my corpus. We could extrapolate this to include *else* e.g., *else* I will seek to refine my theory. A strategy is structured arrangement of cognitive tactics. Finally, metacognition is a learner's management of their own cognitive strategies, and the development of an overarching knowledge management strategy, encompassing self-awareness.

2.2 Analytics of Learning Tactics and Strategies

The use of trace data to study learning strategies has been galvanised through the foundation of the field of learning analytics. Several authors proposed the use of unsupervised methods for the study of learning strategy. Lust et al. [5] used clustering to identify user-profiles through learner behaviours, identifying profiles through frequency of activity engagement of content management system supported course. In an attempt to add a temporal dimension, Lust et al. [14] augmented their research with an analysis to identify changes in learner strategies between the first and second half of the course. Similarly, Kovanović et al. [6] use a hierarchical cluster analysis to extract learning strategies of learners and to understand the extent to which those strategies were associated with the learners' level of cognitive presence in online discussions. Although the results of these studies are relevant for understanding the connection between learning strategy, academic performance, and cognitive presence, these studies offer little insight into how learners sequence their activities with each of the strategies identified. Thus, learning strategies are looked at as summaries of the quantities of activities rather than temporally sequenced activities based on some strategic choices.

Analysis of temporal links between actions learners take has also been used in the literature on learning strategy. Kinnebrew et al. utilised a computer-based learning environment to measure students' cognitive and meta-cognitive development using sequence mining techniques [15, 16]. Jovanović and her colleagues [3] utilise a combination of an unsupervised machine learning technique with a sequence mining algorithm to explore the extent to which meaningful learning strategies can be extracted from trace data. Their follow-up study showed that learning strategies extracted from trace data are associated with deep and surface approaches to learning [2]. Fincham et al. [7] extract study tactics by using hidden Markov models and then apply a clustering exercise, which partially mirrors Jovanović et al. [3], to extract study strategies. Both Jovanović et al. and Fincham et al. studies found that such the use of learning strategies extracted this way was associated with academic performance. While these studies provide key insights into learner engagement over time, they fall short of providing comparative inter-strategy analyses.

Process mining techniques provide viable tools for comparative inter-strategy analyses, though these methods are typically used on think aloud data. Bannert and her colleagues [17] use process mining techniques to analyse think-aloud data logged from a student-group's navigation through an LMS. The think aloud data were coded for presence of micro-level processes of SRL (e.g., goal-setting) and analysed with the Fuzzy Miner process mining algorithm to compare differences in SRL between high and low performing students. In Sonnenberg and Bannert's follow-up study [18], the same methods are used to measure the impact of metacognitive prompts in similar LM environments.

These studies are significant in that they present a novel way of capturing and measuring SRL on the level of SRL micro-level processes. The studies, however, do not provide insights into learning strategies followed by learners while using an LMS to study.

3 Methodology

3.1 Data Collection

The data for this study were collected from an LMS attached to a computing course at a university in [anonymised]. The course was based on a flipped classroom pedagogy and the data used in this study were about students' engagement with the online activities, which served the purpose of preparation for the face-to-face activities. Each time a student engaged with an element of the LMS, a learning event record was generated containing a *student ID* number, a *timestamp*, and the completed *study action*. The study actions were: watching video; reading textual content; response to summative problem-solving exercise along with information about correct and incorrect responses; response to a question from formative quizzes with information about correct and incorrect responses and whether the students asked to see the correct response; dashboard view, and view of lesson objectives. The student cohort consisted of 290 students who collectively generated 184,211 learning events. The course lasted 13 weeks, comprising two main bouts of activity: Weeks 2 to 5 and 7 to 12. In week 6, the students completed a summative mid-term assessment, and in week 13 a final exam. It is crucial to note that successful completion of summative assessment tasks contributed to 10% to the overall module mark. Scores from mid-term and final exam are also used for analysis.

To understand how students managed individual study actions, we added, for each study action, the following four attributes about time management: *preparing* – completing an action on a topic in the designated week; *revisiting* – completing an action on a topic introduced a previous week, having completed the action in the previous week; *catching up* – completing an action on a topic after the week in which that topic was introduced for the first time; and *ahead* – completing an action on a topic ahead of the designated week. This provides an insight into the access timing of the study actions and therefore time management of student tasks.

3.2 Data Analysis

Extraction of Learning Tactics and Strategies. The work carried out in [3] is of primary importance to this study. It provides a method for automated extraction of learning tactics and strategies from trace data about students' interaction with online resources. The method was composed of two levels of analytics based on unsupervised machine learning methods – i.e. clustering. Firstly, learning tactics were extracted by analysing study sessions. These sessions were delineated by temporal gaps; a simple example would be a group of study actions beginning and ending in a twenty-minute period. If we observe a gap of more than one-hour between the last action of this period and the start of another action sequence, then we can define it as a session. These sessions were clustered based on similarity of the actions performed by the students. Exploratory sequence analysis was implemented using TraMinerR R library [19] and followed up with a hierarchical cluster analysis with Levenshtein distance and Ward's method, as proposed in [3]. This generated four strategy types, based on the predominant study action type: *reading course materials, formative assessment*, *video viewing with associated formative assessment, reading course materials, and summative assessment.* Secondly, learning strategies were extracted through an agglomerative hierarchical clustering with Euclidian distance and Ward's method, based on the frequency of the use of the four study tactics by each individual student in the sample. This analysis identified five learning strategies (also referred as strategy groups) which provided insight into how students sequenced individual study actions within each of the strategy groups. These strategy groups, integral to the study in [3], had a significant part to play in the current study. The strategy groups in this study differ slightly from those in the study [3] as we removed single-event sessions from the dataset. This affected sequence clusters and propagated to strategy groups.

Process Mining. PM seeks to capture event or process-based data. The starting point of PM is a dataset in the form of an event log. The required elements to run a PM algorithm are:

- Case: a process instance. This could represent a human actor, or a more abstract construct, such as a learning cycle. In our study, student ID was the case role.
- Activity: a well-defined step in a broader process. In our study, concatenation of strategy types and time management attributes was used, e.g., Formative Assessment & Catch-up, or Summative Assessment & Preparation
- Timestamp: ideally one for the beginning and the end of the activity, but more usually just one stamp is available. Timestamps of activities in our trace data were used.

In this sense, trace data supply raw material for examining learning processes. Traditional frequency-based analytic methods do not adequately reflect these learning processes as they flow and change over time. The selection of model discovery algorithm is key. Out of the traditional algorithms: we rejected Heuristic Miner because it is more suited to processes with fewer event types than we have; we rejected Multi-phase miner as it is more suitable for cleanly structured, simple log data (unlike ours); Fuzzy Miner produces interesting overviews of learning processes but does not provide the crucial stochastic metrics we seek to use [20]. We chose FOMMs to explore the novel possibility of combining stochastic analysis and temporal event data [21]. We employ the R package pMineR [21, 22] to train and generate FOMMs based on the learner strategy groups extracted in the procedure as previously explained. The pMineR package provides FOMM visualisations and probability transition matrices which allow analysis and comparison of temporal patterns of process engagement. Examining these patterns provides some insight in the tactical differences between the identified strategy groups in relation to SRL traits.

Strategy Group Characterisation – Intra-Strategy Group Analysis. FOMMs were trained and generated for each strategy group. Characterisation is informed by Winne's construction of learner strategy and study tactics, as articulated by Fincham [7]. We provide an interpretive narrative for each group, and then characterise them accordingly.

Strategy Group Comparison – Inter-Strategy Group Analysis. We first identified significantly distinct strategy groups by assessment performance. We undertook pair-wise comparisons based on mid-term scores and by final assessment (see Table 2). As ANOVA assumptions were not satisfied, we undertook a Kruskal Wallis test, followed by pairwise Mann Whitney U tests, using False Discovery Rate (FDR) to accommodate alpha inflation. From our pairwise analysis, we elected to compare two pairs of strategy groups. Firstly, we chose only pairs that demonstrate statistical difference in assessment means. From these pairs, we made a valued assessment on the most potentially insightful comparisons, based on high versus low mid-term/final exam performances. To provide comparative insights, we interpreted the comparison diagrams of two pairs of strategy group FOMM models. In each case one strategy group is mapped onto another group (see Fig. 2). The arcs in black represent similar transition probabilities (TPs). Red arcs represent a comparatively lower TP of the mapped model; green arcs represent a higher TP. In cases of disparate TPs, both probabilities are shown. To simplify presentation, a TP threshold of 0.05 is has been set.

4 Findings

The findings present the intra-and inter-strategy group analysis performed by using the FOMM. Due to the size of the diagrams representing the final FOMMs, this section includes only excerpts of the main FOMM diagrams. Complete results of the FOMM analysis can be found here:
https://www.dropbox.com/s/yqtw20uwiwbnmob/FOMM%20Results.pdf?dl=0.

4.1 Strategy Group Characterisation: Intra-Strategy Analysis

The strategy extraction method proposed in [3] identified five strategies, also referred to as strategy groups i.e. they represent groupings of the students based on similarities of their learning strategies. By way of context, Table 1 shows the mean and median sample scores for each strategy group, and a measure of group activity i.e. number of events divided by the group sample size.

Table 1. Strategy group assessment scores

Strategy group	n	Mean mid-term score	Median mid-term score	Mean final assessment score	Median final assessment score	Events per student
1	19	15.3	15	24.7	24	1634
2	70	14.9	16	22.5	20	1295
3	117	12.9	13	17.4	15	986
4	25	15.5	16	23.7	25	1737
5	59	10.7	11	14.6	14	576

Strategy Group 1. This is a relatively well-performing and active group. Figure 1 shows a section of this group's FOMM, relating to content access. It demonstrates a temporally cohesive approach to the reading tasks. The students, when they are engaged in reading tasks, tend not to get distracted by other activities. There is clear interplay between the four temporal instances of reading activity. Reasonably enough, in some cases reading preparation leads to formative preparation. This is a manifestation of well-formed study patterns. There is a demonstration of movement from video formative assessment and formative assessment in terms of temporal groupings. For example, there is 0.09 chance that students will, on completion of video catch-up session, move to a non-video formative catch-up session. Summative tasks present a neater temporal grouping. Students are likely to stick within this activity group e.g., students are more likely, once they decide on a summative activity, to stick with, or move between time-contextual iterations of the summative task e.g., between summative assessment catch-ups to revisits, or between summative ahead to preparation. In summary, this group show elements of cohesive learning but also a tendency to embrace multiple activity types. In this sense, the students represent an **Active Agile** strategy group.

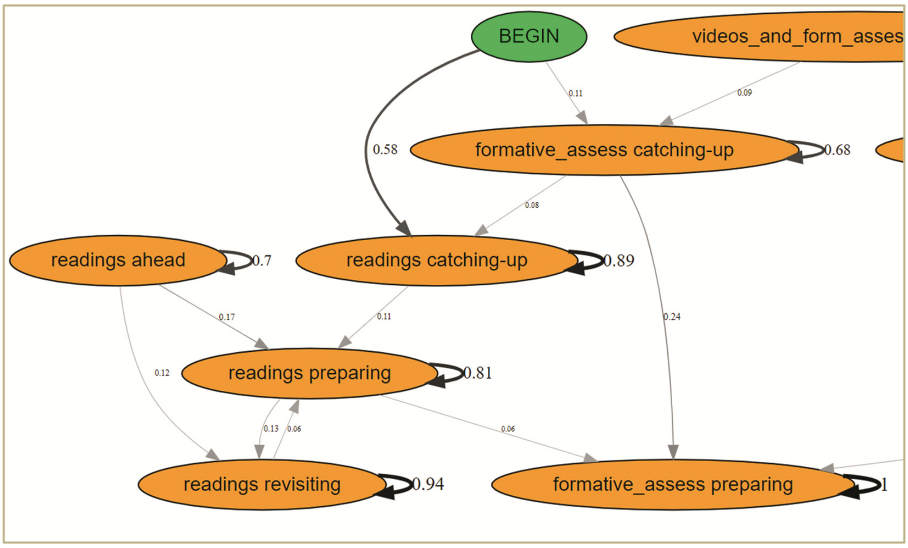

Fig. 1. Partial first order Markov model of strategy group 1 (Active Agile)

Strategy Group 2. This group is less active than group 1, and assessment scores suggest an engagement drop-off in the second half of the course. Nonetheless, this group displays a similarly cohesive approach to reading tasks. Formative video tasks are partially associated with certain reading activities; there is a tendency to touch on these video tasks before reading catch-up and preparation. This could represent an attempted strategy to streamline knowledge acquisition through video, before falling back on traditional content access. It demonstrates a regulation of cognitive learning tactics and a broader self-regulatory learning strategy. Formative assessment activities are grouped temporally, so students do not tend to move out of formative cycles once started. They do not tend to move freely within the summative groupings, aside from a movement between catch-up and preparation. Aside from this, once a summative task is attempted, it is pursued almost without distraction. This group can be typified as **Efficient**.

Strategy Group 3. This group shows less engagement with all activities. There is a greater likelihood to attempt the main summative activity without adequate preceding formative preparation. This group's approach points to a minimalist strategy, with inherent gambles on summative success. This group's FOMM diagram highlights a movement to summative and reading revisits after several reading activities. This could indicate a less proactive approach to advanced reading preparation, hinting at a reaction to poor performance in the summative tests. This still indicates regulation of tactics but potentially a less effective learning strategy. This group can be typified as **Summative Gamblers**.

Strategy Group 4. This is a strong and active group. It presents a healthy and cohesive approach to preparatory work. In fact, it presents the tightest adherence to activity focus in the sense of the activity self-loops. The students in this group do not tend to move freely from one activity type to another, or even from one activity to another. There is a real sense of disciplined engagement. Interestingly, this group favours video formative assessments more than others, and shows tendencies to engage in focussed video preparation and catch-up tasks. This could indicate a desire to streamline learning using more varied media, in combination with traditional knowledge acquisition tactics. In formulating the best combination, learners are assessing their own comprehension of knowledge, and adjusting to fit. This group is typified as **Active Cohesive**.

Strategy Group 5. This is the least active group, and the weakest performer. Apart from the overemphasis on summative assessment without preparation, there is a distinct lack of strategic cohesion. We see a tendency to bounce from activity (type) to activity (type). The exception to this is the formative activity grouping, where there is a semblance of temporal coherence. It is difficult to determine whether this group represents strategic incoherence, or that the collective paucity of engagement data provides inconsistent results. This group exhibits non-ideal navigation through its learning environment. The group is typified as **Extreme Minimalists**.

4.2 Strategy Group Comparison: Inter-Strategy Analysis

A pairwise comparison of the five strategy groups on mid-term and final examination scores is reported in Table 2. We use this to inform choices of pairs in our comparative analysis.

Table 2. Pairwise comparison of assessment scores

Mid-term Scores					Final exam scores				
G1	G2	Z	P	r	G1	G2	Z	p	r
2	5	4.3526	0.00001*	0.3832	2	5	4.3792	0.00001*	0.3856
4	5	3.5534	0.00019*	0.3877	1	5	3.9427	0.00004*	0.4464
1	5	3.3147	0.00046*	0.3753	2	3	3.6004	0.00016*	0.2633
2	3	3.3147	0.00046*	0.2424	1	3	3.4207	0.00031*	0.2933
4	3	2.9387	0.00165*	0.2466	4	5	3.4207	0.00031*	0.3732
1	3	2.4740	0.00668*	0.2121	4	3	2.4227	0.00770*	0.2033
3	5	2.2516	0.01217*	0.1697	3	5	1.8368	0.03312*	0.1385
4	2	0.2475	0.40227	0.0254	1	2	0.4706	0.31897	0.0499
4	1	0.3806	0.64826	0.0574	1	4	0.5112	0.69538	0.0771
1	2	0.5730	0.71669	0.0607	4	2	0.5112	0.69538	0.0524

Comparative Analysis: Efficient (2) and Summative Gamblers (3). In this comparison, the *efficient* group are significantly better performers than the *summative gamblers*, based on both midterm and final exam scores. Figure 2 presents a partial example of the comparison diagram for this case.

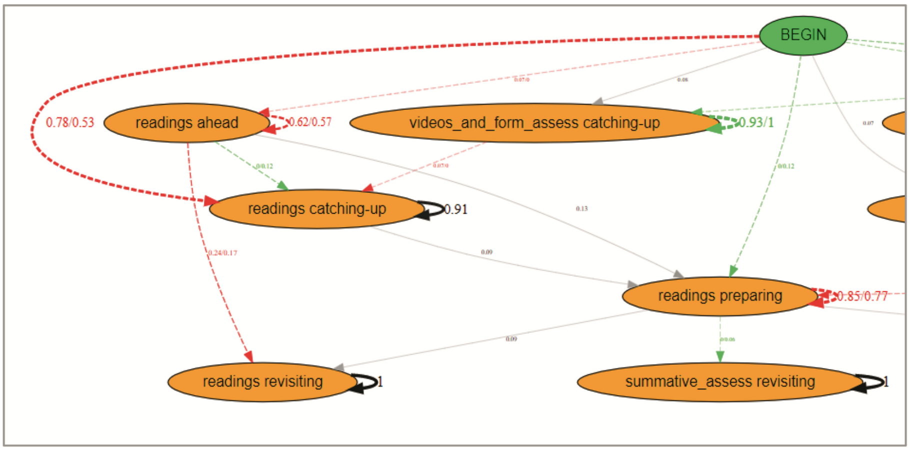

Fig. 2. Partial FOMM comparison diagram: Efficient vs Summative gamblers (Color figure online)

Reading Activities. The efficient group demonstrate a greater emphasis on initial reading tasks. The initial TP of 0.78 for reading-catch-up sessions (versus 0.53 for the summative gamblers) points to a greater awareness of the value of preparatory content-based activity. Both groups display a similar self-loop TP of around 0.9 reading catch-ups. The gamblers are more likely to break out of a reading-ahead session to attempt a reading catch-up session (0.12). They are, however, less likely to break out of reading revisit sessions (0.24/0.17). This points to a slightly more considered approach to reading strategy by the efficient group. In the reading preparation task, the efficient group show a higher self-loop TP than the gamblers (0.85/0.77), whereas the gamblers show a more likely propensity to attempt a summative revisit whilst doing this task. This shows that the efficient group are more focussed on the reading task in hand.

Formative Assessment. The efficient group demonstrate higher self-loop TPs for formative ahead (0.83/0.63) and catch-ups (0.9/0.83). The gamblers are more likely to break out of these task loops to try formative preparation and revisits. Again, this points to a slightly more considered approach to task management by the efficient group. The gamblers demonstrate a slightly more scattergun approach in this case. Both groups exhibit a strong self-loop focus on formative preparation and revisiting.

Video Formative Assessment. Interestingly, the efficient group demonstrate a similar video ahead self-loop. They are, however, more likely to break out of this loop to do video preparation (0.22/0.07) and/or reading preparation (0.11/0). The gamblers are more likely to break out to revisit video assessment (0.2/0) and/or attempt a summative assessment ahead of schedule (0.07/0). Again, we can infer that the efficient group are slightly more mindful of preparatory strategies, as befits a self-regulated learner.

Summative Assessment. This is, by far, the most popular activity, as it relates to achievable marks on the course. The key point of interest is that gamblers are more likely to attempt this initially, without any other preparation, than efficient members (0.07/0). Regarding catch-up, efficient members are more likely to break out from this loop (0.1/0) to do the main summative preparation activity. This indicates that the efficient group are more likely to move between weekly summative assessments and to tie up loose ends, assessment-wise. This demonstrates a strong sense of self-regulation, as they recognise potential gaps in their understanding that require extra work.

Comparative Analysis: Active Cohesive (4) and Extreme Minimalist (5). In this comparison, the active cohesive group are significantly better performers than the extreme minimalists, based on both mid-term and final exam scores.

Reading Activities. The cohesive group display a healthy regard for reading activities, as can be seen by the initial activity TPs. This group is nearly half as likely to embark on an initial reading activity as any other, with a combined TP of 0.48 for preparation and catch-up. The minimalist group's likelihood of starting with a reading activity is 0.28 (specifically catching-up). The weekly-current preparation task is approached differently by the two groups. The minimalist group tends to approach it in isolation, whereas for the cohesive group it provides a valid option from various states: Begin 0.09, video catch-up 0.15, reading catch-up 0.14, reading ahead 0.15. This differs from the normal behaviour of this group but indicates an ongoing focus on this task. In terms of the preparation, the cohesive group maintains a tighter self-loop (0.91), whereas the minimalist group is more likely to move off to other tasks (0.77).

Formative Assessment. The cohesive group displays a more considered temporal focus. There is a greater tendency to engage consistently with the formative task in hand, as highlighted by the higher self-loop TPs around the four formative activities (between 0.9 to 1). We see the minimalist group moving more freely between catch-ups, revisits, and preparation, indicating a less disciplined approach to formative learning. For example, the minimalist group has TP of 0.11 in moving from catch-up to revisiting. It also has a TP of 0.07 in moving from preparation to revisiting. The cohesive group has a TP of 0 in both cases. Temporally, the cohesive group sticks to its formative task groups more closely with less jumping between the week-specific material. This could indicate a different emphasis on controlled, strategy-driven learning.

Video Formative Assessment. The cohesive group places more stock in the use of video assessments, particularly preparation and revisits. They are more likely to transition to these activities from other activities, than the minimalist group. Once engaged with these tasks, the cohesive group does not tend to divert, with self-loop TPs of 1 for the two most popular video tasks. The minimalist group approaches these tasks more in isolation. That being the case, they do retain strong self-loops.

Summative Assessment. As in the previous comparison, there are differences in the lead-up to this key activity. The minimalist group is much more likely to attempt this as an initial task (0.25/0.09 for prep, 0.23/0 for catch-up), whereas the cohesive group explores content access and preparatory formative activity first. Regarding the minimalists, it is interesting to note that the main summative preparation task could be a destination from several other activities: reading ahead (0.06); reading preparation (0.07), and summative revisits (0.05). For the cohesive group, this task is done more in isolation, apart from as a destination from one task. The cohesive group treat the summative task as a more significant event in and of itself. Both groups, once engaged in the task, retain a tight self-loop.

5 Discussion and Conclusion

Self-Regulation and Summative Tasks. As previously reported in [3], summative tasks dominate the main activity cycles (as successful completion contributes to the final overall module mark). Using FOMMs, we can gain insights into strategic navigation around the other activity types in the context of these summative main tasks. The two strongest groups, Active Agile and Active Cohesive both demonstrate a healthy regard for pre-summative preparation and engage in more content access and formative assessment before engaging in the summative tasks. Interplay between such states indicates a healthy self-regulatory strategy. In context of the other notable studies that analyse this data [3, 7], this study provides a genuine insight into inter and intra-tactic dynamics, providing a different dimension to the narrative around learning strategy.

Summative Gambling. Conversely, the weaker groups exhibit a greater tendency to attempt the summative work without commensurate preparation. There seems to be an underlying attempt to by-pass traditional patterns of self-regulation and gamble on success in the summative tasks. This is a gamble which does not appear to pay off. We also see reactive outcomes in the groups' relationship with catch-up and revisits to past material. This indicates a more passive, yet performance avoidance, goal-oriented regulation strategy. Whereas previous studies have provided a characterisation of weaker performing groups [3–5, 7, 14], our study provides a view of learning malformation as typified by movement through and between study actions. We therefore have a temporal context.

Transition Probability Self-loops. Activity self-loops provide insight into temporal adherence to tasks. It is too simplistic to say that higher self-loop TPs indicate academic discipline. Movement between tasks and task groups can indicate assured self-regulation in learning tactics. Nonetheless, we see that disparate task engagement does seem to indicate a lack of academic focus. This is more apparent in the weaker student groups. Again, through analysing activity engagement patterns, we can pick up on measures of learner focus or lack thereof. This dimension is unseen in previous studies.

Performance-based Analysis. There are interpretable differences between higher and lower performing strategy groups. In this sense, we can say that the method can highlight effective versus less-effective learning strategies. Discernible patterns, such as those found in the clustered groups, do appear to exist. This reinforces the need to use effective non-supervised machine learning techniques in studies of this nature. In this sense we are not advancing insight on the fact that we can detect performance differences. Previous studies have linked strategy to performance [3, 7], so in a sense this corroboration provides partial validation of the method.

Implications for Practice. This is the first use of a process mining method in combination with unsupervised and sequence mining methods to understand learning strategy. In exploring temporal inter-process dynamics, we have the potential to identify positive and negative instances of learning strategy management. In instances of malformed student learning, interventions and remedial actions are a possibility. We also have the possibility to measure idealised models of student learning against recorded models to inform course design; if we detect weak engagement points in the model, it may indicate weaknesses in course design.

Limitations and Future Direction. The study does not provide a set of benchmark metrics for analysis, so its generalisability and replication value cannot be ascertained until more similar studies are undertaken. The option to compare high vs low performers regardless of strategy group, or first half of term vs second half of term, was not explored. This may have provided more crucial strategic insights than the comparison of strategy groups alone. These options will be explored in the next cycle of analysis. FOMMs, by their very definition, provide transition probabilities based on the current event, and therefore lack event “memory”. We are keen to build on this research and explore higher order Markov models, hidden Markov models, and other related techniques, such as conditional random fields.

References

1. O'Flaherty, J., Phillips, C., Karanicolas, S., Snelling, C., Winning, T.: The use of flipped classrooms in higher education: a scoping review. Internet High. Educ. **25**, 85–95 (2015). https://doi.org/10.1016/j.iheduc.2015.02.002
2. Gašević, D., Jovanović, J., Pardo, A., Dawson, S.: Detecting learning strategies with analytics: links with self-reported measures and academic performance. J. Learn. Anal. **4**, 113–128 (2017). https://doi.org/10.18608/jla.2017.42.10
3. Jovanović, J., Gašević, D., Dawson, S., Pardo, A., Mirriahi, N.: Learning analytics to unveil learning strategies in a flipped classroom. Internet High. Educ. **33**, 74–85 (2017). https://doi.org/10.1016/j.iheduc.2017.02.001
4. Kovanović, V., Gašević, D., Joksimović, S., Hatala, M., Adesope, O.: Analytics of communities of inquiry: effects of learning technology use on cognitive presence in asynchronous online discussions. Internet High. Educ. **27**, 74–89 (2015). https://doi.org/10.1016/j.iheduc.2015.06.002
5. Lust, G., Vandewaetere, M., Ceulemans, E., Elen, J., Clarebout, G.: Tool-use in a blended undergraduate course: in search of user profiles. Comput. Educ. **57**, 2135–2144 (2011). https://doi.org/10.1016/j.compedu.2011.05.010
6. Kovanović, V., Gašević, D., Dawson, S., Joksimović, S., Baker, R.S., Hatala, M.: Does time-on-task estimation matter? Implications for the validity of learning analytics findings. J. Learn. Anal. **2**, 81–110 (2015). https://doi.org/10.18608/jla.2015.23.6
7. Fincham, O.E., Gasevic, D.V., Jovanovic, J.M., Pardo, A.: From study tactics to learning strategies: an analytical method for extracting interpretable representations. IEEE Trans. Learn. Technol. 1–13 (2018). https://doi.org/10.1109/tlt.2018.2823317
8. Zimmerman, B.J.: A social cognitive view of self-regulated academic learning. J. Educ. Psychol. **81**, 329–339 (1989). https://doi.org/10.1037//0022-0663.81.3.329
9. Boekaerts, M.: Self-regulated learning: a new concept embraced by researchers, policy makers, educators, teachers, and students. Learn. Instr. **7**, 161–186 (1997). https://doi.org/10.1016/S0959-4752(96)00015-1
10. Butler, D.L., Winne, P.H.: Feedback and self-regulated learning: a theoretical synthesis. Rev. Educ. Res. **65**, 245–281 (1995). https://doi.org/10.3102/00346543065003245
11. Jamieson-Noel, D., Winne, P.H.: Exploring students' calibration of self reports about study tactics and achievement. Contemp. Educ. Psychol. **27**, 551–572 (2002). https://doi.org/10.1016/S0361-476X(02)00006-1
12. Bjork, R.A., Dunlosky, J., Kornell, N.: Self-regulated learning: beliefs, techniques, and illusions. Annu. Rev. Psychol. **64**, 417–444 (2013). https://doi.org/10.1146/annurev-psych-113011-143823
13. Winne, P.H.: A metacognitive view of individual differences in self-regulated learning. Learn. Individ. Differ. **8**, 327–353 (1996). https://doi.org/10.1016/S1041-6080(96)90022-9
14. Lust, G., Elen, J., Clarebout, G.: Regulation of tool-use within a blended course: student differences and performance effects. Comput. Educ. **60**, 385–395 (2013). https://doi.org/10.1016/j.compedu.2012.09.001
15. Kinnebrew, J.S., Biswas, G.: Identifying learning behaviors by contextualizing differential sequence mining with action features and performance evolution. In: Proceedings of the 5th International Conference on Educational Data Mining (EDM 2012), pp. 57–64 (2012)
16. Kinnebrew, J.S., Segedy, J.R., Biswas, G.: Analyzing the temporal evolution of students' behaviors in open-ended learning environments. Metacognition Learn. **9**, 187–215 (2014). https://doi.org/10.1007/s11409-014-9112-4

17. Bannert, M., Reimann, P., Sonnenberg, C.: Process mining techniques for analysing patterns and strategies in students' self-regulated learning. Metacognition Learn. **9**, 161–185 (2014). https://doi.org/10.1007/s11409-013-9107-6
18. Sonnenberg, C., Bannert, M.: Discovering the effects of metacognitive prompts on the sequential structure of SRL-processes using process mining techniques. J. Learn. Anal. **2**, 72–100 (2015)
19. Gabadinho, A., Ritschard, G., Mueller, N.S., Studer, M.: Analyzing and visualizing state sequences in R with TraMineR. J. Stat. Softw. **40**, 1–37 (2011). https://doi.org/10.18637/jss.v040.i04
20. van der Aalst, W.: Process Mining: Data Science in Action. Springer, Heidelberg (2016). https://doi.org/10.1007/978-3-662-49851-4
21. Gatta, R., et al.: Generating and comparing knowledge graphs of medical processes using pMineR. In: Proceedings of the Knowledge Capture Conference 2017, Austin, Texas (2017)
22. Gatta, R., et al.: pMineR: an innovative R library for performing process mining in medicine. In: ten Teije, A., Popow, C., Holmes, J.H., Sacchi, L. (eds.) 16th Conference on Artificial Intelligence in Medicine, AIME 2017, Vienna (2017)

3.3 Summary

This study addressed the research question two (RQ2) by utilising the strategy groups captured by Jovanović et al. (2017) and providing temporally focused insights through the use of first order Markov models. In doing this, we were able to characterise groups of learners according their engagement with types of learning sequences. In addition, we also associated the groups with course performance by calculating the group mean and median scores for the required course assessments. It was interesting to note that although student groups who engaged more actively with the LMS tended to perform better, a richer set of insights could be gained from our process maps. In general, we detected a more cohesive set of learning patterns in groups who performed better in the assessments.

One of the more interesting insights related to the design of the learning. Aside from the two main assessment points (mid-term and end-of-term), ten percent of the final mark could be attained by attempting randomised online summative multiple-choice quizzes. This assessment hook was designed to encourage learners to engage with a broader set of learning materials before engaging with it. We noted that the less engaged students tended to focus more heavily on the summative work but prepared less well for it; in fact, we characterised one of the groups as *summative gamblers*. This type of learner was clearly attempting to shortcut the broader learning design in order to maximise the mark. We were able to make use of the comparative transition probabilities provided by the process maps, and argue that these types of behaviours, and others described in the study, would not be detectable using statistics alone. This, we feel, is the major contribution of this study.

Although this work presents a novel and insightful set of methods for exploring learning strategy and time management, the interpretations are not embedded in a recognised theoretical model of learning. Although SRL is discussed in the study, it represents a broad theoretical context, as opposed to a defined set of embedded constructs. To truly embed SRL, we need to design and implement a codification framework based on an accepted model of learning. To achieve this, whilst building on the methods discussed in the current chapter, we explored the use of an automated codification process to transform raw trace data into SRL processes. The study designed to achieve this goal is discussed in Chapter four.

4 Embedding Trace data in SRL

Tell me and I forget, teach me and I may remember, involve me and I learn.

— Xun Kuang, *Ruxiao ("The Teachings of the Ru")*.

4.1 Introduction

In the previous chapter, we presented a novel process analytic method to analyse the temporal dimensions of learner tactics and strategies. In this chapter, we aim to build on this work by transforming the same type of raw data into SRL processes. The transformation or categorisation of raw data can be motivated by a number of factors. In many cases, raw data are messy or noisy and this makes meaningful analyses very challenging. In some cases, there is a need to reduce the dimensionality of a set of data, that is, to reduce the amount of variables collected into a smaller, still representative, set of variables which can be more readily analysed; techniques such as factor analysis (Brown, 2015) or principal components analysis (Jolliffe, 2002) are very common in variable-centric research domains. In studies which pool qualitative data, such as think-aloud utterances (e.g., Bannert et al. (2014)), it is critical that these data are coded into meaningful and consistent constructs before they are subject to formal analysis. These are all very important reasons, but we argue that a major driver for data transformation should primarily be to embed analyses in recognised models of learning, and in doing so, answer the rallying call of Gašević et al. (2015) to connect LA research more explicitly to existing research into learning and teaching. In this thesis, the theoretical basis is SRL, and the study reported on in this chapter explores the articulation of SRL processes from trace data.

The empirical landscape of SRL process analysis, in which raw data are directly transformed or coded, has been dominated by studies that rely on self-report collection methods or some form of verbal/observational data capture from video or message forums (e.g., Sonnenberg and Bannert (2015), Munshi et al. (2018), and Heirweg et al. (2020)), and with some justification; Greene et al. (2011), amongst others, provide convincing arguments for think-aloud methods in the capture of

SRL. The arguments against such methods, as stated in the previous chapter, still have weight in this context. Nonetheless, the study by Siadaty et al. (2016) was, at the time of its publication, the only study to employ the Greene and Azevedo (2009) micro-level process method to transform raw trace data into recognised SRL (micro-)processes. These data were, however, generated from essentially experimental settings, and in the context of professional knowledge workers, not authentic learners in educational settings. No studies employ micro-level process analysis with authentic learner trace data. Our study seeks to explore this empirical gap and demonstrate a formal method for the curation and transformation of authentic LMS trace data into temporally focused SRL insights.

As such, this chapter reports on a study which outlines a conceptual and methodological framework to address some of the challenges set out by Gašević et al. (2015), and serves to investigate these research questions:

(RQ2) *How effectively can we measure the temporal dynamics of learning strategies in delineated student groupings, using process analytic techniques?*

(RQ3) *To what extent can we develop a framework to embed temporally focused analysis of learning in a theoretical model of self-regulated learning?*

4.1.1 Chapter overview

In this chapter, we build on the process analytic exploration of Chapter three by proposing a methodological framework which we call "Trace-SRL". The purpose of the framework is to uniquely join together a number of existent techniques to provide a temporal and probabilistic view of the learning process as underpinned by a recognised model of SRL. As stated variously throughout this thesis, several models of SRL have been conceptualised, tested and developed over the years (e.g., Pintrich (2000), Winne and Perry (2000), and Zimmerman (2000)), which presents researchers with important decisions on which model(s) to deploy, as well as questions over the nature of the deployment. As discussed in Chapter two, SRL model deployment is subject to nuance and variation. One of the key questions in making this choice is how well does a model fit our study scope (and vice versa). The Boekaerts (2011) model, for example, places emphases on affective state, motivational beliefs, and well-being. In order to fully explore this model, a researcher would have to think carefully about the type of data capture that would allow the articulation of SRL in these terms; one would imagine that self-report or observational methods would be key here. For trace data alone, this model may not be the correct choice.

We nominated the Zimmerman (2000) model as a theoretical basis for our "Trace-SRL" framework but in truth, it is more realistically a reflection of common cyclical elements of a number of SRL models (see Panadero (2017)) in the context of the sequence and temporality. To restate, the SRL phases which we termed: *planning*, *engagement*, and *evaluation/reflection*, are reflected in the majority of major SRL models. One of the key contributions of this study is the demonstration of how to reconcile the model constructs described above, which are macro in conception, with the raw data generated from the chosen LMS. The challenge of this reconciliation was outlined by Molenaar (2014), and provided the impetus for our method. The work undertaken by Siadaty et al. (2016) is also a key inspiration, as it was the first demonstration of the use of the Greene and Azevedo (2009) micro-level process analysis method with trace data. Our study pushed this method forward by using authentic educational trace data settings, as opposed to the experimental settings in the Siadaty et al. (2016) study. We were able to use the resultant SRL output data to supply to the novel first order Markov process mining algorithm to unlock new temporally focused SRL insights.

4.2 Publication: Trace-SRL

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

> Saint, J., Whitelock-Wainwright, A., Gašević, D., & Pardo, A. (2020). Trace-SRL: A Framework for Analysis of Microlevel Processes of Self-Regulated Learning From Trace Data [Conference Name: IEEE Transactions on Learning Technologies]. *IEEE Transactions on Learning Technologies*, *13*(4), 861–877. https://doi.org/10.1109/TLT.2020.3027496

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Trace-SRL: A Framework for Analysis of Microlevel Processes of Self-Regulated Learning From Trace Data

John Saint, Alexander Whitelock-Wainwright, Dragan Gašević, and Abelardo Pardo

***Abstract*—The recent focus on learning analytics (LA) to analyze temporal dimensions of learning holds the promise of providing insights into latent constructs, such as learning strategy, self-regulated learning (SRL), and metacognition. These methods seek to provide an enriched view of learner behaviors beyond the scope of commonly used correlational or cross-sectional methods. In this article, we present a methodological sequence of techniques that comprises: 1) the strategic clustering of learner types; 2) the use of microlevel processing to transform raw trace data into SRL processes; and 3) the use of a novel process mining algorithm to explore the generated SRL processes. We call this the "Trace-SRL" framework. Through this framework, we explored the use of microlevel process analysis and process mining (PM) techniques to identify optimal and suboptimal traits of SRL. We analyzed trace data collected from online activities of a sample of nearly 300 computer engineering undergraduate students enrolled on a course that followed a flipped class-room pedagogy. We found that using a theory-driven approach to PM, a detailed account of SRL processes emerged, which could not be obtained from frequency measures alone. PM, as a means of learner pattern discovery, promises a more temporally nuanced analysis of SRL. Moreover, the results showed that more successful students regularly engage in a higher number of SRL behaviors than their less successful counterparts. This suggests that not all students are sufficiently able to regulate their learning, which is an important finding for both theory and LA, and future technologies that support SRL.**

***Index Terms*—First-order Markov models (FOMMs), learning analytics (LA), microlevel process analysis, process mining (PM), self-regulated learning (SRL).**

I. Introduction

One of the key aspirations of learning analytics (LA) research is the data-driven identification of learner behaviors from engagement with learning environments [1], [2]. True blended learning environments rely heavily on technology mediation but, more crucially, on the effective mobilization of proactive learning in their member students. Such environments invite participation outside of traditional face-to-face monologues/dialogues and rely on learner traits, such as academic motivation and self-reliance. The measurement of such constructs has an empirical bedrock in the domain of self-regulated learning (SRL) [3].

Theoreticians seem unanimous that self-regulated learners tend to be more effective and attract higher scores than their passive peers [4], [5]. These students exercise control over their own learning by positioning task engagement within a cyclical framework of, for example, goal setting, planning, and evaluation of feedback. In employing such cognitive tactics and metacognitive strategies, learners of this type benefit from an effective learning experience. As such, learning analysts are increasingly motivated to measure the dynamics and impact of SRL engagement. Winne and Perry [6] outlined numerous ways in which SRL can be measured, each of which entails its own challenges. Self-reports, which conceptualize SRL as an aptitude, have dominated the field, whilst trace methods have increased in favorability as they capture the dynamic nature of SRL in a noninvasive way.

Microlevel process analysis is one of the responses to the challenges of capturing and identifying SRL. Significant work in this area was pioneered by Greene and Azevedo [7] and further explored by Cleary and Zimmerman [8], and Siadaty *et al.* [9]. It provides a means of contextualizing sequences of engagement activities into recognized categorizations of SRL. These categorizations are themselves subcategories of macrolevel processes, which form the main constructs of the chosen SRL model. For example, we could record a series of "task engagement" clicks and then a series of "dashboard" clicks (microlevel processes). We could make separate inferences about each of these sequences, but this may blind us from a broader context. A more optimal inference lies in categorizing a coupling of both sequences as a state of "reflection" or "evaluation," which are macrolevel processes representing identified phases of theoretical models of SRL [10]. Building on this idea, the goal of microlevel process analysis is to articulate a set of event categorizations which fit into a model of SRL. This measurement process is, therefore, designed as a way of embedding trace data analysis in a recognized theoretical framework of SRL.

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SRL event categorizations, or microlevel processes, can then be viewed as learner events and passed to the final-phase analysis. There is certainly value in identifying individual microlevel processes and counting them to compare "average count" differences across groups of learners, but this view only offers a limited insight into how SRL works; there is an innate inability to capture patterns of SRL using conventional frequency-based statistical methods. As Reimann *et al.* state [11], such analyses are dimensionally limited and, as such, suffer from an ontological flatness. This has motivated researchers to study temporal and sequential dimensions of SRL. Citing Reimann [12], Knight *et al.* [13] posit that optimal problem resolution involves temporal phasic shifts (which could, e.g., be modeled as Markov processes), articulating state transitions as probabilities. Chen *et al.* [14] further build on this argument by stating that temporally focused analyses tend to ignore interprocess dynamics of association and duration.

Key questions also exist around the sources of data used to study SRL in contemporary research. Think-aloud studies—for example, [7], [15], and [16]—are typically used to identify specific SRL processes, as they afford the sophistication of verbal articulation of cognitive and metacognitive tactics. Despite this, the validity of think-aloud data has been called into question [17]. These studies are typically done in the laboratory setting as the use of think-aloud protocols in ecologically valid settings is rather limited. To address this, pure trace data analyses have been undertaken with some success, for example, [18] and [19]. These successes are tempered by limitations borne out of two main flaws: 1) the learning environments are so specialized as to prevent generalizability of any kind; and 2) learning strategies are effectively detected but provide little specific insight into the temporal unfolding of SRL processes.

In order to address these limitations, this article reports on an exploratory methodological study that does the following.

1) It proposes an approach for the measurement of SRL microlevel processes from digital traces collected in a common learning environment.
2) It proposes a stochastic process mining (PM) approach that analyses sequences of extracted SRL microlevel processes to provide insights into the ways in which students self-regulate their learning in common learning environments.
3) In a temporal and sequential context, it identifies differences in SRL between high- and low-performing students.
4) It outlines an approach that allows for the qualitative comparison of the SRL processes engaged by learners who followed different learning strategies.

We apply the term "Trace-SRL" framework to the methodological sequence of techniques and tools used to transform raw trace data into SRL-informed learner events.

II. Background

A. Measuring SRL

Measuring SRL processes can either be approached subjectively or objectively. With the former referring to self-reports such as questionnaires and think-aloud procedures; whereas, the latter relates to event traces. An important caveat of measuring SRL through questionnaires employed at a single instance in time is that it fails to consider the temporal nature of SRL processes. Thus, the results obtained through the measurement of SRL using a frequency-based approach (e.g., the averages across all learners) will not provide an accurate account of an individual's learning processes [12]. Additionally, when questionnaires are used to measure the self-reported use of study tactics, students are generally found to be biased [17]. A limitation of this work is that self-reported study tactics were recorded after completing a series of study activities, resulting in a biased recount of memories [20], whilst objective traces were recorded throughout; thus, alignment of the two measures would be unlikely. Nevertheless, Winne and Jamieson-Noel's work demonstrates the advantages of an objective approach to measuring SRL as an event, particularly as it is unobtrusive and less susceptible to bias.

Measuring SRL using traces of data captured within learning environments present its own challenges, particularly with regards to granularity, time, and generalizability [21]. Despite the importance of each individual learning activity, the focus here is upon exploring the granular events that make up the SRL processes that students engage over the course of a module. As discussed by Winne [22], the level of granularity taken when analyzing trace data will affect the understanding of the SRL processes that are obtained. In any case, the trace data alone, without grounding in a theoretical framework, are unlikely to convey any meaning beyond what action it represents [1]. Put in a different way, traces need to be mapped onto constructs that can help us better understand SRL processes and can lead to actionable feedback.

B. Macrolevel and Microlevel of SRL

A framework to add meaning to traces is offered by Siadaty *et al.* [9] and, critically, it is grounded in the model of SRL theorized by Zimmerman [5]. More importantly, this framework addresses the challenges of granularity by deconstructing SRL into macrolevel and microlevel processes. An example of a macrolevel process would be planning, which encompasses the microlevel processes of task analysis, goal setting, and making personal plans [23]. Thus, whilst the macrolevel processes provide a general depiction of students engaging in SRL, the microlevel process breakdown provides a way to conceptually define traces of learning. Given the utility of Siadaty *et al.* [9] framework in grounding event traces in SRL, the current work applies the conceptualization of microprocesses to understand learning behavior within a higher education setting.

Alternative frameworks to inform the categorization of trace data into microlevel processes can also be considered. For example, the work of Greene and Azevedo [7] represented a significant milestone in SRL microprocess analysis. Like Siadaty *et al.*, Greene and Azevedo defined a valid model of SRL that categorizes raw learner behaviors into microlevel processes. This model, however, was not based on the use of the learning management system (LMS) trace data, but think-aloud data. In this instance, learners are asked to verbally articulate learning tactics and strategies, which are then categorized into appropriate microprocesses. This protocol, as reported in [24] and [25], was also used in SRL studies by Bannert *et al.* [26] and Sonnenberg and Bannert [15]. These studies were significant in that they paved the way for a potentially robust way of measuring SRL, by codifying learner behaviors from think-aloud data and employing PM techniques to examine it.

Greene *et al.* [27] (amongst others) provide convincing arguments in favor of think-aloud as a method; it facilitates the capture of conceptually rich verbal narratives of strategy and metacognition that are critical to the measurement of SRL. Methodologically, however, this comes at a price. One identified phenomenon is that of reactivity, which pertains to three impactful elements [28]: 1) the ability of a participant to think and attend to a task at the same time; 2) talking aloud in activities that are normally undertaken in silence; and 3) the effect of drawing the attention of the experiment participant to the cognitive process. These factors can lead to a loss of integrity and, therefore, validity of the collected data. Again, this informs the debate on the use of self-report data in general as a means to measure SRL processes, specifically with regard to the accuracy of the reports themselves [25]. Nevertheless, it is important to recognize that, despite limitations, when utilized in a suitable and thoughtful manner, think aloud, and other self-report measures, can provide insights into SRL behaviors that cannot be determined from objective measures (e.g., trace data) alone. Potential lies in combining self-report and trace data, as demonstrated by, for example, [29], [30], and [31]. Azevedo *et al.* [32] posit the possibility of eliciting richer sources of trace data from multimodal methods, such as facial recognition and eye-tracking. Whilst discussions on the use of multimodal analytics are beyond the scope of this article, the LA/SRL community cannot ignore its potential.

The decision to use trace data brings with it the complex challenges of construct/internal validity that some see as insurmountable without the use of some sort of corroborated self or observatory report mechanism [33]. Multimodal studies, such as those reported in [34] and [35] can provide insights otherwise undetected in single-mode settings. Nonetheless, we should not lose sight of the benefits of trace data capture, especially in the light of the push to provide more immediately impactful and scalable LA research. We aim to prescribe a methodological framework than can be deployed in authentic settings, where scaling up specialized multimodal detection equipment may pose a challenge.

As such, this article seeks to extract meaningful insights from pure trace data. Its theoretical approach adopts the framework of Siadaty *et al.* [9], [23] as it represents the most complete encapsulation of (trace) data-driven SRL research utilizing microlevel process analysis. Even though the current work applies the same framework as a means of understanding SRL processes, there are four points that can be used to differentiate the two research streams. Siadaty *et al.'s* studies [9], [23]:

1) leverage data from a system specifically designed to support SRL, with specially tailored mechanisms for collection of trace data about SRL;
2) are not concerned specifically with blended learners, but with knowledge workers;
3) are focused on user behaviors in social and organizational contexts, as opposed to personal learner self-regulation;
4) have access to a comparatively small sample of user data, compared to the current study;
5) do not consider data about learning performance but only data about learning processes.

We, therefore, employ an SRL-contextualized study which captures data from an authentic data-rich-blended learning environment.

C. Analysis of SRL Temporal Sequences

1) Conceptual Considerations: A pattern of events alone does little to provide an explanation of the underlying processes being carried during SRL, particularly within the contexts of open systems [11]. To move beyond such ontologically flat accounts of learning, it is necessary for any work that analyzes trace data to be theoretically grounded [36]. Thus, captured events become tied to theoretical constructs that can provide an understanding to mechanisms in action, in contrast to a descriptive narrative of event sequences [11]. More importantly for LA, adopting atheoretical practices to inform interventions is concerning as it assumes that all students follow the same processes to reach an end state. To allay such concerns, members of the LA community have called for research to inform and build upon theory [1].

This article follows the recommendations put forward by Gašević *et al.* [1] through the adoption of a framework that theoretically grounds event traces into a model of SRL [5]. Even with this framework in mind, there are further considerations that need to be made with regards to the processing of the data itself. SRL is not a static process, it involves multiple sequences of events unfolding over a period of time [37]. Through this temporal perspective of SRL processes, the following questions, originally posed by Winne [22], can be asked.

1) Can we identify a temporally discrete sequence of events, that is, does the sequence have a beginning and end?
2) Are the events patterned to such a degree that they can be mined or parsed?
3) What are the parameters of the pattern?
4) Can we detect a performance-based effect of specific pattern adoption?

By answering these questions, it can provide a more informed insight into the complexities of temporal SRL processes.

2) Sequential and Temporal Analysis of SRL: Recent research has recognized the limitations of conventional statistical methods for the analysis of SRL. Sequential and temporal dimensions are emphasized [37], [38] in order to model SRL as a developmental and dynamic process with several external and internal feedback loops [10]. This has prompted exploration of many different analytic techniques, such as graph theory, PM, sequence mining, and statistical discourse analysis. This trend in SRL research is well-aligned with recent developments in LA to study the temporal nature of learning. A growing number of researchers are providing increasingly compelling reasons to explore this area with the hope of enhancing explanatory power and increasing levels of validity [11], [13], [14]. SRL constructs formerly viewed as traits are now perceived in the context of sequence and temporality [37]. This raises new questions about the temporal characteristics of these constructs and their dynamic interplay with learner and context. This article focuses on this trend to analyze temporal and sequential characteristics of constructs important to learning and instruction.

Even though the value of analyzing temporal characteristics is becoming evident, Molenaar and Järvelä [37] identifies several challenges to be addressed in order to make progress in the field of learning and instruction.

1) We need to be aware of the paradigm shift that temporal analysis entails.
2) Facilitation of a time-related research dialogue demands a common understanding of different dimensions of time and temporal characteristics.
3) A better understanding of how to answer time-related questions with appropriate methodological approaches needs to emerge.
4) Researching temporal characteristics requires procedures and guidelines for segmenting time units.
5) Temporal data are mostly collected at the microlevel, whereas most theory is defined at a macrolevel; consequently, we need to bridge these differences in the granularity used between collecting, coding, and theorizing to enhance meaning and validity.

3) Process Mining: This article examines the use of PM. PM as an analytical discipline, straddles data mining, machine learning, and business process modeling. As such it is seen as one of the answers to the question: How do we effectively articulate temporal process dynamics? This is achieved through PM discovery algorithms, which allow the identification of unique arrangements of processes in a temporal space [39]. PM does not rely on conventional statistical measures, such as correlation and means comparison. The phenomena that it seeks to measure are event or process-based, as is the data on which it relies. Thus, the starting point of PM is a dataset in the form of an event log. The key elements are an activity—a well-defined step in a broader process; a case—a process instance; and a timestamp.

PM is historically grounded in the field of business and industrial analytics. It seeks to provide insights into the sequential and procedural nature of business processes, with a view to optimizing their flow and connectivity [40]. As well as a process model discovery, PM employs techniques such as performance analysis and conformance checking to compare process models against a predefined exemplar (which may itself be derivation of a previous discovery cycle) [41]. Whilst these benchmarking techniques are perfectly at home in procedurally defined business environments, it is more challenging to deploy them in educational settings that focus on the sequential nuances of learner engagement. Nonetheless, PM discovery algorithms do provide the promise of articulating the unfolding temporality of learner behaviors.

Various PM algorithms are available and have been used in key studies. Bannert *et al.* [26] demonstrated a variation on SRL microlevel analysis of think-aloud data in conjunction with Fuzzy Miner. This is a seminal study in many ways, but the heuristics used have not been truly subjected to empirical validation. Cerezo *et al.* [42] utilized Inductive Miner to ground Moodle data analysis in Zimmerman's model of SRL [43]. Romero *et al.* [44] also used Moodle data, but in conjunction with Heuristics Miner, to visualize SRL patterns of learning. These studies, however, did not employ a strict framework of SRL microanalyses.

The use of the first-order Markov models (FOMMs) as a PM discovery algorithm is relatively novel in the literature. FOMMs describe process dynamics in terms of probabilistic association of previous events, that is, stochastic PM [45]. Saint *et al.* [46] proposed the use of this PM algorithm as a means of capturing the stochastic dynamics of learner engagement. Matcha *et al.* [47] also used FOMMs to describe strategic and tactical groupings of blended learners. Both studies provided an interesting insight into learner engagement in the context of PM but did not strictly embed the analysis in recognized models of SRL. Saint *et al.* [48] succeeded in grounding the FOMM PM method in a model of SRL, but provided only a partial focus on FOMM PM. This article seeks to capture the narrative of probabilistic transition—stochastic analysis—in order to explore SRL behaviors in the context of sequence and temporality.

Our choice of PM algorithm is influenced by Winne and Hadwin's [10] early work on SRL in its emphasis on conditional probabilities to study relevant SRL processes. This model is inherently based on the recursive transitions from one phase to another. Therefore, we posit that the use of FOMMs is consistent with Winne's theoretical perspective of modeling SRL. It is also reflected in his emphasis on the use of graphs for modeling of SRL [49] and conditional probabilities [50]. The choice of PM discovery algorithm is important, but the systematic assessment of available algorithms is beyond the scope of this study and lends itself to a separate inquiry. This study can be more accurately characterized as an exploration of a novel trace data SRL analysis framework.

As such, our framework has certain demands.

1) SRL events are not excluded or merged so that a complete SRL model is encompassed, as per the theory we followed. Fuzzy Miner, for example, excludes and merges certain processes.
2) The desire to calculate conditional probabilities for transitions from one SRL microprocess to another one, as theorized to explain SRL in the use of trace data about SRL [9], [22].
3) That differing strategic learner groups can be readily compared. Our chosen PM algorithm, pMineR, satisfied all three criteria.

D. Strategy Extraction From Trace Data

The use of trace data to study learning strategies has been galvanized through the foundation of the field of LA. Several authors proposed the use of unsupervised methods for the study of learning strategy. Lust *et al.* [51] used clustering to identify user profiles through learner behaviors, identifying profiles through frequency of activity engagement of a content management system supported course. Jovanović *et al.* [52] used a hierarchical cluster analysis to extract learning strategies of learners and to understand the extent to which those strategies were associated with the learners' level of cognitive presence in online discussions. Although the results of these studies are relevant for understanding the connection between learning strategy and learning outcomes, they offer little insight into how learners sequence their activities with each of the strategies identified in terms of their SRL microlevel processes.

Analysis of temporal links between learner actions has also been used in the literature on learning strategy. Jovanović *et al.* [52] utilized a combination of an unsupervised machine learning technique with a sequence mining algorithm to explore the extent to which meaningful learning strategies can be extracted from trace data. Fincham *et al.* [18] extracted study tactics by using hidden Markov models, which they then used as an input to a clustering process. Both the Jovanović *et al.* and Fincham *et al.* studies found associations between extracted learning strategies and academic performance. These studies also identified common strategy typologies, based on levels and characteristics of engagement. This triangulation does go some way to informing a more generalizable method of strategy detection in a temporal context. Ahmad Uzir *et al.* [53] report on a promising study exploring the use of the bupaR PM method to articulate strategy and tactics in the context of surface and deep learning. It does, however, deal in dimensions of SRL, as opposed to embedding it in a cohesive model. Though these studies provide key insights into learners' strategic and tactical deployment of learning, they fall short of providing comparative interstrategy analyses in terms of SRL processes.

E. Study Context and Justification

This article presents a methodological framework for the analysis and interpretation of learner behaviors, embedded in a recognized model of learning. Its focus is not one tool or technique, but an empirically supported construction of various tools and techniques.

The study of SRL has gained traction with the increased digitalization of education, although its basic tenets traverse digital and analogue forms of teaching. The concept of taking control of one's own learning, and its posited benefits, is one which can be applied in many educational settings. The affordances of digital technology, however, naturally shift a portion of the responsibility of learning from the educator to the learner. SRL, therefore, holds a significant position within the field of LA. In this context, the decision to use or not use self-report data, wholly or partially, is important. Self-report measures have a vital role in SRL research as they provide the means of articulating the nuances of meta-cognitive and cognitive behaviors not afforded by pure trace data [16], [26], [27]. This, however, positions both the educational and the inquiry space as experimental. There must be room for authentic noninvasive SRL trace data research, as, ultimately, we need to see an increase in projects which can be systematically deployed in authentic, nonexperimental environments. In attempting to harness the advantages of trace and self-report, bespoke systems, such as Winne and Hadwin's nStudy [54] and Siadaty *et al.*'s Learn-B environment [23], promise noninvasive SRL insights from trace data. These platforms certainly have a place, but they cannot be described as systems commonly used in education. The current study uses trace data from authentic settings, in an educational and systemic sense.

The studies undertaken by Fincham *et al.* [18], Matcha *et al.* [47], Ahmad Uzir *et al.* [53], and Boroujeni and Dillenbourg [55] represent significant milestones in pure trace data analysis. They provide critical insights into study tactics and strategies and mark out strong methodological cases in this context. They all demonstrate very effective unsupervised machine learning methods, which unlock genuine insights into tactic and strategy. They do not, however, seek to embed their analyses in models of SRL with the aim to extract information about relevant SRL processes and use such information to analyze SRL processes as a whole and compare different groups of students. The current study presents a formalization of a process of SRL-informed analysis, utilizing microlevel analysis as a data transformation process.

Microlevel analysis provides a practical means of framing SRL analyses in a theoretical model of SRL, and in doing so, forcing the articulation of raw trace data into SRL sequences. Key studies by Greene and Azevedo [7], Bannert *et al.* [26], and Siadaty *et al.* [9] show the potential of the microlevel analysis as means of capturing and articulating learner behavior in the context of SRL. Only the Siadaty study used trace data as a source; however, all the others relied solely on self-report data (i.e., think alouds). As stated previously, the Siadaty *et al.* study derived data from a specially designed system—Learn-B—as opposed to a commonly used LMS. As a move toward authenticity, the current study uses the same robust model of learning, but harnesses authentic LMS trace data. We are unaware of any other studies that use authentic educational trace data as feed to the SRL microlevel analysis procedure. The use of PM in this context is also novel.

We use PM to explore learner SRL processes through the lens of sequence and temporality. There are several studies that employ PM to articulate patterns of SRL in data-rich environments. Maldonado-Mahauad *et al.* [31] extracted interaction sequences from the raw learner behavioral traces of three Massive Open Online Courses (MOOCs). They codified interaction sequences and embedded them into empirical SRL strategies, using the Disco PM method [56], itself derived from the Fuzzy Miner algorithm [39]. The Maldonado-Mahauad *et al.* study provides an empirical grounding of MOOC interaction patterns in dimensions of SRL, but it falls short of embedding these patterns in a unified model of SRL.

Maldonado-Mahauad *et al.* [57] built on this work by employing PM-informed predictive analytics to indicate probable likelihoods of course completion across SRL-informed strategic learner groups. Intriguingly, this article presented a potentially impactful method of identifying course success from learner articulations of SRL. Both studies demand a challenging conceptual leap between trace-data sequence and SRL construct. The study by van den Beemt *et al.* [58] provides another example of learner group clustering based on a similar PM algorithm. Although useful, its connection to SRL is nominal, rather than integral. Nonetheless, the value of these studies lies in the categorization of types of learners in this context. This categorization further crystalized in the current study, where our groups fall into broadly similar categories. Our specific articulation of these categorizations can be found in Section III-D.1.

We are unaware of any studies that combine this unique set of techniques in a consolidated methodological framework. We call it the "Trace-SRL" framework.

F. *Trace-SRL Framework*

This article is underpinned by the Trace-SRL framework outlined in Fig. 1.

1) Clustering of the Learner Data: The question around the choice of delineation is important. Unsupervised machine learning methods can uncover illuminating clusters of tactic and strategy groups, otherwise undetectable [18], [47], [52]. Directed segmentation—such as extracting high and low performing learners based on assessment scores—can provide insight into the link between performance and SRL behaviors. In this study, the data were supplied in preclustered groups.

2) Eventization Sequence: We use the term "eventization" to describe the sequence of techniques involved in transforming raw trace data into SRL (micro) processes. The outcome of this sequence is the "eventized" log. There are three parts to this sequence.

1) Defining the SRL microprocesses: In order to strengthen the empirical base of the study, a recognized model of learning is deployed—we used the model deployed by Siadaty *et al.* [9]—as a theoretical study foundation. Having established this model, the generation of subcategorized microprocesses lays the foundation for the practical implementation of the framework.
2) Building the microprocess pattern library: Having defined the microprocess event set, LMS trace data can then be analyzed to identify appropriate SRL sequence patterns as subcategories of the defined microprocesses (see Table II). This is a significant phase, as it raises questions over sequence exclusivity and priority, not to mention validity. In this study, we used a single channel (trace data), but the use of other channels, such as self-report or multimodal, can also be harnessed and processed in combination.
2) Generation of the eventized log: The raw trace data are parsed and the final eventized logs are generated. REGEX routines were used in this article but there is potential for the development of better-suited bespoke solution, or a combination thereof.

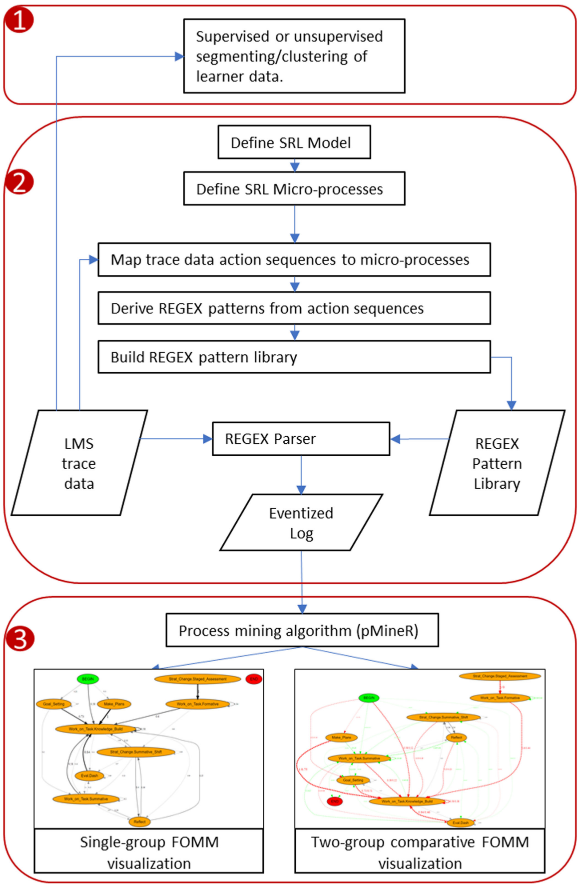

Fig. 1. Trace-SRL framework.

3) Process Analysis: This article uses a stochastic PM algorithm to derive the final outputs. These outputs provide an articulation of the temporal and sequential associations between groups SRL microlevel activities in the context of transition probabilities. The choice around tools for this task is driven by the ontological thrust of the study. In this case, this thrust is temporal and sequential in nature. This algorithm also affords the interpretation of comparison between groups; an important part of this article.

G. *Research Questions*

Using our Trace-SRL framework, this article aims to use LMS-generated trace data as its source, eliminating the empirical shortcomings of self-report data and retaining the vital characteristics of SRL. We propose the use of microlevel analytics as a means of preprocessing/transforming raw data into SRL sequences. These sequences form the input to pMineR, a stochastic PM discovery algorithm. The output of this—FOMMs—affords us a means of articulating the temporal and transitional characteristics of learner groups in terms of these SRL sequences. We are unaware of anyone deploying this

TABLE I
LMS LEARNING ACTION CODES

Learning Action	Description
EXE_CO	Correctly solving a summative assessment item
EXE_IN	Incorrectly attempted summative assessment item
MCQ_CO	Correctly solved formative assessment item (MCQ)
MCQ_IN	Incorrectly attempted formative assessment item (MCQ)
MCQ_SR	Solution request for an MCQ
VIDEO_PLAY	Viewing of course video
COTENT_ACCESS	Reading materials access
MC_EVAL	Dashboard access
MC_ORIENT	Accessing the schedule and the learning objective pages

method in this specific context that is applying microlevel analysis to authentic LMS source and utilizing a novel stochastic PM algorithm to articulate and compare learner SRL behaviors. Through this method, we aim to answer these questions.

1) What can we interpret from the key statistical measures of SRL microlevel processes, as extracted from trace data?
2) To what extent can we qualitatively characterize students' differing learning strategies, through analysis of temporally ordered event sequences of SRL microlevel processes, as extracted from trace data?
3) To what extent do contrasting learner strategy groups differ in patterns of temporally ordered event sequences of SRL microlevel processes, as extracted from trace data?

III. METHODOLOGY

A. Trace Data Collection

The data for this study were collected from an LMS attached to a computing course at a university in Australia. Table I provides a list of learning action codes with descriptions. The course was based on a flipped classroom pedagogy and the data used in this study were about students' engagement with the online activities, which served the purpose of preparation for the face-to-face activities. Each time a student engaged with an element of the LMS, a learning event record was generated containing a *student ID* number, a *timestamp*, and the completed *learning action*.

The student cohort ($N = 290$) collectively generated 184 211 learning events. The course lasted 13 weeks, comprising two main bouts of activity: Weeks 2–5 and 7–12. In week 6, the students completed a summative mid-term assessment, and in week 13 the final exam. The students were provided with a dashboard as a real-time feedback that allowed for engagement and performance monitoring and comparison with their peers (average number actions completed and score). Successful completion of summative assessment tasks contributed 10% to the overall module mark. The details of this course design can be found in [59].

B. Translation of Trace Data to SRL Microprocesses

1) Microlevel Processing: Building on the work undertaken by Siadaty *et al.* [9], we elected to employ regular expression (REGEX) parsing in order to extract defined learning sequence patterns. This proved successful in the Siadaty study, as it provides a controlled technique for encoding text patterns. It affords this study the same benefits.

Table II represents a macrolevel to microlevel mapping, based on the same theoretical model of SRL as used by Siadaty *et al*. Raw trace datasets were input to the REGEX parser developed for this study, utilizing a REGEX pattern library. The first pass produced a set of categorized logs, which, effectively, represent an SRL-informed coarsening of the original trace data. For example, an uninterrupted sequence of content access events was mapped to the microlevel process *Work_on_Task.Knowledge_build*; a transition from a series of exercise attempts to content access was mapped to *Reflect*. A full set of mapped sequences is outlined in the *microlevel action mapping* column in Table II, as subcategories of microlevel processes (such as *Working on a Task* and *Reflection*). These, in turn, are subcategories of the main macrolevel processes (see Section III-C.1). In this way, we effectively characterize learner behaviors in the context of our SRL model. The parser, thus, consolidates event sequences into microlevel processes.

2) SRL Eventization: As part of the eventization sequence, all relevant raw log data were passed through our REGEX engine. The eventization sequences comprise two passes, as this first pass produced event sequences that overlapped. A second pass was designed to eliminate this overlap though the use of prioritization rules, ensuring mutual temporal exclusivity of SRL processes in the final eventized logs.

C. Theoretical Model

1) Model Deployment: As stated, this study uses a version of the SRL model employed by Siadaty *et al.* [23]. Table II fully outlines the constructs of the model and how it maps to trace data sequences derived for this article. Trace data sequences are mapped to microlevel processes, which are themselves already categorized under macrolevel processes. The macrolevel processes represent the three cyclical phases of our SRL model of Planning, Engagement, and Evaluation/Reflection. In order to distinguish variations of microlevel processes, the term microlevel action (or microaction) is employed. In Table II, the microlevel action is identified and accompanied by a description of the trace data sequence from which it was derived. For example, the Work on a task microlevel process comprises three subcategorized microactions: *1) Work_on_Task.Summative; 2) Work_on_Task.Formative;* and *3) Work_on_Task.Knowledge_build.* At the same time, it is also a subprocess of the macroprocess, Engagement; one of the three main constructs of the SRL model.

In embedding our analysis in a model of learning, we go some way to providing a stronger sense of empirical validity. It does not, however, go far enough. In the absence of conventional statistical measures of validity, other mechanisms are necessary.

2) Model Validity: We utilize Winne's framework of questions informed by the mapping of his own SRL heuristic [22]. Although we are not directly utilizing the Winne SRL model, his validity framework nonetheless provides a usable set of directives for interrogating categorized trace data inferences. The key to its deployment is the emphasis on SRL's inherent structures of temporal and sequential patterns.

TABLE II
SRL MACROLEVEL TO MICROLEVEL MAPPING

Macro-level process	Micro-level process	Description	Micro-level action mapping
Planning	Goal Setting	To explicitly set, define or update learning goals	**Goal_Set** MC_ORIENT (single event or small sequence)
	Making Personal Plans	To create a plan and select strategies for achieving a set learning goal	**Make_Plans** MC_ORIENT to a small cycle of Content/Video access then back to MC_ORIENT
Engagement	Working on a Task	To consistently engage with a learning task and use tactics and strategies	**Work_on_Task.Summative**: EXE_CO or EXE_IN (in a randomly assorted sequence)
			Work_on_Task.Formative: MCQ_CO or MCQ_IN (in a randomly assorted sequence)
			Work_on_Task.Knowledge_build: CONTENT_ACCESS or VIDEO_PLAY (in a randomly assorted sequence)
	Applying Appropriate Strategy Changes	To revise learning strategies	**Strat_Change.Formative_shift** (To transition from content access to formative assessment) CONTENT_ACCESS OR VIDEO_PLAY (Series of randomly assorted) and then MCQ actions
			Strat_Change.Summative_shift (To transition from content access to summative assessment) CONTENT_ACCESS OR VIDEOPLAY (Series of randomly assorted) and then EXE actions
			Strat_Change.Staged_Assessment (To transition from formative assessment to summative assessment) MCQ to EXE
Evaluation and Reflection	Evaluation	Evaluating one's learning process and comparing one's work with others	**Eval.Dash** MC_EVAL sequence
			Eval.Formative_Answer MSQ_SR sequence
	Reflection	Reflecting on individual learning	**Reflect** EXE actions (both correct and incorrect, assorted) before switch to CONTENT_ACCESS or VIDEO_PLAY sequence

a) Can we identify a temporally discrete sequence of events? On two levels: Raw learner actions were presented in temporally ordered groups or sessions (each being assigned a session ID). The parsing engine performs its processing bound by these session events. The REGEX coding then provides discrete event delineations based on sequence patterns. This applies to both elemental sequences (i.e., comprising one learning action, e.g., MC_ORIENT) and more complex patterns.

b) Are the events patterned to such a degree that they can be mined or parsed? For elemental and semielemental sequences (i.e., learning actions with dichotomous outcomes, e.g., EXE_CO and EXE_IN) allocation of meaning was logical. In the example of learning action MC_ORIENT, each action represented access to course instruction materials (as opposed to content access); thus, we the inferred goal setting (*Goal_Set*). The microprocess *Work_on_Task.Knowledge_build* was an informed consolidation of two learning actions: *1) Content_Access;* and/or *2) Video_Play*. Composite processes, such as typified by the strategy change (*Strat_Change*) groupings and the *Reflect* process, were derived from an informed judgement on the manifestation of SRL. For example, the *Reflect* microprocess represented a change in sequential engagement between summative attempts and content access.

c) What are the parameters of the pattern? This can be articulated in terms of sequence lengths, durations, and nesting (i.e., whether patterns exist within larger pattern sequences). We recorded sequence lengths and durations but have not included them into this article due to the space limitations. Pattern/subpattern exclusivity was coded into the parsing engine. The implementation of pattern priorities is a key area and requires greater examination for the future work.

TABLE III
ASSESSMENT SCORE BY STRATEGY GROUP

	Mid-term test percentiles			Final test percentiles		
	Median	25th	75th	Median	25th	75th
Active Agile (N = 19)	16	13	18	24	18.5	30
Summative Gamblers (N = 59)	11	8	15	14	9	19
Active Cohesive (N = 25)	16	13	17	21	16	31
Semi-Engaged (N = 117)	13	11	16	15	12	23

d) Can we detect a performance-based effect of specific pattern adoption? The extracted microlevel SRL processes were further analyzed to compare across four different performance (or strategy) groups (see Table III).

D. Data Analysis

1) Extraction of Learning Tactics and Strategies: The work carried out in [52] was of primary importance to this study, in identifying study strategies of high- and low-performing students. It provided a method for automated extraction of learning tactics and strategies from trace data about students' interaction with online resources. The method was composed of two levels of analytics based on unsupervised machine learning methods, that is, clustering. First, learning tactics were extracted by analyzing study sessions and clustering these sessions based on similarity of actions within the sessions. The sequence analysis was done using the exploratory sequence analysis implemented in the TraMinerR R library [60] and followed up with a hierarchical cluster analysis with Levenshtein distance and Ward's method, as proposed in [61]. This generated four strategy types, based on the predominant study action type. Second, five learner strategy groups were extracted through an agglomerative hierarchical clustering with Euclidian distance and Ward's method, based on the frequency of the use of the four study tactics by each individual student in the sample

For this study, we selected four of the five learner strategy groups that we characterize, respectively, as "Active Agile" ($N = 19$), "Summative Gamblers" ($N = 59$), "Active Cohesive" ($N = 25$), and "Semiengaged" ($N = 117$). We chose these groups as they present contrasting learner strategies, allowing for a more distinct comparative analysis. The "active" groups outperformed the summative gamblers and the semiengaged group in summative assessments, and are, therefore, presented as the more successful groups or "high" groups. The median, 25th, 75th percentile values for mid-term and final exam groups scores are described in Table III. The clustering techniques used here underpin all three research questions, as they provide us with the requisite group characterizations, which are articulated in terms of learning strategies.

2) Statistical Analysis: Following the identification of student strategy groupings using cluster analysis and SRL eventization, we characterized these groups using basic and relative statistical frequency measures. We further explored intergroup SRL differences through the use of path analysis, which was carried out using Mplus 8.1 [62]. A negative-binomial model was used to analyze the data, which was based on the data being in the form of counts and the variance exceeding the sample mean. The analysis involved the regression of the nine SRL events onto three grouping variables representing Active Agile, Active Cohesive, and Semiengaged learning strategies; in all cases, the Summative Gamblers group was used as the baseline (i.e., Active Agile = 1, Summative Gamblers = 0). These techniques were used primarily to address research question 1, but also in partial answer to research question 3.

3) Process Mining: FOMMs were used to explore the novel possibility of combining stochastic and temporal analysis of eventized data about SRL microlevel processes. We employed the R package pMineR [45], [63] to train and generate FOMM probability transition matrices for the four strategy groups. This allowed analysis and comparison of temporal patterns of microlevel process engagement. The three mandatory PM roles are populated; thus, Microlevel Action → Activity; Start Time stamp → Timestamp; Student_ID → Case. The choice of the case role is a significant one. In choosing the student ID, we committed to positioning the analysis strategically, as opposed to tactically. Process paths are articulated for each student across the entire 12-week course duration. In using the alternative, Session ID, we would have analyzed the same 12-week period but as a sequence of learning sessions. This would necessarily present a more tactically oriented view of process dynamics. This is no less valid and could be the subject of future research, but does not fit the more strategic focus of this article.

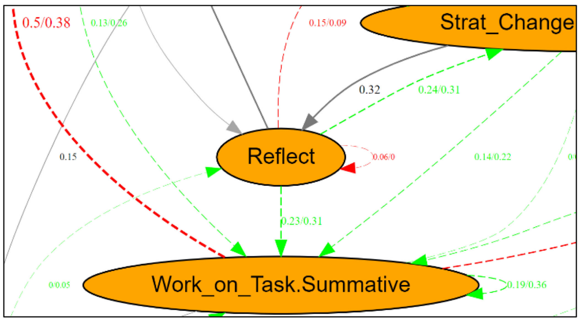

Fig. 2. Snapshot example of a FOMM comparison model.

4) FOMM Diagram Interpretation: The diagrams are schematic representations of the transition matrices produced for each FOMM. The arc between one node (microlevel event) and the next shows a stochastic measure of the likelihood of transition between one node and another; the transition probability (TP). We conduct high-level visual interpretations from the thickness of the lines, which reflects the magnitude of the TPs. We provide more forensic analyses by interpreting the actual TP values. Thus, we can identify probabilistically informed learning paths and relationships between the SRL constructs identified in our theoretical model.

To provide comparative insights, we interpreted the comparison diagrams of the FOMM models. In each case, one strategy group is mapped onto another group. The arcs in black represent similar TPs. Red arcs represent a comparatively lower TP of the mapped model; green arcs represent a higher TP. In cases of disparate TPs, both probabilities are shown. To simplify presentation, a TP threshold of 0.05 has been set. Fig. 2 shows a partial example of a FOMM comparison plot. For each of the comparisons, we mapped the low performer onto the high performer: Summative gamblers mapped to active agile; semiengaged mapped to active cohesive. Crucially, it allows not just to articulate contrasting modes of SRL but to measure against an assessment benchmark.

FOMM interpretation represents the methodological heart of this article and fundamentally underpins research questions 2 and 3.

IV. Results and Discussion

A. Engagement Statistics

In this section, we aim to answer research question 1 (see Section II-G): What can we interpret from the key statistical measures of SRL microlevel processes, as extracted from trace data?

1) Descriptive Statistics: The statistics in Tables IV and V provide a descriptive insight into the SRL for each strategy group, in context of the Mean (M) and Standard Deviation (SD) of engagement frequency in each activity for the whole term. From this, we can infer the respective foci of the groups in terms of SRL engagement.

The starkest contrast lies in engagement with knowledge building activity, with the two stronger groups exhibiting a

TABLE IV
SRL STATISTICS BY GROUP: ACTIVE AGILE (AA) AND SUMMATIVE GAMBLERS (SG)

SRL events	N AA	M(SD) AA	N SG	M(SD) SG
Work_on_Task. Summative	19	17(7.36)	55	8(3.88)
Strat_Change. Summative_Shift	19	9(4.49)	40	2(1.42)
Goal_Setting	17	6(2.8)	40	2(1.37)
Reflect	19	9(4.81)	48	3(1.79)
Work_on_Task. Knowledge_Build	19	63(13.62)	57	7(3.59)
Eval.Dash	18	11(9.34)	30	3(3.16)
Work_on_Task. Formative	12	3(1.73)	3	3(1.41)
Make_Plans	4	1.3(0.43)	3	1.3(0.47)

TABLE V
SRL STATISTICS BY GROUP: ACTIVE COHESIVE (AC) AND SEMIENGAGED (SE)

SRL events	N AC	M(SD) AC	N SE	M(SD) SE
Work_on_Task. Summative	25	15(5.4)	116	13.3(4.6)
Strat_Change. Summative_Shift	24	6(3.3)	107	4.4(3)
Goal_Setting	25	5.4(4.2)	107	4(3.2)
Reflect	23	7.4(3.8)	111	4.4(2.7)
Work_on_Task. Knowledge_Build	25	57(14)	117	19(7)
Eval.Dash	23	27(22.8)	87	8.6(8.7)
Work_on_Task. Formative	13	3.(1.8)	14	2.8(1.2)
Make_Plans	4	1.3(0.43)	6	1.3(0.7)

TABLE VI
INTERGROUP PATH ANALYSIS

Group	Variable	Estimate	Standard Error	P-Value
Active Agile	Work_on_Task. Summative	.732	.119	<.001
	Strat_Change. Summative_Shift	1.733	.177	<.001
	Goal_Setting	1.178	.188	<.001
	Reflect	1.401	.167	<.001
	Work_on_Task. Knowledge_Build	2.158	.084	<.001
	Eval_Dash	1.834	.305	<.001
	Work_on_Task. Formative	2.449	.669	<.001
Active Cohesive	Work_on_Task. Summative	.580	.099	<.001
	Strat_Change. Summative_Shift.	1.290	.181	<.001
	Goal_Setting	1.194	.200	<.001
	Reflect	1.120	.167	<.001
	Work_on_Task. Knowledge_Build	2.050	.084	<.001
	Eval_Dash	2.696	.292	<.001
	Work_on_Task. Formative	2.352	.669	<.001
Semi-Engaged	Work_on_Task. Summative	.482	.073	<.001
	Strat_Change. Summative_Shift	.941	.152	<.001
	Goal_Setting	.795	.152	<.001
	Reflect	.627	.130	<.001
	Work_on_Task. Knowledge_Build	.980	.075	<.001
	Eval_Dash	1.346	.255	<.001
	Work_on_Task. Formative	.711	.682	.297

much greater overall engagement with means of 63 (active agile) and 57 (active cohesive), as opposed to the weaker groups with seven (summative gamblers) and 19 (semiengaged). The stronger groups are seen to engage more with goal setting, dashboard evaluation, and reflection, although this does not tell the full story.

2) Path Analysis: The initial path model with all nine variables (*Work_on_Task.Summative*, *Strat_Change.Summative_Shift*, *Goal_Setting*, *Reflect*, *Work_on_Task.Knowledge_Build*, *Eval_Dash*, *Work_on_Task.Formative*, *Make_Plans*, and *Strat_Change.Staged_Assessment*) could not be identified, which was attributed to the *Make_Plans* and *Strat_Change. Staged_Assessment* variables for the Active group. An inspection of the counts for the *Make_Plans* variable showed that no students engaged in this behavior within the Active Agile nor the Summative Group. As for the Active Cohesive and Semiengaged groups, the maximum counts for the *Make_Plans* variable were three and two, respectively. Similarly, the *Strat_Change.Staged_Assessment* had a maximum count of zero for the Active Agile, Active Cohesive, and the Summative Gambler groups; whereas, the Semiengaged had a maximum count of two.

Based on these outcomes, the path analysis was rerun with the *Make_Plans* and *Strat_Change.Staged_Assessment* variables dropped. The results are presented in Table VI. As can be seen across all variables for the Active and Active Cohesive groups, they demonstrated an increased rate of engagement in these behaviors (*Work_on_Task.Summative*, *Strat_Change.Summative_Shift*, *Goal_Setting*, *Reflect*, *Work_on_Task.Knowledge_Build*, *Eval_Dash*, and *Work_on_Task.Formative*) than the Summative Gambler group. Likewise, the Semiengaged group engaged in six of the measured variables (*Work_on_Task.Summative*, *Strat_Change.Summative_Shift*, *Goal_Setting*, *Reflect*, *Work_on_Task.Knowledge_Build*, and *Eval_Dash*) at a higher rate than the Summative Gambler group, but not for the *Work_on_Task.Formative* behavior ($p = 0.297$).

We can infer that the more optimal learners engage more fully in many of the SRL events, and that less optimal learner focus slightly more on the credit-bearing summative task. This is a useful insight but suffers from the ontological flatness referred to by Reimann *et al.* [11]. We cannot gain a sense of the interprocess relationships in terms of sequence or time. We can use these measures as useful context, rather than critical insight.

B. Strategy Group Characterization

In this section, we aim to answer research question 2 (see Section II-G): To what extent can we qualitatively characterize students' differing learning strategies, through analysis of temporally ordered event sequences of SRL microlevel processes?

Note: Larger scale versions of the FOMM visualizations presented below are accessible as supplementary material.

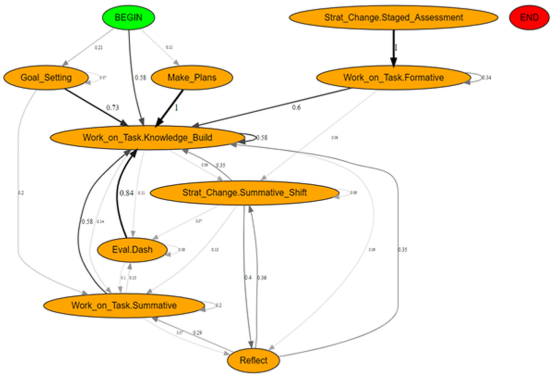

Fig. 3. FOMM diagram for active agile (higher performers).

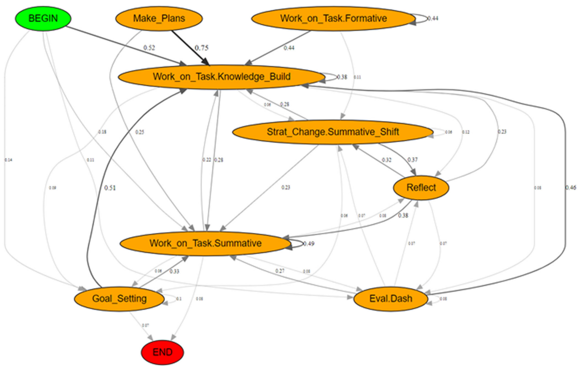

Fig. 4. FOMM diagram for summative gamblers (lower performers).

1) SRL Analysis: Active Agile Group: This group is one of the successful groups, in terms of assessment scores. Telling insights can be articulated from the preferred initial activities of our learner groups. Looking at Fig. 3, we can see that building knowledge (by accessing course content and/or video) carried a TP of 0.58. This makes it the most likely opening move in a learning session. Aside from this, we see a definite emphasis toward goal setting (with a TP of 0.21) and plan-making (0.11). As such, this group exhibits a logical approach to its learning sessions and a leaning toward functional SRL behaviors. If we consider the constructs of Winne and Hadwin's model, planning and goal-setting are behaviors that we expect to see in the earlier stages of a learning cycle [10].

The preference to move toward knowledge building tasks after dashboard evaluation is interesting (0.84); this represents a definite metacognitive trigger between two SRL events. Again, Winne and Hadwin's model [10] provides empirical parallels, specifically in relation to the relationship between external feedback and SRL behaviors. Also in support of this, the Winne and Butler model [64] points to narrative of optimal feedback digestion after access to artefacts such as dashboards. The active agile students use this feedback to orchestrate an improved learning scenario. In our case that was through engaging in knowledge building. Similarly, periods of reflective behavior were followed by knowledge building (0.35) or knowledge building followed by summative activity (summative shifting, 0.36).

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Working on summative tasks (which counted to toward the overall final summative mark) was, in raw event terms, one of most frequently engaged tasks. We see that our successful group was more likely to move from a cycle of summative engagement to knowledge building (0.58) than to any other activity. This points to a sense of self-motivation, which can be identified as the use of more than one strategy to keep the learner on track for the final goal [65]. As such, it indicates a sense of self-autonomy [8]. In our case, the students evaluated the finite reward of summative attempts before changing to knowledge building to seek a longer-term learning benefit.

In this group, although we do see free transition between the SRL behaviors, there was a general sense of cohesion. It should be noted that microlevel processes, such as *Strat_Change.Summative*, *Strat_Change.Staged_Assessment*, *Reflect*, and *Make Plans*, are composites of lower level learning actions (see Table II) and as such we would expect to see a degree of linkage between them. Yet, we still see a pattern of recognizable learner self-regulation.

2) SRL Analysis: Summative Gamblers Group: This was one of the least successful groups of the four (see Fig. 4). On first analysis, it seems difficult to distinguish traits of less functional learner behavior. We can, however, elicit indications through inspecting behaviors in initial sessions. Like the previous group, there was an understandable (and admirable) initial focus on knowledge building. There was, however, an added tendency for some learners to jump straight to an uncontextualized summative task sequence (nearly 20%). In general, we see a slightly less controlled approach to initial strategizing, which is reflected in general behaviors around the whole FOMM diagram. It contains more disparate arcs of transition than that of the better performers. This indicates a less considered approach to learning strategy and SRL.

That aside, there were intergroup behavioral parallels (explored more in Section IV-C) in the learning patterns, such as engagement with plan-making, goal-setting, and evaluative activities before moving to task engagement of some kind. We see that after a goal setting, there is a 0.51 TP to knowledge building, but also a 0.33 TP to the main summative task. This could indicate suboptimal learning behaviors and possibly an internal renegotiation of outcome aspirations in this task; a

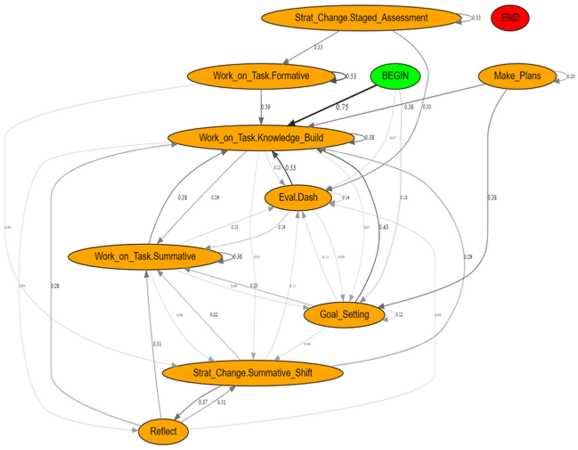

Fig. 5. FOMM diagram for active cohesive (higher performers).

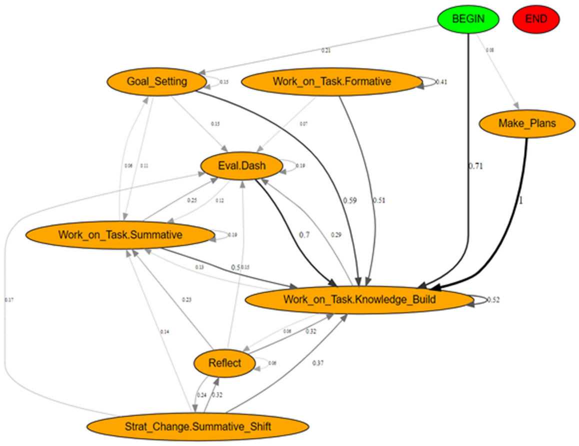

Fig. 6. FOMM diagram for semiengaged (lower performers).

phenomenon noted by Hattie and Timperley [66]. In a process of planning and goal setting, one would assume the next step would be knowledge building, not summative fast-tracking. After dashboard evaluation, the most likely shift was toward knowledge building (0.46), which is admirable. It is less easy to account for the other TPs, which indicate the unstructured nature of this group.

3) SRL Analysis: Active Cohesive Group: This group is identified as a strong group, attracting similar assessments scores to that of the active agile group. Viewing initial session behaviors (see Fig. 5), we see that the overriding tendency was to build knowledge (0.71). The next most likely move was toward goal setting (0.21). There was an 0.8 likelihood that plan-making is embarked upon at this stage. As with the other higher performers group, this strategy group exhibited a seemingly well-planned approach to learning. Knowledge building was generally important to this group; we can see that it was the most likely destination, learning-wise, after a good number of other activities.

After goal setting, we see an inclination to knowledge building (0.59), as was the case with formative work (0.51), summative work (0.5), and especially dashboard evaluation (0.7). In this behavior, we see a sense of contextualized knowledge acquisition, that is, some learners move toward it via a set of preparatory tasks. Interaction with the summative task was typified by regular connections with knowledge building (0.5) and, to a lesser extent, dashboard evaluation (0.25). Overall, through their learning patterns, this strategy group demonstrates what some would theorize as optimal SRL.

4) SRL Analysis: Semiengaged Group: This group, like the summative gamblers, tended to gravitate more toward the main summative task, albeit not to the same degree. Taking a relatively simplistic view of the diagram (see Fig. 6), we see that paths between the major activities were not as sharply defined probabilistically, and there were more of them (within the designated probability thresholds).

Although there were some cases where a prevalent next step is evident, it is not a behavioral norm. This indicates a lack of cohesion in movement between tasks. We could infer that there was a less strategic aspect to this group, indicating a looser deployment of SRL. Picking up on a few examples of this, if we look at the summative task activity, aside from the self-loop TP (0.36), there was no one dominant probable next step, such as displayed by the higher groups. Looking at the knowledge building task, we can see a comparatively weak self-loop TP (0.38), and a more disparate spread of TPs to other activities. Again, we could interpret this as a slight lack of focus and possibly a more speculative tactical move.

This group did not display suboptimal learning in all areas; there is, indeed, evidence of occasional optimal behaviors. Specifically, after evaluating the dashboard, there is a healthy 0.53 TP toward knowledge building tasks as the next step. There is still a 0.19 TP to the summative task, demonstrating come tendency to attempted short-cutting of learning. We cannot say that this group was typified completely by dysfunctional learning behaviors, but there was evidence of a lack of coherence in certain areas.

C. Strategy Group Comparison

In this section, we aim to answer research question 3 (see Section II-G): To what extent do contrasting learner strategies groups differ in patterns of temporally ordered event sequences of SRL microlevel processes?

1) Frequency Statistics: Although the main thrust of our analysis was PM, we can glean some of the narrative from simple relative frequency statistics. Table VII describes relative engagement in terms of frequency.

Counter-intuitively, the lower performers seem to place slightly greater emphasis on reflection. This, however, is quite consistent with the literature [67]. In certain cases, students who are less self-regulated (i.e., lower prior knowledge and/or knowledge of relevant learning strategies) are more inclined to engage into metacognitive monitoring in the need to uncover the right strategy to help them with their learning. This constant metacognitive monitoring, in turn, increases

TABLE VII
MICROLEVEL ACTION RELATIVE FREQUENCIES BY GROUP (%)

Micro-level Action	**Active Agile: *High***	**Summative Gamblers: *Low***	**Active Cohesive: *High***	**Semi-engaged: *Low***
Work_on_Task. Knowledge_Build	54.44	35.42	48.86	37.87
Work_on_Task. Summative	14.60	32.65	12.56	25.71
Eval.Dash	9.05	7.29	21.45	12.56
Reflect	7.78	9.67	5.88	8.11
Strat_Change. Summative_Shift	7.64	6.81	4.91	7.83
Goal_Setting	4.60	7.13	4.67	7.08
Work_on_Task. Formative	1.64	0.71	1.49	0.65
Make_Plans	0.23	0.32	0.17	0.13
Strat_Change. Staged_Assessment	0.05	n/a	n/a	0.05

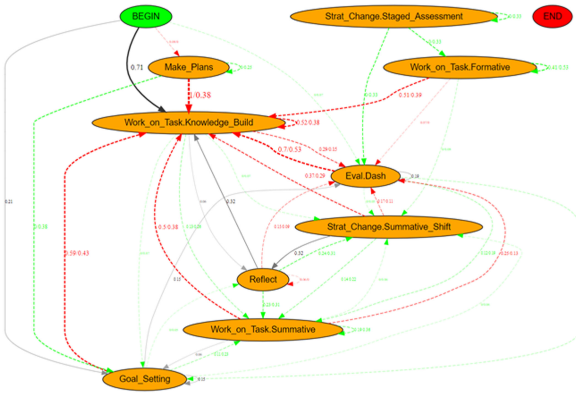

Fig. 7. FOMM Comparison: Active agile and summative gamblers.

cognitive load and reduces opportunities for successful learning [68], [69]. The telling difference is in the distributions of knowledge building and summative assessment. We see a more balanced engagement in that of the higher performers than that of the lower. This provides an initial clue as to the differing behaviors.

2) FOMM Comparison: Active Agile (High) and Summative Gamblers (Low): The FOMM comparison diagram (see Fig. 7) provides a view of contrasting behaviors in the context of probabilistic differences. At the start of learning sessions, the lower performers were more than three times likely to engage (unprepared) with the summative task than the higher performers (with respective TPs of 0.05 and 0.18). This indicates a less disciplined approach to self-regulation; these learners were attempting to fast-track the learning process to cheaply achieve the summative outcome. We also see that the low group showed no inclination to make plans from the outset, as compared to the high group (0.11). *Note: From this point forward, comparative TPs will mostly be shown in parentheses, in this format (n.nn/n.nn); the order of comparison is determined by the containing sentence*. The high group was more likely to transition initially to goal setting than the low group (0.21/0.14). Counterintuitively, the low group was more likely to access the dashboard on initial access (0.07/0). Engagement with dashboards, as a means of comparison with the class average on the amounts of activities performed, is shown to promote performance goal orientation [68]. Although a healthy balance between mastery and performance goal orientation is desirable [69], the dominance of performance orientation can lead to a surface approach to learning, the focus of which is mostly on assessment and leads to limited understanding [70], [71]; the summative gamblers exhibit a strong inclination toward surface learning approach even through seeking the type of feedback that may not be healthy for performance.

Viewing activities associated with dashboard evaluation throws up some telling comparisons. After dashboard engagement, the high-performance group was much more inclined to move to knowledge building tasks than the low-performance group (0.84/0.46). In addition, the low group was nearly three times more likely to engage directly with the summative tasks than the high group (0.1/0.27). These transitions again indicate a less optimal inclination toward planned learning. Accessing the dashboard was more likely to inspire uncoordinated and speculative summative attempts in the lower performers. This is similarly reflected in goal setting associations. After this engagement, the higher performers were more likely to access knowledge building exercises than their counterparts (0.73/0.51), but less likely to jump straight to summative attempts (0.2/0.33). This can be explained by higher levels of judgement of learning, that is, high-performing students were more accurate at judging how well they mastered a topic, in comparison to the lower performers [72]. Other behavior associations with knowledge building indicate that the high-performance group tends to stick in tighter self-loops (0.58/0.38). This could indicate a more disciplined approach to engagement in learning, as they showed less inclination to divert to other behaviors. This consistency in choices and systematic use of study strategy has also been proven in the literature on problem solving [17]. We can also see that, after engaging in formative work, the high group was more likely to transition to knowledge building than the low group (0.6/0.44). This is interesting, as it indicates an assessment of academic standing and then a decision to address this through knowledge building; clearly an SRL trait.

Finally, regarding summative engagement, we see predictable patterns. The low group was more inclined to engage in sustained cycles of this behavior, as indicated by the self-loop TP (0.49/0.2). Conversely, the high groups were nearly three times more likely to disengage with summative attempts and move to knowledge building (0.58/0.22). This indicates a greater inclination of the higher group to reflect on their engagement and attempt to remedy matters; again another clear SRL trait demonstrated by strong metacognitive monitoring and control of own learning [65]. This shift was codified in this study as *Reflect*. The reason we see the composite elements in our FOMM was because the codified shift must have happened within a learning session. In this case, it represented SRL in a more strategic light.

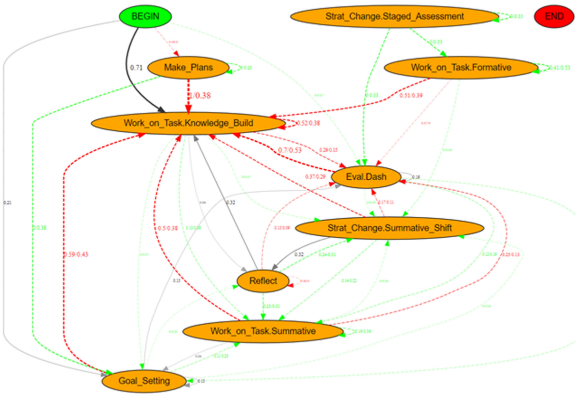

Fig. 8. FOMM Comparison: Active cohesive and semiengaged.

In summary, we can typify a broader set of behaviors that define SRL function and dysfunction; thus, sustained cycles of reflection, evaluation, and assessment, leading to further knowledge-building (good SRL); unprepared speculative fast-tracking to the summative assessments (no SRL).

3) FOMM Comparison: Active Cohesive (High) and Semi-engaged (Low): Viewing the comparative opening moves of the two groups in the FOMM comparison diagram (see Fig. 8), there appears to be no significant differences in initial learning behaviors. Both groups display a similar probabilistic proclivity in terms of goal setting (0.21/0.18) and knowledge building (0.71/0.75). A small percentage of the active group engages initially in making plans (0.08).

If we look at the dashboard evaluation task, we can detect differences in next-step engagement. The active group displayed a strong inclination to build knowledge after viewing the dashboard (0.7) as compared to the semiengaged group (0.53). The active group was less likely to move straight to summative task after evaluation (0.5/0.38), displaying a little more composure in regard to self-regulation. Similar behavior can be seen with the goal-setting task: The semiengaged group were twice as likely to move from this task to the summative task (0.23/0.11). Again, here we see increased evidence of minor summative-gambling traits, although not as pronounced as the other lower performing group (summative gamblers). Also, after goal setting, we see that the active group displayed a slightly greater tendency to access knowledge building, although this was less pronounced (0.59/0.43).

In viewing the knowledge building task, the active group displayed a stronger sustained focus with a TP self-loop of 0.52, as compared to 0.38. Although margins seem slim, this does indicate a greater sense of value in sustained knowledge building in the active group. If we look at the paths going into this activity, we see the active group was more likely to move here from other activities than the semiengaged group. This highlights a stronger emphasis on knowledge building, as opposed to summative attempts. The semiengaged group displayed a greater focus on the summative assessments (0.19./0.36.), a trait they shared with the summative gamblers (although to a lesser degree). We can see a larger TP self-loop, and likelier tendency to attempt this activity after tackling others.

It is interesting to note that the active group was twice as likely to move from summative work to dashboard evaluation (0.25/0.13). This is also reflected in TPs from other activities, such as knowledge building, formative work, and reflection activities. One could speculate that this demonstrates a tendency toward an optimal SRL tactic of postactivity evaluation; it could also be viewed as a cynical surface learning tactic to maximize dashboard metrics. Either way, it is a manifestation of self-regulation.

V. Conclusion

Using the Trace-SRL framework, we categorized raw learner actions into SRL microprocesses. In doing so, we outlined a method of transforming raw trace data into SRL event data. This in turn allowed for the meaningful analysis of SRL processes in temporal and probabilistic context. Whereas the study by Saint *et al.* [46] tested a novel way of analyzing event dynamics, sustained activity engagement produced very high self-loop TPs, making interpretation challenging in some cases. SRL categorization has removed these data-skewing TPs. We can view a learning sequence as a single event, and thus, it provides a clearer view. Contextualizing sequences of learning actions in a paired or transitional context provides us with a much richer view of behavior, not just strict frequency counts. We can still see the strong urge for students to engage in summative tasks, but in parsing these sequences contextually, we can, to an extent, distinguish between unregulated summative engagement and considered summative engagement.

The findings also reflect the divisive nature of dashboard usage. As posited by both Biggs [70] and Entwistle [71], an unhealthy focus on performance orientation indicates a surface learning approach, indicating an overbalanced focus on summative assessment, and therefore, a suboptimal level of considered, incremental learning. Whilst being useful for certain types of learner, dashboards do not promote effective learning for all groups of students. Clearly, process and self-regulation feedback [66] would be much more beneficial than relying on the comparative measures typically afforded such interfaces.

The findings have genuine empirical echoes. We see a suboptimal overreliance on unsubstantiated reflection and goal setting from the weaker learners, as reported by Veenman [67] and Pintrich [73]. Contrasting movements through Winne and Hadwin's model of SRL [10] are definable between the groups. Optimal learners plan and construct more cohesive patterns of learning. Effective strategy changes, as discussed by Hattie and Timperley [66], are evidenced throughout. Students with optimal SRL processes are seen to favor movement from goal setting to knowledge acquisition (as opposed to summative short-cutting), demonstrating a higher level of metacognitive judgement than their counterparts, as also evidenced by Schraw [72]. This consistency with literature is pleasing, but impactful research needs to go beyond empirical ratification. Only once the method gains its own theoretical traction, can we hope to uncover genuinely novel insights.

This study still represents a simplistic formulation of SRL, notwithstanding the limits to the levels of SRL sophistication, we can glean from trace data. We do not grade the usefulness of learning sequence, for example, a sequence of mainly incorrect summative tests without remedial action (undesirable SRL) or a sequence of mainly incorrect summative tests, then engagement with formative/content access, then a succession of successful actions (good SRL). This metric-based assessment, the parameters of the pattern, as described by Winne in his COPES heuristic framework [73], could afford a rich potential for SRL analysis of trace data. Caution is advised when making inferences on behaviors. Despite its usage, non-objective inferences are sometimes difficult to avoid, even in context of our chosen model of SRL [9]. A more robust framework of validity will be investigated in future work. FOMMs have a short memory; whilst they have provided us with engaging insights into learning behaviors, it would be worth exploring more sophisticated methods of temporal and procedural dynamics in the next cycle of research. The generalizability of this study is limited, and further replications would be constrained to highly similar learning contexts, as opposed to those that use different learning designs and in different subject areas.

Nonetheless, the proposed Trace-SRL framework offers some opportunities to study SRL learning in more general terms that are aligned with the literature of SRL. As such it also offers opportunities for deployment across different learning designs where, previously, LMS platforms exist in conceptual abstraction to SRL. Analysis with PM could allow for early diagnosis of undesirable patterns in SRL and articulation of personalized feedback, as explored in [74].

Our study should be viewed as a groundwork on which to develop technological solutions that support personalized scaffolding of SRL in real-time. We foresee the development of mechanisms that both detect the nuanced details of students' SRL processes and offer guidance on how to improve them. Such solutions do not currently exist but are critical to the systematic and impactful advancement of SRL. For example, the development of an SRL-informed approach proposed here could be used to address some of the critical issues raised by Matcha *et al.* [75] in their systematic review of SRL in learning analytics dashboards (LADs). Our approach could integrate with the next-generation intelligent LADs, such as the one proposed by Shabaninejad *et al.* [76]. Such solutions could provide teachers with valuable insights into students' SRL behaviors. Educators could reflect on and improve their learning designs, thus, enhancing support for students in the context of their own SRL. Student facing systems could also benefit from the use of the proposed approach for the analysis of SRL. This could inform the development of automated methods for the provision of feedback in real-time. This could be achieved by creating rules to trigger specific indicators to the students in a learning system. For example, if the absence of goal setting or metacognitive monitoring is observed, the students would be recommended to take time to review relevant information in the course materials (e.g., learning outcomes or marking criteria) or attempt certain formative assessments.

In order to progress this type of work from exploratory to confirmatory, a more formalized articulation is required. The next logical step is a systematic review of the literature in the context of temporal and sequential approaches to the analysis of SRL. Once relevant dimensions described in the literature are identified, we propose a study that explores how different PM algorithms address all these different dimensions. This could provide critical insights into the trajectory of the next cycle of our research and provide a strong empirical base for an impactful technological solution. The aim is always to improve learning and, as such, we perceive the eventual creation of an *in-situ* mechanism to identify and inform learners in the context of their own SRL.

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References

[1] D. Gašević, S. Dawson, and G. Siemens, "Let's not forget: Learning analytics are about learning," *TechTrends Link. Res. Pract. Improve Learn.*, vol. 59, no. 1, pp. 64–71, Jan. 2015.

[2] I. Roll and P. H. Winne, "Understanding, evaluating, and supporting self-regulated learning using learning analytics," *J. Learn. Anal.*, vol. 2, no. 1, pp. 7–12, Jul. 2015.

[3] P. H. Winne, "A metacognitive view of individual differences in self-regulated learning," *Learn. Individual Differ.*, vol. 8, no. 4, pp. 327–353, Jan. 1996.

[4] P. R. Pintrich and E. V. de Groot, "Motivational and self-regulated learning components of classroom academic performance," *J. Educ. Psychol.*, vol. 82, no. 1, pp. 33–40, Mar. 1990.

[5] B. J. Zimmerman, "A social cognitive view of self-regulated academic learning," *J. Educ. Psychol.*, vol. 81, no. 3, pp. 329–339, Sep. 1989.

[6] P. H. Winne and N. E. Perry, "Chapter 16—Measuring self-regulated learning," in *Handbook of Self-Regulation*, M. Boekaerts, P. R. Pintrich, and M. Zeidner, Eds. San Diego, CA, USA: Academic, 2000, pp. 531–566.

[7] J. A. Greene and R. Azevedo, "A macro-level analysis of SRL processes and their relations to the acquisition of a sophisticated mental model of a complex system," *Contemp. Educ. Psychol.*, vol. 34, no. 1, pp. 18–29, Jan. 2009.

[8] T. J. Cleary and B. J. Zimmerman, "A cyclical self-regulatory account of student engagement: Theoretical foundations and applications," in *Handbook of Research on Student Engagement*, S. L. Christenson, A. L. Reschly, and C. Wylie, Eds. Boston, MA, USA: Springer, 2012, pp. 237–257.

[9] M. Siadaty, D. Gasevic, and M. Hatala, "Trace-based micro-analytic measurement of self-regulated learning processes," *J. Learn. Anal.*, vol. 3, no. 1, pp. 183–214, Apr. 2016.

[10] P. H. Winne and A. F. Hadwin, "Studying as self-regulated learning," in *Metacognition in Educational Theory and Practice*. Mahwah, NJ, USA: Lawrence Erlbaum, 1998, pp. 277–304.

[11] P. Reimann, L. Markauskaite, and M. Bannert, "e-Research and learning theory: What do sequence and process mining methods contribute?," *Brit. J. Educ. Technol.*, vol. 45, no. 3, pp. 528–540, Feb. 2014.

[12] P. Reimann, "Time is precious: Variable- and event-centred approaches to process analysis in CSCL research," *Int. J. Comput.-Support. Collab. Learn.*, vol. 4, no. 3, pp. 239–257, Sep. 2009.

[13] S. Knight, A. F. Wise, and B. Chen, "Time for change: Why learning analytics needs temporal analysis," *J. Learn. Anal.*, vol. 4, no. 3, Dec. 2017, Art. no. 3.

[14] B. Chen, S. Knight, and A. F. Wise, "Critical issues in designing and implementing temporal analytics," *J. Learn. Anal.*, vol. 5, no. 1, Apr. 2018, Art. no. 1.

[15] C. Sonnenberg and M. Bannert, "Evaluating the impact of instructional support using data mining and process mining: A micro-level analysis of the effectiveness of metacognitive prompts," *JEDM J. Educ. Data Mining*, vol. 8, no. 2, Dec. 2016, Art. no. 2.

[16] K. Engelmann and M. Bannert, "Analyzing temporal data for understanding the learning process induced by metacognitive prompts," *Learn. Instruct.*, May 2019. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0959475218307163?via%3Dihub

[17] P. H. Winne and D. Jamieson-Noel, "Exploring students' calibration of self reports about study tactics and achievement," *Contemp. Educ. Psychol.*, vol. 27, no. 4, pp. 551–572, Oct. 2002.

[18] E. Fincham, D. Gasevic, J. Jovanović, and A. Pardo, "From study tactics to learning strategies: An analytical method for extracting interpretable representations," *IEEE Trans. Learn. Technol.*, vol. 12, no. 1, pp. 59–72, Jan.–Mar. 2019.

[19] G. Lust, J. Elen, and G. Clarebout, "Regulation of tool-use within a blended course: Student differences and performance effects," *Comput. Educ.*, vol. 60, no. 1, pp. 385–395, Jan. 2013.

[20] M. Zhou and P. H. Winne, "Modeling academic achievement by self-reported versus traced goal orientation," *Learn. Instruct.*, vol. 22, no. 6, pp. 413–419, Dec. 2012.

[21] P. H. Winne, "Learning analytics for self-regulated learning," in *Handbook of Learning Analytics*, First., C. Lang, G. Siemens, A. Wise, and D. Gasevic, Eds. Society for Learning Analytics Research (SoLAR), Alberta, Canada, 2017, pp. 241–249.

[22] P. H. Winne, "Issues in researching self-regulated learning as patterns of events," *Metacognit. Learn.*, vol. 9, no. 2, pp. 229–237, Aug. 2014.

[23] M. Siadaty, D. Gašević, and M. Hatala, "Associations between technological scaffolding and micro-level processes of self-regulated learning: A workplace study," *Comput. Human Behav.*, vol. 55, pp. 1007–1019, Feb. 2016.

[24] K. A. Ericsson and H. A. Simon, "Verbal reports as data," *Psychol. Rev.*, vol. 87, no. 3, pp. 215–251, May 1980.

[25] K. A. Ericsson and H. A. Simon, in *Protocol Analysis: Verbal Reports As Data*. Cambridge, MA, USA: MIT Press, 1984, p. 426.

[26] M. Bannert, P. Reimann, and C. Sonnenberg, "Process mining techniques for analysing patterns and strategies in students' self-regulated learning," *Metacognit. Learn.*, vol. 9, no. 2, pp. 161–185, Aug. 2014.

[27] J. A. Greene, J. Robertson, and L.-J. C. Costa, "Assessing self-regulated learning using think-aloud methods," in *Handbook of Self-Regulation of Learning and Performance*. New York, NY, USA: Routledge, 2011, pp. 313–328.

[28] K. A. Young, "Direct from the source: The value of 'think-aloud' data in understanding learning," *J. Educ. Enquiry*, vol. 6, no. 1, pp. 19–33, Oct. 2005.

[29] D. Gasevic, J. Jovanović, A. Pardo, and S. Dawson, "Detecting learning strategies with analytics: Links with self-reported measures and academic performance," *J. Learn. Anal.*, vol. 4, no. 2, Jul. 2017, Art. no. 2.

[30] D. Gašević, S. Dawson, T. Rogers, and D. Gasevic, "Learning analytics should not promote one size fits all: The effects of instructional conditions in predicting academic success," *Internet Higher Educ.*, vol. 28, pp. 68–84, Jan. 2016.

[31] J. Maldonado-Mahauad, M. Pérez-Sanagustín, R. F. Kizilcec, N. Morales, and J. Munoz-Gama, "Mining theory-based patterns from big data: Identifying self-regulated learning strategies in massive open online courses," *Comput. Human Behav.*, vol. 80, pp. 179–196, Mar. 2018.

[32] R. Azevedo *et al.*, "Using trace data to examine the complex roles of cognitive, metacognitive, and emotional self-regulatory processes during learning with multi-agent systems," in *International Handbook of Metacognition and Learning Technologies*. R. Azevedo and V. Aleven, Eds. New York, NY, USA: Springer, 2013, pp. 427–449.

[33] S. F. E. Rovers, G. Clarebout, H. H. C. M. Savelberg, A. B. H. de Bruin, and J. J. G. van Merriënboer, "Granularity matters: Comparing different ways of measuring self-regulated learning," *Metacognit. Learn.*, vol. 14, no. 1, pp. 1–19, Apr. 2019.

[34] Y. Fan *et al.*, "Measuring micro-level self-regulated learning processes with enhanced log data and eye tracking data," in *Proc. Companion 10th Int. Conf. Learn. Anal. Knowl.*, Frankfurt, Germany, Mar. 2020, pp. 433–436.

[35] K. P. Lim *et al.*, "Triangulating multimodal data to measure self-regulated learning," in *Proc. Companion 10th Int. Conf. Learn. Anal. Knowl.*, Frankfurt, Germany, Mar. 2020, pp. 98–100.

[36] P. H. Winne, "How software technologies can improve research on learning and bolster school reform," *Educ. Psychol.*, vol. 41, no. 1, pp. 5–17, Mar. 2006.

[37] I. Molenaar, "Advances in temporal analysis in learning and instruction," *Frontline Learn. Res.*, vol. 2, no. 4, Dec. 2014, Art. no. 4.

[38] I. Molenaar and S. Järvelä, "Sequential and temporal characteristics of self and socially regulated learning," *Metacognit. Learn.*, vol. 9, no. 2, pp. 75–85, Aug. 2014.

[39] C. W. Günther and W. M. P. van der Aalst, "Fuzzy mining – Adaptive process simplification based on multi-perspective metrics," in *Business Process Management*. Berlin, Heidelberg: Springer, Sep. 2007, pp. 328–343.

[40] W. van der Aalst *et al.*, "Process mining manifesto," in *Proc. Bus. Process Manage. Workshops*, Berlin, Heidelberg, Aug. 2011, pp. 169–194.

[41] W. van der Aalst, *Process Mining: Data Science in Action*, 2nd ed., Berlin, Heidelberg: Springer-Verlag, 2016.

[42] R. Cerezo, A. Bogarín, M. Esteban, and C. Romero, "Process mining for self-regulated learning assessment in e-learning," *J. Comput. Higher Educ.*, vol. 32, no. 1, pp. 74–88, Apr. 2020.

[43] B. J. Zimmerman, "Chapter 2—Attaining self-regulation: A social cognitive perspective," in *Handbook of Self-Regulation*, M. Boekaerts, P. R. Pintrich, and M. Zeidner, Eds. San Diego, CA, USA: Academic, 2000, pp. 13–39.

[44] C. Romero, R. Cerezo, A. Bogarín, and M. Sánchez-Santillán, "Educational process mining," in *Data Mining and Learning Analytics*. Hoboken, NJ, USA: Wiley, 2016, pp. 1–28.

[45] R. Gatta *et al.*, "Generating and comparing knowledge graphs of medical processes using pMineR," in *Proc. Knowl. Capture Conf.*, 2017, pp. 1–4, doi: 10.1145/3148011.3154464.

[46] J. Saint, D. Gašević, and A. Pardo, "Detecting learning strategies through process mining," in *Lifelong Technology-Enhanced Learning*. Cham, Switzerland: Springer, Sep. 2018, pp. 385–398.

[47] W. Matcha, D. Gašević, N. Ahmad Uzir, J. Jovanović, and A. Pardo, "Analytics of learning strategies: Associations with academic performance and feedback," in *Proc. 9th Int. Conf. Learn. Analy. Knowl.*, Tempe, AZ, USA, Mar. 2019, pp. 461–470.

[48] J. Saint, D. Gašević, W. Matcha, N. A. Uzir, and A. Pardo, "Combining analytic methods to unlock sequential and temporal patterns of self-regulated learning," in *Proc. 10th Int. Conf. Learn. Anal. Knowl.*, Frankfurt, Germany, Mar. 2020, pp. 402–411.

[49] P. H. Winne, L. Gupta, and J. C. Nesbit, "Exploring individual differences in studying strategies using graph theoretic statistics," *Alberta J. Educ. Res.*, vol. 40, no. 2, pp. 177–193, 1994.

[50] P. H. Winne, "Learning strategies, study skills, and self-regulated learning in postsecondary education," in *Higher Education: Handbook of Theory and Research: Volume 28*, M. B. Paulsen, Ed. Dordrecht, Netherlands : Springer, 2013, pp. 377–403.

[51] G. Lust, M. Vandewaetere, E. Ceulemans, J. Elen, and G. Clarebout, "Tool-use in a blended undergraduate course: In search of user profiles," *Comput. Educ.*, vol. 57, no. 3, pp. 2135–2144, Nov. 2011.

[52] J. Jovanović, D. Gašević, S. Dawson, A. Pardo, and N. Mirriahi, "Learning analytics to unveil learning strategies in a flipped classroom," *Internet Higher Educ.*, vol. 33, pp. 74–85, Apr. 2017.

[53] N. Ahmad Uzir, D. Gašević, J. Jovanović, W. Matcha, L.-A. Lim, and A. Fudge, "Analytics of time management and learning strategies for effective online learning in blended environments," in *Proc. 10th Int. Conf. Learn. Anal. Knowl.*, New York, NY, USA, 2020, pp. 392–401.

[54] P. H. Winne and A. F. Hadwin, "nStudy: Tracing and supporting self-regulated learning in the Internet," in *International Handbook of Metacognition and Learning Technologies*. R. Azevedo and V. Aleven, Eds. New York, NY, USA: Springer, 2013, pp. 293–308.

[55] M. S. Boroujeni and P. Dillenbourg, "Discovery and temporal analysis of MOOC study patterns," *J. Learn. Anal.*, vol. 6, no. 1, Apr. 2019, Art. no. 16.

[56] C. W. Günther and A. Rozinat, "Disco: Discover your processes," in *Proc. Demonstration Track 10th Int. Conf. Bus. Process Manage.*, 2012, pp. 40–44.

[57] J. Maldonado-Mahauad, M. Pérez-Sanagustín, P. M. Moreno-Marcos, C. Alario-Hoyos, P. J. Muñoz-Merino, and C. Delgado-Kloos, "Predicting learners' success in a self-paced MOOC through sequence patterns of self-regulated learning," in *Lifelong Technology-Enhanced Learning*. Cham, Switzerland: Sep. 2018, pp. 355–369.

[58] A. van den Beemt, J. Buijs, and W. van der Aalst, "Analysing structured learning behaviour in massive open online courses (MOOCs): An approach based on process mining and clustering," *Int. Rev. Res. Open Distrib. Learn.*, vol. 19, no. 5, pp. 38–60, Nov. 2018.

[59] A. Pardo and N. Mirriahi, "Design, deployment and evaluation of a flipped learning first-year engineering course," in *The Flipped Classroom: Practice and Practices in Higher Education*, C. Reidsema, L. Kavanagh, R. Hadgraft, and N. Smith, Eds. Singapore: Springer, 2017, pp. 177–191.

[60] A. Gabadinho, G. Ritschard, N. S. Müller, and M. Studer, "Analyzing and visualizing state sequences in r with tramineR," *J. Stat. Softw.*, vol. 40, no. 1, Art. no. 1, Apr. 2011.

[61] V. Kovanović, D. Gašević, S. Joksimović, M. Hatala, and O. Adesope, "Analytics of communities of inquiry: Effects of learning technology use on cognitive presence in asynchronous online discussions," *Internet Higher Educ.*, vol. 27, pp. 74–89, Oct. 2015.

[62] L. K. Muthén and B. O. Muthén, *Mplus Statistical Analysis With Latent Variables: User's Guide*. Los Angeles, CA, USA: Muthen and Muthen, 2017.

[63] R. Gatta *et al.*, "Generating and comparing knowledge graphs of medical processes using pMineR," in *Proc. Knowl. Capture Conf.*, Austin, TX, USA, Dec. 2017, pp. 1–4.

[64] D. L. Butler and P. H. Winne, "Feedback and self-regulated learning: A theoretical synthesis," *Rev. Educ. Res.*, vol. 65, no. 3, pp. 245–281, Sep. 1995.

[65] R. A. Bjork, J. Dunlosky, and N. Kornell, "Self-regulated learning: Beliefs, techniques, and illusions," *Annu. Rev. Psychol.*, vol. 64, no. 1, pp. 417–444, Mar. 2013.

[66] J. Hattie and H. Timperley, "The power of feedback," *Rev. Educ. Res.*, vol. 77, no. 1, pp. 81–112, Mar. 2007.

[67] M. V. J. Veenman, *Intellectual Ability and Metacognitive Skill: Determinants of Discovery Learning in Computerized Learning Environments*. Faculteit Psychologie, Universiteit van Amsterdam, 1993.

[68] S. J. Aguilar, "Examining the relationship between comparative and self-focused academic data visualizations in at-risk college students' academic motivation," *J. Res. Technol. Educ.*, vol. 50, no. 1, pp. 84–103, Jan. 2018.

[69] C. Senko, C. S. Hulleman, and J. M. Harackiewicz, "Achievement goal theory at the crossroads: Old controversies, current challenges, and new directions," *Educ. Psychol.*, vol. 46, no. 1, pp. 26–47, Jan. 2011.

[70] J. Biggs, "What the student does: Teaching for enhanced learning," *Higher Educ. Res. Develop.*, vol. 31, no. 1, pp. 39–55, Feb. 2012.

[71] N. Entwistle, *Teaching For Understanding at University: Deep Approaches and Distinctive Ways of Thinking*. Basingstoke, U.K.: Palgrave Macmillan, 2009.

[72] G. Schraw, "A conceptual analysis of five measures of metacognitive monitoring," *Metacognit. Learn.*, vol. 4, no. 1, pp. 33–45, Apr. 2009.

[73] P. R. Pintrich, "The role of metacognitive knowledge in learning, teaching, and assessing," *Theory Pract.*, vol. 41, no. 4, pp. 219–225, Nov. 2002.

[74] A. Pardo, D. Gašević, J. Jovanović, S. Dawson, and N. Mirriahi, "Exploring student interactions with preparation activities in a flipped classroom experience," *IEEE Trans. Learn. Technol.*, vol. 12, no. 3, pp. 333–346, Jul.–Sep. 2019.

[75] W. Matcha, N. A. Uzir, D. Gašević, and A. Pardo, "A systematic review of empirical studies on learning analytics dashboards: A self-regulated learning perspective," *IEEE Trans. Learn. Technol.*, vol. 13, no. 2, pp. 226–245, Apr.–Jun. 2020.

[76] S. Shabaninejad, H. Khosrav, S. J. J. Leeman, S. Shazia, and M. Indulska, "Recommending insightful drill-downs based on learning processes for learning analytics dashboards," in *Proc. 21st Int. Conf. Artif. Intell. Educ.*, Ifrane, Morocco, Jul. 2020, pp. 486–499.

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4.3 Summary

This chapter represents the first exploration SRL model deployment in authentic trace data settings. We acknowledge the debt to Greene and Azevedo (2009) for developing the micro-process analysis method, and to Siadaty et al. (2016), who highlighted the use of regular expressions (REGEX) to parse raw data into SRL processes. We developed a REGEX script in R to parse authentic LMS data, using a pattern library derived from informed analysis of sequences of the raw data. Although this was not highlighted in the publication, we actually used the first order Markov model process mining algorithm to undertake initial research on the data. This provided us with a broad view of the commonly occurring action sequences on which to inform our definition of the micro-process pattern library which provided the rules for the data transformation.

The generation of such pattern libraries throws up a number of questions around action sequence priority. To clarify, certain higher cognition SRL pattern sequences are composites of lower cognition sequences. For example, we determined the high cognition *Make Plans* micro-level process as a sequence of orientation tasks, then content access, then back to orientation. In this context, content access is seen as a low-level cognitive activity, which is an SRL process in its own right, and is also part of a more complex high level process. In our study we employed a priority mechanism which prevented content access from being part of two concurrent SRL processes. This mechanism remained in place for the remainder of our studies but it opens up an interesting ontological question. Can a learner engage in two levels of self regulation, and should we represent it?

Notwithstanding this, and the broader question of construct validity, we maintain that the study reported on in this chapter provided a bedrock on which similar trace-based SRL studies can be built. As with the Chapter three study, we made use of the pMineR "compare models" to elicit key difference in learner behaviours from a position of temporal and sequential likelihood, but critically in this study, we were able to employ the context of SRL. For example, we detected that, at the start of learning sessions, low performing learners were more than three times likely to engage with summative assessment tasks without any session preparation, than high performers. This indication of a less disciplined approach to self-regulation could be used to inform learning design, or could be used to generate specific feedback messages to learners, or as part of a broader message on the importance of SRL.

Whilst we hope that the benefits of using pMineR and stochastic process mining are well articulated in this study, we recognise that even richer insights can be derived from combining analytic methods. As such, we retained the "Trace-SRL" framework for the two studies reported on in Chapter five and Chapter six, but explore a broader set of methods, with the hope of providing richer outcomes.

5 Comparing Discovery Algorithms

Don't compare your beginning to someone else's middle, or your middle to someone else's end.

— Tim Hiller, *Strive: Life is Short, Pursue What Matters*

5.1 Introduction

THE use of multiple and/or mixed methods is common in many research disciplines, and this use has itself been the source of a reasonable body of research (e.g., Morse (2003), Johnson et al. (2007)). In the context of the exploration of temporally focused SRL, there are two broad categories, as discussed in Chapter two. One is the use of multiple data sources or channels, commonly a mixture of trace data and some sort of self-report mechanism. The other is the use of multiple analytic techniques for the discovery and visualisation of designated phenomena, and it is this diversification of methods that we explore in this chapter.

Several key studies have explored the dynamics of learning using multiple analytic discovery methods. The Sonnenberg and Bannert (2016) and Sedrakyan et al. (2016) studies both used process mining algorithms and dotted chart graphs to provide insights into SRL. The Sonnenberg and Bannert study did not, however, capture authentic trace data. The studies by Ahmad Uzir et al. (2020) and Fan et al. (2021) both used combinations of process mining and epistemic network analysis, which provided key insights into the sequence and duration of learner tactics and their transitions (as afforded by process mining), and the temporal co-occurrence of the same learner tactics (as afforded by epistemic network analysis). This combined interpretation did prove to offer richer insights into tactic use. In our study, we explored this multi-perspective analysis, but further explored how combining them provided a more ontologically complete view of the SRL processes analysed. No one, as far as we are aware, has presented a study which explores the combination and consolidation of various analytic methods to analyse systematically generated SRL process data.

To that end, building on the trace-SRL method explored in Chapter four, we expand the analytic scope to present a study which serves to investigate these research questions:

(RQ2) *How effectively can we measure the temporal dynamics of learning strategies in delineated student groupings, using process analytic techniques?*
(RQ3) *To what extent can we develop a framework to embed temporally focused analysis of learning in a theoretical model of self-regulated learning?*
(RQ4) *To what extent can we combine analytic methods to further explore self-regulated learning from a perspective of temporality and sequence?*

5.1.1 Chapter overview

In the previous studies, reported on in Chapter three and Chapter four, we established the use of a novel stochastic process mining algorithm (pMineR's first order Markov models) as a means of exploring learner behaviours from authentic trace data, and a way of framing this authentic trace data in a recognised model of SRL (Trace-SRL). In this chapter, we seek to build on this work by exploring the use of multiple analytic discovery methods on a common SRL-transformed dataset. Although the data comes from the same LMS as was used in the previous two studies, we extracted different learner groups, based purely on assessment performance. The key insights from this study come from the comparison of insights from the following techniques:

- Frequency-based statistics: we produced a very simple set of descriptive measures relating to the absolute and relative engagement in SRL activities of our two learner groups (high and low performers). This serves as a base-level discovery method, and is overtly simplistic in design.
- Epistemic Network Analysis: a method which categorises features of individual and group learning (e.g., action or communication), which it then uses to create nodes in an epistemic network. Associative connections are established through relative weighting and statistical techniques. In simpler terms, this technique does emphasise transition between activities (like process mining), but through temporal co-occurrence, as well as using singular value decomposition to identify salient properties (Shaffer et al., 2016).
- Stochastic process mining: The main stochastic process mining method explored in the previous studies in this paper, utilising the pMineR algorithm (Gatta, Lenkowicz, et al., 2017). It provided us with a sense of likelihood of transition from one SRL process to the next.
- Temporal process mining: more accurately, time-based process mining. The bupaR package (Janssenswillen et al., 2019) was used to analyse SRL process engagement in which median duration/lag was deployed as the main metric.

5.2 Publication: Combining analytic methods to unlock sequential and temporal patterns of self-regulated learning

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

> Saint, J., Gašević, D., Matcha, W., Ahmad Uzir, N., & Pardo, A. (2020). Combining analytic methods to unlock sequential and temporal patterns of self-regulated learning. *Proceedings of the Tenth International Conference on Learning Analytics & Knowledge*, 402–411. https://doi.org/10.1145/3375462.3375487

Combining Analytic Methods to Unlock Sequential and Temporal Patterns of Self-Regulated Learning

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ABSTRACT

The temporal and sequential nature of learning is receiving increasing focus in Learning Analytics circles. The desire to embed studies in recognised theories of self-regulated learning (SRL) has led researchers to conceptualise learning as a process that unfolds and changes over time. To that end, a body of research knowledge is growing which states that traditional frequency-based correlational studies are limited in narrative impact. To further explore this, we analysed trace data collected from online activities of a sample of 239 computer engineering undergraduate students enrolled on a course that followed a flipped class-room pedagogy. We employed SRL categorisation of micro-level processes based on a recognised model of learning, and then analysed the data using: 1) simple frequency measures; 2) epistemic network analysis; 3) temporal process mining; and 4) stochastic process mining. We found that a combination of analyses provided us with a richer insight into SRL behaviours than any one single method. We found that better performing learners employed more optimal behaviours in their navigation through the course's learning management system.

CCS CONCEPTS

• Applied computing → Education → Learning management systems • Computing methodologies → Machine learning → Learning settings → Active learning settings

KEYWORDS

Learning Analytics, Self-regulated Learning, Micro-level Processes, Epistemic Network Analysis, Process Mining

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1 INTRODUCTION

There is an increasing focus on the capture and analysis of learner data to provide insights into patterns of self-regulated learning (SRL). In Learning Analytics (LA), the temporal nature of SRL is inspiring researchers to augment conventional statistical measures with techniques more suited to capturing the dynamics of temporality in learner engagement [10,19]. Despite this positive trajectory, many challenges exist in articulating the nuanced dimensions of SRL from data extracted from online and blended educational environments. Such data can be noisy, which presents challenges in the moderation of data dimensionality. More crucially, although lip service is often paid to SRL, many studies do not strictly employ recognised theoretical models of SRL to underpin their analyses e.g. [30].

The increasing focus on SRL has inspired the creation and ongoing development of numerous models of SRL [27,38,39]. A general theme is a cyclical dynamic of 1) Planning and forethought; 2) Performance and monitoring; and 3) Reflection and evaluation. To facilitate the framing of analyses in models of SRL, a technique known as micro-level process analysis was developed [16]. Raw log data (digital or self-report) are categorised into event sequences – micro-processes – which represent sub-processes of a broad SRL construct, or macro-process. The aim of micro-level process analysis is to articulate a set of event categorisations which form the requisite model of SRL.

Several approaches have been proposed to analyse sequential and temporal aspects of SRL. Most of these studies are based on self-reported extraction of SRL micro-level processes, and they typically use a single methodological approach for analysis. Some of these approaches emphasise sequencing through the use of sequence mining algorithms such as optimal state matching [37]. Others employ process-oriented approaches, e.g., process mining algorithms such as FuzzyMiner or Heursitic Miner e.g. [5,35] and co-temporal approaches e.g., graph-based methods [36]. These studies provided useful comparative insights but not in the context of micro-level processes of SRL. Studies by [34] employed trace data in an embedded model of micro-level process SRL. These studies, however, utilised a single method of model discovery, providing a useful, but limited analytical view of the event activities. A study by [23] introduced a multi-method approach to learner data analysis but was not embedded in a recognised model of SRL.

We argue that the following factors underpin impactful studies of this kind: 1) An explicit usage of recognised theoretical model of SRL; 2) A data-driven method of capture that is authentic, yet nuanced enough, to reflect the patterns of learner behaviour outlined in the chosen model of SRL; 3) An analytical method capable of articulating SRL in a dimensional way, using a range of methods i.e. frequency-based, sequential, and temporal. As far as we are aware nobody has attempted a combined frequency-based, temporal and cotemporal study embedded in a recognised model of SRL.

We therefore present a novel study which:

- Adopts an approach for the measurement of SRL micro-level processes from digital traces collected from an authentic learning environment.
- Proposes a complementary method combining epistemic network analysis (ENA) and process mining techniques on sequences of extracted SRL micro-level processes.
- Identifies patterns of self-regulation across different learner groups.
- Presents an approach for the qualitative and quantitative comparison of SRL across learner groups.

2 BACKGROUND

2.1 Measurement of Self-Regulated Learning

The benefits of effective self-regulation have been well-documented [9]. A common theme is the idea that effective learners take control of their own learning through a cyclical process of internal and external feedback mechanisms. The main procedural elements of the cycle are planning, performance (monitoring), and reflection [27,38,39]. There is, however, an ongoing ontological disparity between what is described in theoretical models of SRL and what can be captured to support their constructs. For this reason, there is still a heavy reliance on self-report mechanisms to support the capture of the (meta-) cognitive and motivational elements of SRL [21]. While self-reports provide the requisite level of conceptual articulation, there are proven shortcomings. Students generally exhibit suboptimal reporting of their own learning processes, introducing a kind of cognitive sample bias. In addition, post-event recollections are subject to natural memory degradation [13].

The choice to forgo self-report data and use pure trace data to measure SRL eliminates some issues but introduces new ones. For studies that seek to extract trace-data from authentic settings, challenges exist around validating engagement sequences as actual constructs of SRL. Some researchers advise against analysing trace-data at all without employing a complementary off-line self-report method [40]. This notwithstanding, one of the techniques available to dampen the noise of raw data and embed analysis in a recognised model of SRL, is micro-level process analysis.

2.2 Micro-level Process Analysis

Raw learner data, whether it is self-report or trace, can be quite noisy. Extracting valid meaning from it poses challenges around interpretation, validity, and generalisability. To answer this challenge Greene and Azevedo [16] devised a system of categorisation which defined a set of self-regulatory activities as micro-level SRL processes. These micro-level processes were themselves sub-categories of broader macro-level processes: planning, monitoring activities, strategy use, handling task difficulties and demands, and interest. These elements form the constructs of their chosen SRL model[4]. This thus represents a hierarchy: macro-level processes → micro-level processes → system specific learner activities. A majority of existing studies into micro-level processes are based on self-report instruments. A notable exception is Siadaty et al. who use trace data in their analyses [34]. From this data, a comprehensive picture of workplace learners' self-regulation was interpreted in the context of the model of SRL, as theorised by Zimmerman [39]. This paper builds on this method to similarly embed the analyses in a model of SRL.

2.3 Temporal Analysis

A large body of LA research is based on conventional, frequency-based statistical analysis. The prevalence of such analyses is understandable; correlational analysis is, as a method, the lingua franca of social sciences quantitative analysis. Its rules are widely known, and it has the empirical weight of many years of applied experimentation. It is, however, limited in its expression and measurement of temporal dynamics [28].

The idea that learning and, more specifically SRL, is a process that unfolds in temporal, yet cyclical, space [9] is well-established. Indeed, given the trajectorial nature of learning and the significance of temporal factors in LA, we would expect a great wealth of time-based analyses in the field. Temporality is, however, relatively underexplored in relation to its importance, despite the availability of data relating to the learning process in context of time and order [19]. Chen, Knight, and Wise [10] highlight temporal analytics in two modes: 1) the passage of time and frequency/lengths of engagement; 2) the order of sequence of engagement events. It would be prudent to consider a third direction; the analysis of the change in patterns of engagement over time, as evidenced in [14] and [24].

Oshima, Oshima, and Fugita use a mixed-method approach in their study in an effort to articulate multiple scales of temporality

[25]. As posited by Knight et al., "Such efforts towards triangulation are important for validating results and offering robust interpretations of the data with which to inform practice" [19, p.13]. To that end, descriptive statistics are employed to augment, if not underpin, the analytical narrative of this study. This study seeks to establish a novel direction in promoting the multi-method measurement of SRL temporal dynamics using complementary approaches that emphasise network [22] and process dimensions [15,17].

2.4 Methodological Choices

2.4.1 Network analysis. Network-based approaches fall into several categories. Transition graphs provide insight into process movement in terms of likely temporal sequence. Cotemporal methods allow us to frame activity engagement in terms of co-occurring temporal associations[33]. Swiecki et al. [36] provide a compelling account of the relative efficacy of cotemporal methods and sequential methods also used in the current study, sugg[26]esting that cotemporal methods provide stronger analyses. Epistemic network analysis (ENA) is a cotemporal analytical technique which utilises epistemic frames theory to analyse log/trace data in individual and collaborative settings [32]. The theory of epistemic frames views expertise in complex domains as a network of connections among knowledge, skills, values, and decision-making processes [33]. ENA categorises features of individual and group learning e.g. action, communication, and cognition, which it then uses to create nodes in an epistemic network. Associative connections are established through relative weighting. Statistical techniques are employed to compare the salient properties of networks generated in the context of the content of the network and traces of learning processes [33].

2.4.2 Process Mining. Process mining (PM) is an event-based analytical method that derives sequential, associative and temporal analyses from log data files. It has steadily gained traction in educational science as LA and EDM researchers continue to explore alternatives to variable-centric analytical methods. Taking event log files as its input, PM utilises discovery algorithms which allow the identification of common logical arrangements of processes in a temporal space [1]. This can be seen in SRL studies reported in [5,6,20]. These studies provide crucial insights into sequential and temporal dynamics of SRL, however, the empirical weight of some of the PM metrics employed has not been fully established.

2.5 Research Questions

To our knowledge, there have been limited attempts to analyse patterns of SRL through the lens of frequency-based, temporal and cotemporal models. We posit that the combined analytical picture provided by these methods is richer than their individual contribution. We aim to combine these methods on authentically generated LMS trace data to address these questions:

1. To what extent can we qualitatively and quantitively characterise students' learning behaviours from event sequences of SRL micro-level processes, using frequency measures, network analysis, and process mining?
2. To what extent can we articulate contrasting patterns of SRL behaviours across different student groups, based on assessment performance, by using frequency measures, network analysis, and process mining?
3. To what extent can we consolidate these analytical methods to provide a coherent temporal/sequential narrative on SRL, as enacted in a blended-learning environment?

3 METHODOLOGY

3.1 Trace Data Collection

The data for this study were collected from a Computer Engineering course at a university in Australia. The course material and activities were managed using a bespoke LMS with a set of additional tools for instrumentalisation. Three student cohorts of data provided the initial combined trace dataset from which we took a sample of 239 students' action logs. For each of the three years, 12 weeks of LMS engagement data are present. The course was based on a flipped classroom pedagogy. The data used in this study were generated from students' engagement with the online LMS activities. These activities served the purpose of preparation for the classroom-based face-to-face activities. Every time a student engaged with an element of the LMS, a timestamped log was generated, identifying the learning action. Table 1 contains a list of the recorded learning actions. A more detailed account of the educational and methodological settings of the course can be found in [26].

Table 1: LMS learning actions and descriptions

Learning Action	Description
EXE_CO	Correctly solving a summative assessment item
EXE_IN	Incorrectly attempted summative assessment item
MCQ_CO	Correctly solved formative assessment item (MCQ)
MCQ_IN	Incorrectly attempted formative assessment item (MCQ)
MCQ_SR	Solution request for an MCQ
VIDEO_LOAD	Course video load
VIDEO_PL	Course video play
VIDEO_PA	Course video pause
VIDEO_END	Course video end
CONTENT_ACCESS	Reading materials access
MC_EVAL	Dashboard access
INDEX_ACCESS	Index page access
PROJECT_ACCESS	Project page access
MC_ORIENT	Accessing the schedule and the learning objective pages

3.2 Data Preparation

3.2.1 Session Identification. As part of a study reported in [18], the LMS trace data were, for each learner, further segmented into temporally discrete sessions, so as to distinguish separate passages of engagement over the course of the taught term. A session included all timestamped traces of events between log-in and log-out events. In cases of too long time between two consecutive activities (several hours), implicit log-out and log-in pairs were inserted whenever activities were longer than 95th percentile, as per the approach proposed in [18]. This is a critical point in this study, as sessions are used as an important unit of analysis (see Data Analysis section).

3.2.3 Decile Extraction. Previous studies have demonstrated the usefulness of comparing contrasting groups to identify differences in learning processes. In studies where access to assessment marks is provided, e.g. [5], researchers can use these to distinguish higher vs lower performers. We accessed the midterm and final exam scores for all students and combined them to derive the overall marks. Based on these marks, we identified the top and bottom 10 percent of students, in terms of overall assessment performance. The two groups were named 'top decile' (n = 107, $n_{learner\_actions}$ = 159,125) and 'bottom decile' (n = 132, $n_{learner\_actions}$ = 128,267).

3.2.2 SRL Categorisation (micro-process analysis). In order to represent the log data in an SRL context, we derived a theoretical model of macro- and micro-level processes, building on the work undertaken by Siadaty et al. [34]. Based on this model, we created a regular expression (REGEX) parsing engine to categorise sequences of learner actions into micro-level actions. For example, a sequence of MC_ORIENT activities is categorised as SRL micro-process action *Goal_Set*; a sequence of CONTENT_ACCESS or VIDEO access actions is categorised as *Work_on_Task.Knowledge.Build.* Table 2 contains a full account of the macro to micro-level mappings, based on a theoretical model of SRL similar to that used by Siadaty et al. In this way, we characterise learner behaviours in the context of an established theoretical model of SRL.

Table 2: SRL Micro Process Mapping

Macro-level process	Micro-level process	Micro-level activity mapping
Planning	Goal Setting	**Goal_Set** MC_ORIENT, INDEX ACCESS, PROJECT ACCESS (single event or sequence)
	Making Personal Plans	**Make_Plans** MC_ORIENT to a cycle of Content/Video access then back to MC_ORIENT
Engagement	Working on a Task	**Work_on_Task.Summative** EXE_CO or EXE_IN (in a randomly assorted sequence)
		Work_on_Task.Formative MCQ_CO or MCQ_IN (in a randomly assorted sequence)
		Work_on_Task.Knowledge_build CONTENT_ACCESS or VIDEO activity (in a randomly assorted sequence)
Evaluation and Reflection	Evaluation	**Eval.Dash** MC_EVAL sequence
		Eval.Formative_Answer MSQ_SR sequence
	Reflection	**Reflect** EXE actions (both correct and incorrect, assorted) before switch to CONTENT_ACCESS or VIDEO activity sequence

The end result is a coarsened dataset of timestamped SRL events ready for input to the next cycle of analyses. For the top decile, the SRL event count is 23,462; for the bottom decile, 13,818.

3.3 Data Analysis

We employed four analysis methods: 1) simple frequency analysis; 2) epistemic network analysis; 3) temporal process mining; and 4) stochastic process mining.

All of these methods were employed to address RQ1 (see Section 4.1). In this section, we present the four methods in discrete succession, as a means of demonstrating the contrasting analytical outcomes as articulated on the same dataset(s). We do not, at this stage, emphasise the differing behaviours of the groups, but rather present general analysis of commonality.

For RQ2 (Section 4.2), we again employed all four methods discretely. We explicitly drew comparisons between the two deciles in order to identify differing optimal, sub-optimal, or neutral shades of learner behaviour.

For RQ3 (section 4.3), we present a combined methodological analysis, contextualised across the phases of our SRL model: Planning, Engagement, and Evaluation & Reflection. In this section, we present a consolidation of methods in order to prove that a richer analytical insight can be derived from combination, as opposed to discrete narratives. In addition, we present an ENA-specific analysis – weekly means rotation – which provides a longer term temporal view.

3.3.1 Frequency Analysis. Frequency distributions were produced for each decile. Both absolute and relative distributions were recorded to provide a simple count-based representation of SRL behaviours. This serves to highlight the usefulness of simple metrics but also their limitations.

3.3.2 Epistemic Network Analysis. To conduct an ENA, we used the rENA package for the statistical programming language [22]. To construct a network model, ENA requires the definition of a unit of analysis, an activity code, and a stanza, i.e., a logical temporal sequence of event data. Network associations are defined as the co-occurrence between codes within the bounds of a stanza [36]. For this study, students (USER_ID) were identified as the unit of analysis. The activity code was the micro-level process (as created by the SRL parsing engine) and the stanza was the session (ID) as identified through the process outlined in Section 3.2.1. The 'week' variable – i.e. the week of the term in which the interaction took place – was also used; we produced a comparative trajectory graph – a weekly means rotation – for the two groups, in support of RQ3. This allowed the tracking of network centroids from week to week, providing temporal insight not possible in the other methods. In this context a centroid is essentially the centre of gravity of a network, based on arithmetic mean of edge weights for a given unit of analysis [33]. In ENA, frequently co-occurring nodes were displayed with thick connecting lines, allowing us to identify cotemporally relevant relationships between SRL phases. We produced two epistemic networks, one for each decile group. To provide a richer comparative view, we produced subtracted performance diagram, which superimposed the two decile ENAs onto each other, visually subtracting network associations to provide a comparative analysis.

3.3.3 Frequency and Temporal Process Mining. We used two PM discovery/visualisation tools. For frequency/temporal analysis, we employed the R package bupaR, which produces sequential process maps with a temporal and/or frequency-based focus. The key PM roles were assigned as follows: Case – Session ID (the session value indicated in section 3.2.1); Activity – Micro-level Action; Start and End Timestamps – as expected. We present a frequency-based process model of the bottom decile group, which identifies the activities in terms of total frequency of engagement (the node metrics) and of associative inter-node total frequency (edge metrics). We also present two temporal process models of both deciles, in which the node metrics represent the median time spent on a particular node (micro-level process) and the edge metrics represent the median time lag between nodes.

3.3.4 Stochastic Process Mining. To explore the same data through the lens of associative process probabilities, we employed the PM R package pMineR [15] to generate and visualise First Order Markov Model (FOMM) probability transition matrices for each of the two deciles. The arc between one node and the next shows a measure of the likelihood of transition between the nodes; the transition probability (TP). We conduct visual interpretations from the thickness of the lines, and more forensic analyses by interpreting the actual TP values. To provide comparative insights, we interpreted the comparison diagrams of the FOMM models. We mapped the bottom decile group onto the top decile group. The arcs in black represent similar TPs. In cases of comparatively disparate TPs, both probabilities are shown. Red arcs represent the lower TP; the green arcs represent a higher. It is in through analysis of these differing TPs that we identified contrasting SRL engagement behaviours across the two groups.

4 RESULTS

4.1 SRL Analysis of learner behaviours (RQ1)

4.1.1 Frequency Analysis. Tables 3 provides relative frequency distributions by activity, recorded for both deciles. The table indicates a certain commonality of engagement in both groups. The distributions are, on first view, quite similar. The first four activities follow the same order with both sets of learners investing most of their resources in building knowledge, formative assessment, summative assessment and goal setting. Evaluative and reflective phases attract the lowest levels of engagement. Goal-setting and plan-making are seemingly deemed of medium importance.

Table 3: Top and Bottom decile frequency statistics

Micro-level SRL Activity	Freq. top decile	Rel. Freq. top decile	Freq. bottom decile	Rel. Freq. bottom decile
Work_on_Task. Knowledge_Build	6,668	28.42%	3,231	23.38%
Work_on_Task. Formative	5,206	22.19%	3,221	23.31%
Work_on_Task. Summative	2,784	11.87%	1,934	14%
Goal_Setting	2,731	11.64%	1,875	13.57%
Make_Plans	2,385	10.17%	1,069	7.74%
Eval.Dash	1,534	6.54%	522	3.78%
Eval. Formative_Answer	1,486	6.33%	1,629	11.79%
Reflect	668	2.85%	337	2.44%

4.1.2 Epistemic network analysis. The high and low deciles exhibit quite similar behaviour patterns, in general terms. As we see in figure 1, both networks indicate, through analysis of relative density connections, strong linkages between formative work and knowledge-building, knowledge-building and summative work, and summative work and goal setting.

The triangle of links between knowledge building, formative quiz work, and accessing of quiz answers (Eval.Formative_Answer) is significant. Both diagrams hint at a lesser focus on reflection and plan making in the context of the other major activities.

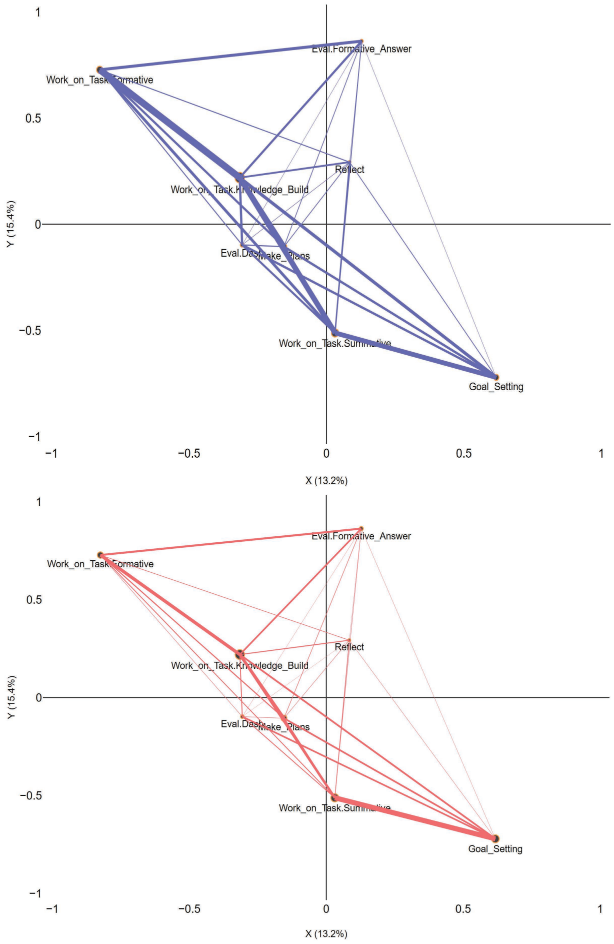

Figure 1: Top decile (blue) and bottom decile (red) ENA

4.1.3 Frequency-based Process Mining. Figure 2 indicates the associative and absolute frequencies of the SRL processes of the bottom decile.

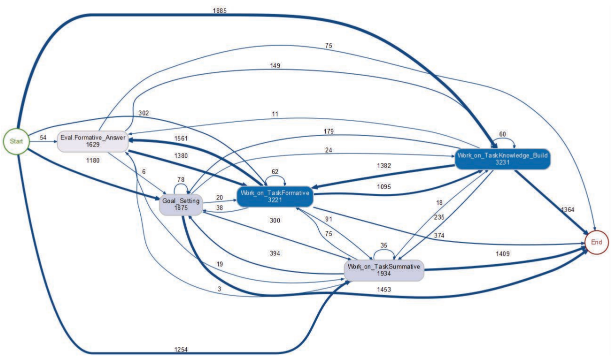

Figure 2: Bottom decile frequency-based PM model

The node values are simply generated frequencies for each SRL activity and are directly linked, for this example, to the metrics in Table 2 (with the less frequent activities filtered out). In this sense, this visualisation does not offer any more than Table 2. Its value, in this case, lies in the edge frequencies, which indicate the strength and direction of association between pairs of activities. We can glean strong associations between formative work, knowledge building, and accessing formative quiz answers. It seems that this group (bottom decile) makes as much use of the free quiz answers as it does of other knowledge-building media. This is one of three main paths, the second being path through goal-setting, and the third being path though summative work. There are linkages between these paths but they are less strong than the intra-path linkages. This type of sequential analysis provides crucial insights but is lacking a temporal focus. By contrast, Section 4.2.3 provides a comparative analysis of this model against the top decile group using temporal metrics.

4.1.4 Stochastic Process Mining. The FOMMs in Figure 3 show commonality between both student groups.

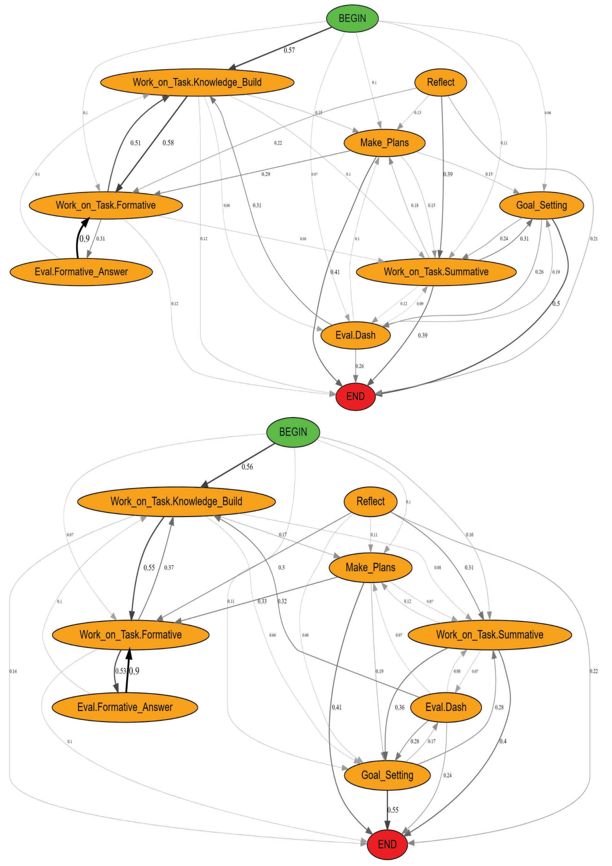

Figure 3: Top decile (top) and bottom decile (bottom) FOMMs

Knowledge building is the most likely first activity for both groups, with almost identical TPs of around 0.57. We also see a common pattern of engagement with formative work and access to the formative answers. There is a clear three-node Markov chain of knowledge building and formative work. Both diagrams indicate a common focus on summative work. This is to be expected as summative activities contribute to overall module scores. The reflection activity is generally followed by formative or summative work, plan making, or session ending. Sessions come to an end after engagement with summative tasks, plan-making, goal-setting, and dashboard evaluation.

4.2 SRL Comparison of learner groups (RQ2)

4.2.1 Descriptive Statistics. On a closer examination, the frequency metrics in Table 1 provide more insight. The top decile students are more inclined to knowledge building, plan-making and dashboard access than the bottom decile. The bottom decile students focus more on summative tasks, goal setting, and accessing answers to formative quizzes. On a more fundamental level, the bottom decile group are, on average, half as active, based on overall engagement frequency.

4.2.2 Epistemic network analysis. We can see from Figure 1 that the relative density connections are stronger for the top decile, indicating a higher level of engagement in almost all the activities. The subtracted performance diagram (Figure 4, top) reinforces this assertion.

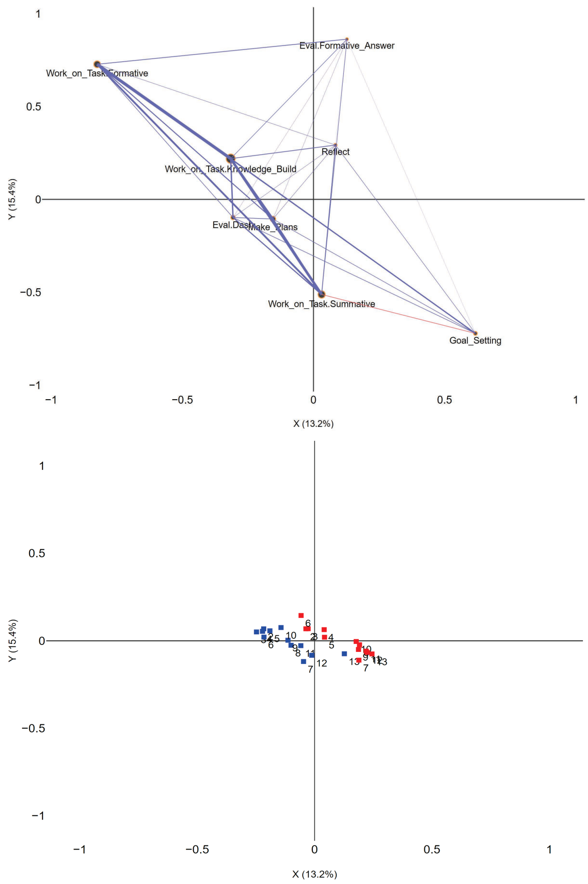

Figure 4: ENA Subtracted Performance (top) and Weekly Means Rotation (bottom)

In addition, for the bottom decile, we observe a stronger connection between work on summative task and goal setting, which shows that students more frequently revisit the goal setting before/after engaging the summative assessment. This points to a less cohesive learner dynamic in relation to the summative test and a surface approach to score accumulation.

The weekly mean network (Figure 4, bottom) depicts the longer-term temporal perspective in showing the centroid movement of the two groups by week; in essence showing the movement of students as the course progresses. The top decile students are located on the left side, focusing on summative assessment, formative assessment activities and knowledge building. The bottom decile students are located on the right side, focusing on goal-setting and summative work. A focus on goal setting is recognised as an optimal trait, but only if accompanied by other actions to achieve an identified goal. From a temporal perspective, we can see evidence of an increasing emphasis on summative work and goal-setting in both groups in the latter weeks of the course.

4.2.3 Temporal Process Mining. The process models for the bottom and top deciles are presented in Figure 5; the node and edge metrics are median minutes.

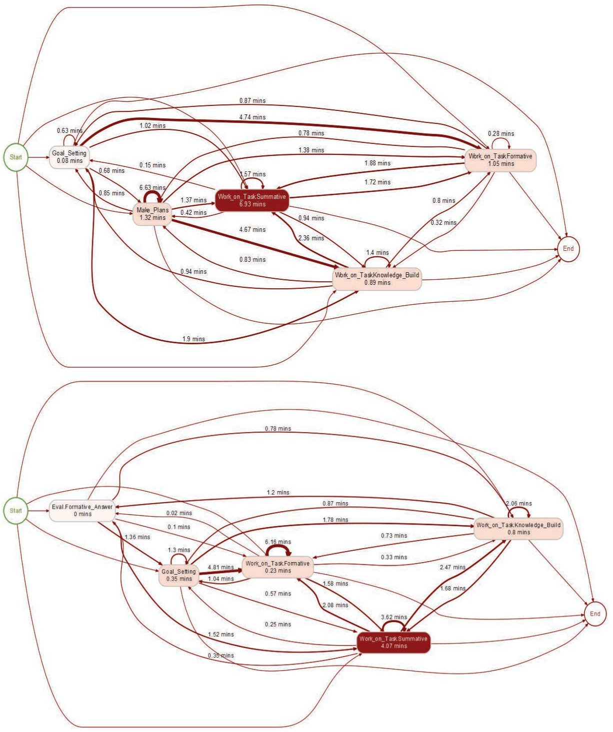

Figure 5: Top decile (top) and bottom decile (bottom) performance PM models

From an SRL phasal point of view, we see that the top decile applies a greater focus on the plan making than the bottom decile, where the Make_Plans node is not present (due to filtering). Instead of this, the Eval.Formative_Answer (accessing formative quiz answers) is present as part of a link between formative work and knowledge building. This distinction hints that the bottom group exhibit a greater inclination toward surface learning as evinced by reliance of formative quiz answers.

From a temporal perspective, the top decile group spend longer on summative activities (median 6.93 minutes as opposed to 4.07 minutes) and also show a lesser lag between these repetitions (1.57/3.62). This hints at an increased level of focus in the top decile. This group's focus on formative tasks is also stronger than its counterpart with 1.05 on-task median and 0.28 repetition median lag compared to 0.23/6.16 for the bottom. Both groups display similar temporal foci on knowledge building activities (0.89/0.8), with a slightly greater repetition lag for the bottom (1.4/2.06).

Visual interpretation is somewhat counterintuitive compared to the equivalent frequency-based analysis (Section 4.1.3). Thicker lines represent higher median lags between SRL phasal engagement. On first look, it seems that the bottom decile displays greater focus generally exhibiting shorter median edges. This is misleading. For example, there appears to be a long edge lag between goal-setting and formative work for both deciles (4.74/4.81). On closer inspection, we see that the top decile goes through plan-making activities prior to formative work, thus indicating a more considered learning dynamic. The plan making sequence is not present on the bottom decile model; it has been replaced, frequency-wise by evaluation of formative quiz answers. Other behavioural clues lie around the summative activity sequence. The bottom group are generally slower to move between this and formative sequences (1.72/2.08), and knowledge building (0.94/2.47). This indicates a sustained attachment to summative work when reflection and further formative/knowledge building may be more beneficial.

4.2.4 Stochastic Process Mining. Figure 6 shows a FOMM comparison of the top and bottom deciles of the entire event sample. Opening behavioural engagement is similar although we do see a slightly greater inclination to summative work from the bottom decile (0.11/0.16), as opposed to planned formative work. We also see that the loop between summative work

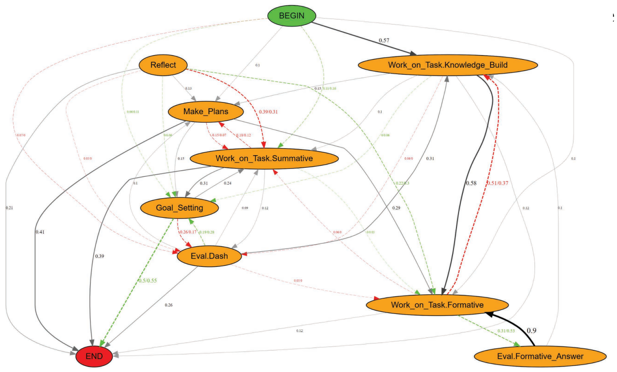

Figure 6: FOMM comparison of top and bottom deciles

The most compelling comparative pattern can be found around engagement with formative quizzes. We see that the top decile exhibit a lesser inclination to break from formative work to look up the free answers to the quizzes, with comparative TPs of 0.31 and 0.53. The top decile likelihood of moving from formative activities to knowledge building is 0.51 compared to the bottom's 0.37. This provides a critical insight into contrasting behaviours. In the context of formative assessment, the better performers incline more towards knowledge acquisition to improve performance, rather than simply accessing the correct answers. This in turn points to a greater focus on deep learning from the top decile.

4.3 Consolidation

To emphasise the overarching SRL framework of Planning, Engagement, and Evaluation & Reflection (Table 2), we delineate a consolidated analysis by each SRL phase.

4.3.1 Planning Phase. This phase comprises the following micro-level activities: Goal setting; Plan-making. Both deciles allocate reasonable amounts of resource to this phase but distribution between the activities differs between the deciles. The bottom decile, in relative terms, engages more frequently with goal setting and less frequently with plan-making than the top decile (table 3). ENA analysis indicates that the bottom decile places a greater focus on this goal-setting and, in the subtracted performance diagram (Figure 4, left), the co-occurrence of goal-setting and summative work is noticeably stronger for the bottom decile. In PM terms (Figure 5), the bottom group spend a longer median period of time on this activity with slightly longer lags in repetition cycles. In stochastic terms (Figure 6), we see a richer view of the gravitational pull that this activity exerts on the bottom decile, compared to the top decile. The green arcs pointing to the goal setting node indicate that the bottom decile is more likely, at any point, to engage with it after other activities. After engaging in goal-setting, both groups are equally likely to end the session (both around 0.50) or go to summative work. A combined analysis indicates not only that the bottom decile concerns itself more with goal-setting in absolute terms, but in sequential and temporal terms, the goal-setting activity is more heavily utilised by the bottom decile in the learning space. Although engagement with goal-setting is generally seen as an optimal trait, our view is that repeated engagement can traverse a point where useful gains begin to diminish [12].

In relative frequency terms, plan-making is more actively engaged in by the top decile. ENA indicates its relatively low priority for the bottom decile, in comparison. Due to filtering, it is not present in the temporal PM analysis for the bottom decile, which tells its own story. For the top decile, we see that there are relatively long lags between activity repetition. Plan making seems to be a bridging node between other activities and formative work. Stochastic analysis also indicates that formative work is the most likely destination after plan making, for both deciles. A combined appraisal here relies more on frequency metrics combined with stochastic analysis. It indicates that the better performers do engage more with plan-making than the lesser performers. This phenomenon has an empirical precedent in the work reported in [31].

4.3.2 Engagement Phase. This phase comprises the following Micro-level activities: Knowledge-building; Formative work; Summative work. Predictably, these activities attract the greatest levels of engagement. The overall phase percentages are similar for both deciles with the top decile favouring more knowledge building, and bottom decile favouring more summative work. This dominance is reflected in temporal terms. The ENA plots indicate that, in addition to relative frequency, the three activities share strong cotemporal links; more specifically knowledge-building shares strong links with formative work, and with summative work. The link between summative and formative work is less emphatic. Analysis of the subtracted performance plot reveals that the top decile, despite being a slightly smaller group of students, engages approximately twice as much in all activities. The bottom decile element is almost completely blanked out, so making it difficult to compare the relative cotemporality of both deciles.

The temporal PM perspective affords us more insight. It is revealed that, despite being a less frequently engaged activity, summative work enjoys a more sustained engagement than knowledge building and formative work. This reflects the pedagogic reality that summative work, in raw learner action terms, dominates in terms of focus. We should remember that the nodes we are examining are not representing LMS click/activities, but SRL categorised sequences. We see that the top decile spend more time on discrete sequences of this activity than the bottom, in median minutes (6.93/4.07) and have a shorter repetition lag (1.57/3.62). This points to a more focussed approach to this task. We cannot discern any real insights into the equivalent temporal metrics of the formative and knowledge-building activities, with both deciles exhibiting a similar focus.

Stochastic PM analysis provides us with another analytical layer, unlocking a behavioural trait unseen to the other methods. ENA and Frequency-based PM identify the presence of a relationship between the three activities, but the FOMM comparison diagram allows us to articulate the probabilistic dynamics. As we saw in the ENA plot, knowledge building seems to be the cotemporal centre of this learning space. The FOMM plot shows us that the top decile is more likely to transition to the formative work to knowledge building than the bottom, with respective TPs of 0.51 and 0.37. The bottom decile is more likely to transition to access of formative quiz answers than the higher decile (0.53/0.31). This offers a key insight into relative behaviours not available to the other methods. Conversely, FOMM analysis does not always convey the significance of an activity in terms of absolute engagement. In this case, the importance of summative engagement is not so apparent.

A combined perspective highlights the relative levels of SRL phase activity engagement, the cotemporal importance of knowledge building, the level of focus on summative work, and the intriguing play-off between formative work and knowledge access/quiz answers. The top decile exhibit more optimal learning behaviours and display a greater mastery in a meta-cognitive context. These behavioural traits have been highlighted in previous research [3] and [7].

4.3.3 Evaluation and Reflection Phase. This phase comprises the following micro-level activities: Dashboard access; Formative quiz answer access; Reflection. This phase attracts the lowest levels of activity for both deciles. The ENA diagrams show us that formative answer access and reflection sit in the same quadrant, indicating a thematic association. It is interesting to note that dashboard evaluation sits in the same quadrant as plan-making, which highlights the ambiguous nature of dashboard access in terms of SRL phases. It can legitimately be part of both reflection and planning phases. This highlights a problematic issue in the codification of cyclical models, such as SRL. ENA provides a means of potential resolution. In this case, we could argue that dashboard evaluation is a pre-engagement activity, not post.

Temporal PM analysis, in this case, offers us only a little insight. Engagement with these activities is light and so compelling analyses are not readily available. Comparative stochastic analysis highlights this focus differential in a broader context (discussed in the previous phase section). Dashboard evaluation is a less likely bottom decile destination from the sessions of reflection, and goal setting. Likely behaviour after a reflective activity is not comparatively distinct, with a slightly greater inclination toward formative work in the top decile.

It is more challenging to form a coherent combined analysis for this phase, with the results being complementary rather than confirmatory. Nonetheless, important insights can be gleaned. The phasal position of dashboard evaluation in our SRL model must now be called into question. In summary, there is an over-reliance on reflection and goal-setting from the bottom decile, reflecting research undertaken by Pintrich [27].

5 DISCUSSION

The results show that combining methods provides us with a richer insight into learner behaviours than would be possible individually. Simple frequency measures provide a basic insight into activity focus, but do not offer insights into sequential and temporal co-occurrence. ENA provides an essential insight into process cotemporality. We can form analyses which position phases of SRL and indicate the strength of association between activities (nodes) within a projected SRL space. This immediately provides us with a more dimensional view from an associative and temporal focus. ENA does not provide an inter-node directional insight. The PM methods allow us to overlay insights into sequential associative direction from a perspective of frequency, temporality, and probability. Each method brings its own type of insight but combining the methods provides a completer and more dynamic ontological viewpoint. Consider the following analyses based loosely around knowledge building:

Frequency: Knowledge building is the most popular activity by engagement count, followed by formative and summative work.

ENA: Knowledge building is a key activity and engaged with in frequent association with formative and summative work. We also see that, to a lesser extent, quiz answer evaluation, combine to form a group of SRL phases.

PM temporal: Despite engagement statistics, we see that learners actually place a heavier focus on summative work than knowledge building and formative work, showing us that it is, in temporal terms, the most engaged activity, especially for the bottom decile.

PM probabilistic: The top decile learners are more likely to break engagement with formative quiz work to engage in knowledge building.

Combined: Learners more actively engage in cycles of knowledge-building, formative work and summative work, than any other. Although knowledge building is most frequently engaged in, more time is actually allocated to summative work, and summative work is the most likely point of engagement after SRL phases of reflection and goal setting. Knowledge building engagement is the most likely destination as a break-out activity during cycles of formative work, for the top decile, with the bottom decile favouring access to quiz answers.

The combined analysis provides a richer temporal narrative than any one of the individual analyses and allows us to capture the likely movements of behavioural clusters in time and (digital) space. Building on this, we could overlay the analyses with metrics relating to frequency, time and/or probability. We also need to consider the synergistic level of consolidation. By this, we mean the level to which the methods are narratively subsumed. From one end of the spectrum, we may merely present a sequence of analyses discretely positioned within each method. At the other end, we may attempt to lose all sense of any single method in pure narrative consolidation. The ideal narrative balance probably lies somewhere between these two extremes. This balance, and the inclusion of metrics, are decisions to be made by researchers in the context of their specific study aims. We should be mindful that empirical evidence already shows that a 'usable' visualisation does not always equate to an effective one in an educational setting [11].

One clear outcome is that the narrative is strengthened by inter-group comparison. As can be found in similar work [5,24,30], comparing learner groups, typically stronger vs weaker performers, provides a critical contextual delineation. More plainly expressed, we can more clearly see good practices if articulated in the context of bad. In the analyses above, we see that high achievers are more inclined to boost knowledge through content access, as opposed to simply accessing quiz answers. This insight may not have been possible without this vital comparative context.

The combination, or consolidation, of methods goes some way to address the concerns raised by Reimann [2], who stated the merit of event-based ontologies, but recognised that important decisions need to be made around the definition of an 'event' and also the assertion of association or causality between these events in a theoretically robust setting [28]. In embedding event codification in a model of SRL, we go some way to addressing important issues of validity and causality. Reimann et al. [28] assert that, despite the merit of event-based analyses, analyses using a single sequential method may suffer from ontological flatness. Whether this study provides the stratified ontological framework that Reimann and colleagues posit, we assert that our blended-method approach provides the ontologically (and epistemologically) nuanced form of investigation into learning phenomena.

From a more temporally specific viewpoint, we need to be mindful of what we are attempting to achieve and in what conceptual context. Knight et al. [19] posit two concepts of temporality; that which relates to quantifiable measures of duration, rate and passage, and that which relates to sequence and progression. This second mode is particularly important in the context of the dynamics of SRL [10] In this study, we hint at a way of combining these temporal modes to articulate patterns of movement through learning spaces. As stated, the analytical narrative can be qualitative, quantitative, or a combination.

6 CONCLUSIONS

We do not claim to be pioneers of combined temporal methods; Malmberg, Järvelä, and Järvenoja explored the change of temporal features over time using multiple methods [21]. We assert that our proposed method provides a similar richness of analysis using trace data, as opposed to Malmberg and colleagues' more experimental focus on self-report data.

A study of this kind invites questions on the utility of a hypothesis-driven method in a live and authentic learning setting. The current study is certainly observational, as opposed to experimental, and as such can benefit from a posteriori theory-driven data transformations, informed by our chosen model of learning. Challenges still exist in the successful deployment of our method in real-time learning setting. How do we use the method to track and remediate some of the sub-optimal behaviours highlighted in this and other similar studies? We submit that the increasing popularity of such studies will reach an empirical critical mass, so that legitimate construct validity is inherent in our chosen theoretical framework. Another path is to explore atheoretical, data-driven methods, as demonstrated by Boroujeni and Dillenbourg [8]. A resolution to this issue would open the door to genuinely impactful in-class interventions.

REFERENCES

[1] W. M. P. van der Aalst, H. T. de Beer, and B. F. van Dongen. 2005. Process Mining and Verification of Properties: An Approach Based on Temporal Logic. In *On the Move to Meaningful Internet Systems 2005: CoopIS, DOA, and ODBASE* (Lecture Notes in Computer Science), 130–147.

[2] Andrew Abbott. 1984. Event Sequence and Event Duration: Colligation and Measurement. *Historical Methods: A Journal of Quantitative and Interdisciplinary History* 17, 4 (October 1984), 192–204.

[3] Stephen J. Aguilar. 2018. Examining the Relationship Between Comparative and Self-Focused Academic Data Visualizations in At-Risk College Students' Academic Motivation. *Journal of Research on Technology in Education* 50, 1 (January 2018), 84–103.

[4] Roger Azevedo and Jennifer G. Cromley. 2004. Does Training on Self-Regulated Learning Facilitate Students' Learning With Hypermedia? *Journal of Educational Psychology* 96, 3 (2004), 523–535.

[5] Maria Bannert, Peter Reimann, and Christoph Sonnenberg. 2014. Process mining techniques for analysing patterns and strategies in students' self-regulated learning. *Metacognition Learning* 9, 2 (August 2014), 161–185.

[6] Sanam Shirazi Beheshitha, Dragan Gašević, and Marek Hatala. 2015. A Process Mining Approach to Linking the Study of Aptitude and Event Facets of Self-regulated Learning. In *Proceedings of the Fifth International Conference on Learning Analytics And Knowledge* (LAK '15), 265–269. Retrieved June 1, 2019 from http://doi.acm.org/10.1145/2723576.2723628

[7] Robert A. Bjork, John Dunlosky, and Nate Kornell. 2013. Self-Regulated Learning: Beliefs, Techniques, and Illusions. *Annual Review of Psychology* 64, 1 (January 2013), 417–444.

[8] Mina Shirvani Boroujeni and Pierre Dillenbourg. 2019. Discovery and Temporal Analysis of MOOC Study Patterns. *1* 6, 1 (April 2019), 16 — 33-16 — 33.

[9] Deborah L. Butler and Philip H. Winne. 1995. Feedback and Self-Regulated Learning: A Theoretical Synthesis. *Review of Educational Research* 65, 3 (September 1995), 245–281.

[10] Bodong Chen, Simon Knight, and Alyssa Friend Wise. 2018. Critical Issues in Designing and Implementing Temporal Analytics. *1* 5, 1 (April 2018), 1–9–1–9.

[11] Vanessa Echeverria, Roberto Martinez-Maldonado, and Simon Buckingham Shum. 2017. Towards data storytelling to support teaching and learning. In *Proceedings of the 29th Australian Conference on Computer-Human Interaction - OZCHI '17*, 347–351. Retrieved September 28, 2019 from http://dl.acm.org/citation.cfm?doid=3152771.3156134

[12] Noel Entwistle (Professor). 2009. *Teaching for Understanding at University: Deep Approaches and Distinctive Ways of Thinking.* Palgrave Macmillan.

[13] K. Anders Ericsson and Herbert A. Simon. 1980. Verbal reports as data. *Psychological Review* 87, 3 (1980), 215–251.

[14] E. Fincham, D. Gašević, J. Jovanović, and A. Pardo. 2019. From Study Tactics to Learning Strategies: An Analytical Method for Extracting Interpretable Representations. *IEEE Transactions on Learning Technologies* 12, 1 (January 2019), 59–72.

[15] Roberto Gatta, Jacopo Lenkowicz, Mauro Vallati, Alessandro Stefanini, Nicola Dinapoli, Berardino De Bari, and Lucia Sacchi. 2017. *pMineR: Processes Mining in Medicine.* Retrieved September 16, 2019 from https://CRAN.R-project.org/package=pMineR

[16] Jeffrey Alan Greene and Roger Azevedo. 2009. A macro-level analysis of SRL processes and their relations to the acquisition of a sophisticated mental model of a complex system. *Contemporary Educational Psychology* 34, 1 (January 2009), 18–29.

[17] Gert Janssenswillen. 2019. *bupaR: Business Process Analysis in R.* Retrieved September 16, 2019 from https://CRAN.R-project.org/package=bupaR

[18] Jelena Jovanović, Dragan Gašević, Shane Dawson, Abelardo Pardo, and Negin Mirriahi. 2017. Learning analytics to unveil learning strategies in a flipped classroom. *The Internet and Higher Education* 33, (April 2017), 74–85.

[19] Simon Knight, Alyssa Friend Wise, and Bodong Chen. 2017. Time for Change: Why Learning Analytics Needs Temporal Analysis. *1* 4, 3 (December 2017), 7–17–7–17.

[20] Jorge Maldonado-Mahauad, Mar Pérez-Sanagustín, René F. Kizilcec, Nicolás Morales, and Jorge Munoz-Gama. 2018. Mining theory-based patterns from Big data: Identifying self-regulated learning strategies in Massive Open Online Courses. *Computers in Human Behavior* 80, (March 2018), 179–196.

[21] Jonna Malmberg, Sanna Järvelä, and Hanna Järvenoja. 2017. Capturing temporal and sequential patterns of self-, co-, and socially shared regulation in the context of collaborative learning. *Contemporary Educational Psychology* 49, (April 2017), 160–174.

[22] Cody L. Marquart, Zachari Swiecki, Wesley Collier, Brendan Eagan, Roman Woodward, and David Williamson Shaffer. 2019. *rENA: Epistemic Network Analysis.* Retrieved September 16, 2019 from https://CRAN.R-project.org/package=rENA

[23] Wannisa Matcha, Dragan Gašević, Nora'ayu Ahmad Uzir, Jelena Jovanović, Abelardo Pardo, Jorge Maldonado-Mahauad, and Mar Pérez-Sanagustín. 2019. Detection of Learning Strategies: A Comparison of Process, Sequence and Network Analytic Approaches. In *Transforming Learning with Meaningful Technologies* (Lecture Notes in Computer Science), 525–540.

[24] Wannisa Matcha, Dragan Gašević, Nora'Ayu Ahmad Uzir, Jelena Jovanović, and Abelardo Pardo. 2019. Analytics of Learning Strategies: Associations with Academic Performance and Feedback. In *Proceedings of the 9th International Conference on Learning Analytics & Knowledge* (LAK19), 461–470.

[25] Jun Oshima, Ritsuko Oshima, and Wataru Fujita. 2018. A Mixed-Methods Approach to Analyze Shared Epistemic Agency in Jigsaw Instruction at Multiple Scales of Temporality. *1* 5, 1 (April 2018), 10–24–10–24.

[26] Abelardo Pardo and Negin Mirriahi. 2017. Design, Deployment and Evaluation of a Flipped Learning First-Year Engineering Course. In *The Flipped Classroom: Practice and Practices in Higher Education*, Carl Reidsema, Lydia Kavanagh, Roger Hadgraft and Neville Smith (eds.). Springer Singapore, Singapore, 177–191. DOI:https://doi.org/10.1007/978-981-10-3413-8_11

[27] Paul R. Pintrich. 2000. Chapter 14 - The Role of Goal Orientation in Self-Regulated Learning. In *Handbook of Self-Regulation*, Monique Boekaerts, Paul R. Pintrich and Moshe Zeidner (eds.). Academic Press, San Diego, 451–502.

[28] Peter Reimann. 2009. Time is precious: Variable- and event-centred approaches to process analysis in CSCL research. *Computer Supported Learning* 4, 3 (September 2009), 239–257.

[29] Peter Reimann, Lina Markauskaite, and Maria Bannert. 2014. e-Research and learning theory: What do sequence and process mining methods contribute? *British Journal of Educational Technology* 45, 3 (2014), 528–540.

[30] John Saint, Dragan Gašević, and Abelardo Pardo. 2018. Detecting Learning Strategies Through Process Mining. In *Lifelong Technology-Enhanced Learning* (Lecture Notes in Computer Science), 385–398.

[31] Corwin Senko, Chris S. Hulleman, and Judith M. Harackiewicz. 2011. Achievement Goal Theory at the Crossroads: Old Controversies, Current Challenges, and New Directions. *Educational Psychologist* 46, 1 (January 2011), 26–47.

[32] David Williamson Shaffer. 2004. Epistemic Frames and Islands of Expertise: Learning from Infusion Experiences. In *Proceedings of the 6th International Conference on Learning Sciences* (ICLS '04), 473–480.

[33] David Williamson Shaffer, Wesley Collier, and A. R. Ruis. 2016. A Tutorial on Epistemic Network Analysis: Analyzing the Structure of Connections in Cognitive, Social, and Interaction Data. *Journal of Learning Analytics* 3, 3 (2016), 9–45.

[34] Melody Siadaty, Dragan Gašević, and Marek Hatala. 2016. Trace-Based Microanalytic Measurement of Self-Regulated Learning Processes Moray House School of Education and School of Informatics. *Journal of Learning Analytics* 3, 1 (2016), 183–214.

[35] Christoph Sonnenberg and Maria Bannert. 2015. Discovering the Effects of Metacognitive Prompts on the Sequential Structure of SRL-Processes Using Process Mining Techniques. *1* 2, 1 (May 2015), 72–100–72–100.

[36] Zachari Swiecki, Zheming Lian, Andrew R Ruis, and David Williamson Shaffer. 2019. Does Order Matter? Investigating Sequential and Cotemporal Models of Collaboration. In *Proceeding of the 13th International Conference on Computer-Supported Collaborative Learning*, 112–120.

[37] Stijn Van Laer and Jan Elen. 2018. Towards a Methodological Framework for Sequence Analysis in the Field of Self-Regulated Learning. *FRONTLINE LEARNING RESEARCH* 16, (December 2018), 228–249.

[38] Philip H. Winne. 1996. A metacognitive view of individual differences in self-regulated learning. *Learning and Individual Differences* 8, 4 (January 1996), 327–353.

[39] Barry J. Zimmerman. 2000. Chapter 2 - Attaining Self-Regulation: A Social Cognitive Perspective. In *Handbook of Self-Regulation*, Monique Boekaerts, Paul R. Pintrich and Moshe Zeidner (eds.). Academic Press, San Diego, 13–39. Retrieved June 3, 2019 from http://www.sciencedirect.com/science/article/pii/B9780121098902500317

[40] Barry J. Zimmerman. 2008. Investigating Self-Regulation and Motivation: Historical Background, Methodological Developments, and Future Prospects. *American Educational Research Journal* 45, 1 (March 2008), 166–183.

5.3 Summary

In this chapter, we applied our SRL transformation framework, *Trace-SRL*, to a different set of learner data (albeit from the same LMS as the previous studies) in order to unlock a similar set of SRL processes. Like the previous studies, we articulated these processes by comparing different learner groups. Unlike the previous studies, where we made use of pre-clustered learner groups (based on tactic usage), we delineated two user groups based solely on assessment performance. This decision was driven by the desire to explore whether the behavioural differences could be effectively articulated in scenarios where learner action sequences did not contribute to the grouping; could grouping based on top and bottom assessment deciles provide compelling outcomes. We argue that these deciles did demonstrate differing behaviours, despite the large (and rather noisy) sample used. In truth, this was only part of the thrust of the study, although it did provide some very useful insights. The main comparative edge was demonstrated in the use of multiple analysis methods.

It is important to note that although we maintain that frequency-based measures are limited, we do not discount their utility, even in the context of the temporally focused analyses in this study. For example, in our study, we noted that the lower decile students engaged in more summative activities but less knowledge-building (in relative terms). This tells its own story but this story, and other narratives can be extracted by interpretation of these types of measures. We presented interpretations of various phases of SRL, that is, *planning*, *engagement*, and *evaluation and reflection*, through the lenses of frequency, temporal co-occurrence, time-focused sequence, and probabilistic sequence, which emphasises this point. For example, we noted that, in relative frequency terms, the lower decile group engaged in more goal-setting activities, which seemed counter-intuitive. In analysing this phenomenon using stochastic process mining, we saw that goal-setting was more likely to be followed by summative assessment work, as opposed to the upper decile. The upper decile displayed more efficiency in goal-setting but a more cohesive subsequent approach which encompassed a more likely broader use of learning resources. The time-focused process mining view also provided a layer of richness. It is this articulation of the dynamic temporal play between SRL processes that we have explored throughout the thesis, and one which is enriched by exploring multiple analytic methods. These types of layered interpretations, we argue, unlock insights not possible using single methods, and provide more dimensional insights into the dynamics of SRL. The key contribution of this study is that it demonstrated and assessed the value of the insights that come from multiple discovery methods, making use of the respective quantitative metrics to present a layered qualitative interpretation. We build on this exploration in Chapter six.

6 Comparing and Combining Process Mining Metrics

> Cooking is like painting or writing a song. Just as there are only so many notes or colors, there are only so many flavors - it's how you combine them that sets you apart.
>
> — Wolfgang Puck, *Puck Goes Back to His (Ginger) Roots*

6.1 Introduction

THE work undertaken in the previous chapter (Chapter five) explored the possibilities of combining analytic methods to analyse SRL. This type of multiple or mixed method analysis has been deployed with some success in other related studies, such as Matcha, Gašević, Ahmad Uzir, Jovanović, Pardo, et al. (2019), in which the authors presented a comparison of three analytic approaches (process, sequence, and network) to detect learning tactics and strategies, and Swiecki et al. (2019), in which the authors championed the use of epistemic network analysis in collaborative learning scenarios, in a comparative study with sequential pattern mining. These types of studies provide critical insights into the relative strengths of certain methods, as well as the collective strength of using them together. They did not, however, embed their analyses in models of SRL (in the manner of "Trace-SRL"), and they did not propose a means of consolidating the metric outcomes which we believe address the shortcomings of using a single metric, that is, the trade-off of relative vs absolute scales of measurement.

To that end, we present a study which explores the use of multiple processing mining algorithms to analyse SRL, providing a systematic comparison of the chosen algorithms and a proposed consolidation of the metrics. The study presented serves to further investigate these research questions:
(RQ2) *How effectively can we measure the temporal dynamics of learning strategies in delineated student groupings, using process analytic techniques?*
(RQ3) *To what extent can we develop a framework to embed temporally focused analysis of learning in a theoretical model of self-regulated learning?*
(RQ4) *To what extent can we combine analytic methods to further explore self-regulated learning from*

a perspective of temporality and sequence?

6.1.1 Chapter overview

This chapter is effectively the second of a two-chapter exploration of multiple analytic methods; their strengths, weaknesses, and the potential of their combination and consolidation. The key development in this chapter is that the incorporated study provides a more specific methodological focus on process mining platforms and the metrics associated with the algorithms they support. To restate, we use the term *metric* in reference to the measures of process activity engagement and transition between these activities. As in the previous study, we used a common data source to ensure a consistent comparison across the platforms. We chose process mining platforms based on their presence within the area of temporally focused SRL, and leveraged the research we conducted in our systematic review of literature (Chapter two). This resulted in the systematic analysis of these four process mining platforms.

- Heuristics Miner (Weijters et al., 2006): Building on the prototypical Alpha Miner algorithm (van der Aalst & Weijters, 2004), its distinguishing feature is the *dependency metric*, a proprietary measure which identifies the level of dependency between one activity and another using a 0-to-1 scale.

- Inductive Miner (Leemans et al., 2014): The Inductive Miner algorithm, at its inception, represented the best attempt at addressing a concept called process model soundness, that is, the extent to which the discovered process model can reproduce the broadest and most accurate permutations of process flows (Buijs et al., 2012). This is key for modelling structured processes, where accurate discovery is critical.

- Fuzzy Miner (Günther & Rozinat, 2012; Günther & van der Aalst, 2007): Unlike Inductive Miner, process model soundness is not a priority. As such there is little focus on the generation of models that represent all permutations of a given process. Its visualisations are suitable for easier, high-level analysis of more organic processes, as typified in SRL.

- pMineR (Gatta, Lenkowicz, et al., 2017): Using first order Markov modelling to train and visualise process models, it has a similar visual feel to Fuzzy Miner but the relationships between activities are measured in terms of transition probability.

In truth, the differences and commonalities between the platforms are conceptually blurred. For example, Heuristic Miner can be configured to produce frequency metrics, as well as its proprietary dependency metric. Inductive Miner can be configured to produce time-based metrics. Fuzzy Miner can be configured to show both in its "modern" incarnation in platforms, such as Fluxicon Disco (Günther & Rozinat, 2012); in its classic form (Günther & van der Aalst, 2007), it provides a set of proprietary *correlation* and *significance* metrics. As such, we were inspired to focus not just on the distinguishing features of the platforms, but on those of the metrics. In broad terms, we compared and commented on the outputs of the algorithms (given a common set of data), and explored the value of combining some of the key metrics that were provided.

6.2 Publication: Using process mining to analyse self-regulated learning

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

> Saint, J., Fan, Y., Singh, S., Gasevic, D., & Pardo, A. (2021). Using process mining to analyse self-regulated learning: A systematic analysis of four algorithms. *LAK21: 11th International Learning Analytics and Knowledge Conference*, 333–343. https://doi.org/10.1145/3448139.3448171

Using process mining to analyse self-regulated learning: a systematic analysis of four algorithms

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ABSTRACT

The conceptualisation of self-regulated learning (SRL) as a process that unfolds over time has influenced the way in which researchers approach analysis. This gave rise to the use of process mining in contemporary SRL research to analyse data about temporal and sequential relations of processes that occur in SRL. However, little attention has been paid to the choice and combinations of process mining algorithms to achieve the nuanced needs of SRL research. We present a study that 1) analysed four process mining algorithms that are most commonly used in the SRL literature – Inductive Miner, Heuristics Miner, Fuzzy Miner, and pMineR; and 2) examined how the metrics produced by the four algorithms complement each. The study looked at micro-level processes that were extracted from trace data collected in an undergraduate course (N=726). The study found that Fuzzy Miner and pMineR offered better insights into SRL than the other two algorithms. The study also found that a combination of metrics produced by several algorithms improved interpretation of temporal and sequential relations between SRL processes. Thus, it is recommended that future studies of SRL combine the use of process mining algorithms and work on new tools and algorithms specifically created for SRL research.

CCS CONCEPTS

• **Applied computing → Learning management systems**; • **Computing methodologies → Online learning settings**.

KEYWORDS

Learning Analytics, Self-Regulated Learning, Process Mining, Micro-level Process Analysis

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1 INTRODUCTION

The study and analysis of self-regulated learning (SRL) is now well established in learning analytics (LA). SRL is conceptually informed by the notion that students can exercise control of their own knowledge-building, given an appropriate learning environment [40]. This environment is now typified less by traditional monologic delivery and more by engagement in interactive digital settings. Several theoretical models of SRL have been developed [20, 36, 41]. Although these models vary in conception, they share a common cyclical dynamic of planning, engagement, and evaluation [19]. One of the challenges of analysing SRL is the meaningful articulation of its temporal and cyclical nature.

To address this challenge, many researchers have adopted the use of Process Mining (PM) to articulate the temporal nature of SRL. PM is an event-based data analytic method that derives sequential, associative, and temporal analyses from trace data files [31]. PM has attracted the interest of SRL researchers who seek to explore alternatives to conventional statistical methods [23]. PM algorithms such as Heuristics Miner [33], Inductive Miner [14], Fuzzy Miner [13], and pMineR [11] have been variously used to explore patterns of SRL from digital and self-report (think aloud) data. Each of these algorithms is typified by the use of metrics to express the relationships between the identified learning processes in terms of sequence and association, informed by metrics such as frequency, time, and probability (amongst others). The choice of algorithm is important, and opportunities to combine algorithms have rarely been grasped.

Although several studies used PM algorithms to study SRL, very little justification for their choice of algorithm is offered. We assert that if PM is chosen as a means of modelling SRL, the choice of PM algorithm should not be arbitrary, but informed by consideration of their major characteristics. Moreover, we are unaware of any studies that conduct a comparison of the use of these different PM algorithms for the analysis SRL. The aim of the current study is to provide a systematic comparison of four PM algorithms used in research of SRL. This comparison was done on a dataset that was processed by following the Trace-SRL approach [25], whereby SRL processes were extracted from digital traces of student interactions with online resources of an online undergraduate course. The Trace-SRL approach is underpinned by an SRL codification framework defined in the study undertaken by Siadaty et al. [27].

In this study, we systematically compared the four PM algorithms that have been most commonly used in SRL research: Inductive Miner, Fuzzy Miner, Heuristics Miner, and pMineR. This comparison informs the choice of algorithms for researchers who seek to analyse SRL as a process that unfolds over time. We provide insights into the factors that demand consideration when choosing PM algorithms in SRL research. We also propose a novel method of interpreting a combined set of metrics, as generated by various PM algorithms. This is, for the first time, a joint interpretation based on the PM algorithm outputs, and one which highlights a new and promising direction in the field of LA.

2 BACKGROUND

The study of SRL and the development of models of learning within this context has gathered at pace and evolved to form a comprehensive ecosystem of research [19]. The concept of SRL is predicated on that notion that learners, at any given moment in a cycle of learning, employ a set of cognitive and meta-cognitive attributes to reach one or more learning goals [21, 35]. As such, learners exercise agency over the path towards these goals [34]. Given a set of external and internal conditions and drivers [36], the management of this agency can be seen as a manifestation of SRL. Such goals may be micro or macro in scale — the completion of a multiple choice test, or the authoring of a dissertation — and the ultimate resolution of the task may be a single SRL cycle or an ongoing sequence of cycles and sub-cycles. In this sense, SRL is viewed as an ongoing process which unfolds and develops over time [2, 38].

The major SRL theorists — Zimmerman [41], Pintrich [20], Winne and Hadwin [36], and Boekaerts [4] — have all developed multiple versions of their models through iterations and empirical testing. As Panadero [19] highlights, these models are defined by thematic variations of the same fundamental cyclic framework of SRL: 1) a preparatory/planning phase; 2) a performance/tactic management phase, and; 3) a reflective/evaluative phase. These variations hinge on differing focuses on, amongst other things, meta-cognition, strategy, tactics, and affective and emotive states.

2.1 Micro-level analysis of SRL processes

Significant advances in SRL framing are made by employing micro-process analysis to codify think-aloud data about learners' verbal accounts of their own learning [12]. In micro-process analysis of think-aloud data, learners were initially coached to verbally articulate tactics and strategies in the course of their learning cycle. The verbal utterances were captured and analysed through content analysis that makes use a coding scheme in which codes represent micro-level processes of a given SRL model. Content analysis is performed by categorising a verbal utterance with the most applicable micro-level process code. So if a student expresses learning aims of some sort, this expression would be manually coded to the micro-level process, *goal-setting*, which itself is part of the *planning* macro-level process. This macro-level process equates to one of the main SRL constructs often referred to as a phase of SRL. In this way, data are transformed through codification into recognisable SRL processes, and are, by definition, embedded in a recognised theoretical model of SRL. This analysis protocol is used in SRL research by several studies such as those by Bannert et al. [3] and Sonnenberg and Bannert [30]. These studies promised an informed way of measuring the nuances of SRL. Methodologically, however, there are trade-offs in the use of think aloud protocols as a form of self-reports. Winne and Jamieson-Noel [37] explored the disparity between students' reporting of their own study tactics and their actual behaviours. In relation to think-aloud protocols for data collection and analysis of SRL, Young [39] highlights such issues as cognitive load, verbal acuity, and the intrinsic veracity of the verbal utterances, and their subsequent inferential value. The use of digital trace data offers resolution to some of these issues. Siadaty et al. [27] applied the same type of micro-level analysis to trace data collected from knowledge workers. In this scenario, the trace data were recorded by a digital learning systems, and parsed into micro-level processes by automated scripts. This mitigates the issues of subjectivity that surround think-aloud and other self-report protocols.

We also define the terminology for micro-level analysis which is used throughout this paper (Figure 1). First, **learning actions** are determined based on the occurrences of learning events recorded in raw trace data. For example, a learner's click to open reading resources would register as a type of READING action. Sequences of learning actions are conceptually mapped as **micro-level SRL processes**, such as *Working On a Task* [24, 26]. For example, when learners engage a sequence of first-reading actions, this would be detected as *building knowledge process*, and could be coded as *Working On a Task.Build Knowledge. Micro-level processes* of reading previous materials could be coded as *Working On a Task.Address Learning Gap*. Such coding is based on relevant models of SRL [36, 41]. These micro-level SRL processes are sub categories of **macro-level SRL process**, which are themselves the main constructs of the chosen model of SRL. The **transitions** between SRL *processes* can be extracted from trace data based on the timestamps of occurrences of event sequences that represent relevant micro-level processes. The transitions between these SRL *processes* are used to form process maps, with the use of PM algorithms, that are referred to as **SRL process models**.

2.2 Process mining for temporal and sequential analysis of SRL

The definition of SRL as a cyclical process that unfolds over time is well-established [7]. In acknowledging this dimension of SRL, researchers are bound to address the methodological demands of process, sequence, and temporality. Quantitative LA research is largely characterised by the use of statistical models for data interrogation and discovery. Despite their value, a body of research suggests the use of statistical methods can impose ontological limitations on temporally focused studies [22, 23]. Constructs formerly measured by frequency of occurrence and analysed with conventional

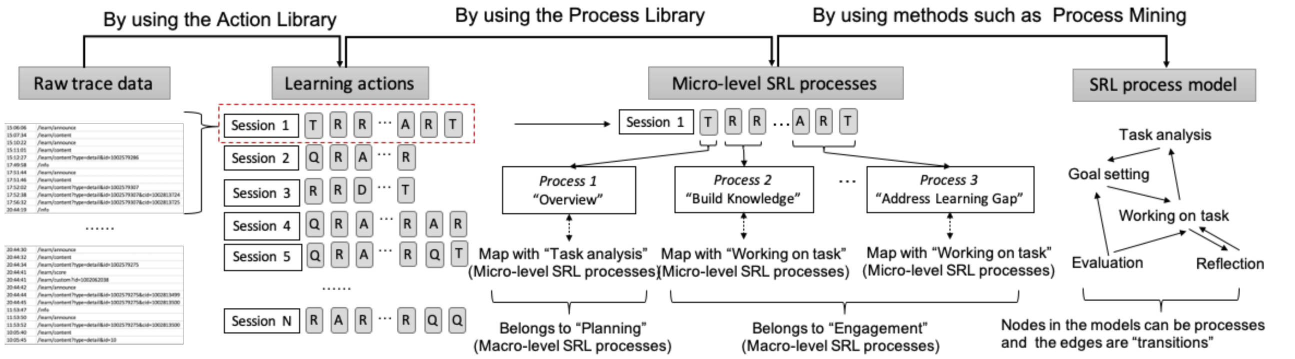

Figure 1: The terminologies and analytic framework in this study

statistical models are now conceptualised in terms of sequence and temporality[18]. PM is a promising choice for SRL researchers seeking to capture a learning dynamic that is not possible using statistical frequency measures alone [22]. PM algorithms are driven by event-based trace data and seek to establish temporal and sequential relationships between *processes* in the form of associative paths and metrics. In outputs of PM algorithms, process transition is visualised in node-based transition diagrams known as process models [31]. Several PM algorithms have been developed and are differentiated by usage of various PM metrics, for example, time, frequency and probability.

The first PM algorithm, Alpha Miner, established the basic design for many of the subsequent algorithms. It generates an associative matrix (the footprint matrix) to derive a set of relationships across all of the event process instances in the trace. Unidirectional antecedent and precedent behaviour is identified in sequential or parallel terms. Its ultimate aim is to articulate a process model that reflects the major permutations of event sequences, which are then visualised using Petri nets [32]. Enhancements were made to accommodate more complex models and looping, but this algorithm has not been used in any significant studies of SRL, and is not assessed methodologically in this study.

In choosing PM algorithms for this study, we assessed their presence in the published studies of SRL as part of a systematic literature review that we have conducted in parallel with the current study. Our systematic review showed that Fuzzy Miner [13] (including its incarnation in commercial platforms, Fluxicon Disco and Celonis) is the most frequently used algorithm, reported in nine SRL studies. The pMineR algorithm [10] is reported on in six SRL studies. Heuristics Miner [33] is reported on in four SRL studies. Inductive Miner [14] is used in two SRL studies.

2.2.1 Heuristics Miner. The Heuristics Miner algorithm [33], which can be deployed in tools like ProM and BupaR, was developed to address the perceived shortcomings of the Alpha Miner. Heuristics Miner builds on the Alpha Miner algorithm by providing frequency metrics and allowing for the articulation of short loops. It generates a process map which can articulate multi-directional metric-informed relationships between the *processes*. Its distinguishing feature is the dependency metric, which is built around the following formula:

$$a \Rightarrow_W b = \left(\frac{|a >_W b| - |b >_W a|}{|a >_W b| + |b >_W a| + 1} \right) \quad (1)$$

where $|a >_W b|$ is the frequency of b directly following a in the event log, and $|b >_W a|$ is the converse relationship. This produces a real-number value between -1 and +1. If the two event instances of a following b and b following a are very close in frequency, the metric value will tend toward zero. If there are large differences in ordering between a and b, the value will tend toward 1 or -1. It is, in a sense, a measure of reciprocation between *processes*. Figures of dependency close to zero do not always signify a lack of relationship, but a lack of dependency between one *process* and another. The dependency metric has been used in several SRL studies, for example, contrasting learning-challenge situations [29], and the use of meta-cognitive and cognitive prompts as deployed in a computer-based learning environment [9].

2.2.2 Inductive Miner. At its inception, the Inductive Miner algorithm, first developed in the ProM platform, represented the best attempt at addressing process model soundness, that is, the extent to which the discovered model can reproduce the various permutations of *processes* flows in the context of their cases [6]. Using a process tree design, Inductive Miner is able to model case paths which can branch in parallel or be exclusive choices. This is useful for modelling structured business processes, where exclusive choice and parallelism are key to accurate discovery. In the context of LA and SRL, this distinction may be viewed as redundant, as the cycles of SRL are typified by more random associations of learning processes. The algorithm has been used in two studies of SRL which explored contrasting models of passing and failing students [5, 8].

2.2.3 Fuzzy Miner. The Fuzzy Miner algorithm [13], first developed in the ProM platform, represents a significant diversion from the previous algorithms in that it does not seek to distinguish parallelism and choice in process sequence. This reduction of logic granularity is a trade-off. The Fuzzy model cannot be used to provide a strict articulation of sequential process permutations, and is therefore not able to address the demands of the PM tests of soundness, unlike Heuristics and Inductive. However, its visualisations are suitable for the analysis of the loosely structured patterns of SRL. This algorithm can also be configured to identify less impactful processes and merge them with other low frequency/high correlation processes, in order to simplify process models. Its more immediate practical value has seen Fuzzy Miner rise to prominence through its incorporation into commercial products such as Fluxicon Disco and Celonis. Frequency and time are its prominent discovery metrics; they have been used in SRL studies to explore high and low performing groups as extracted from self-report data [16] and MOOC interaction sequences, and how they differ across academic performance [15].

2.2.4 pMiner. The pMineR algorithm [10] is the only one to use probability as a metric. First order Markov modelling (FOMM) is deployed to train and visualise process models. It shares a similar visual layout as Fuzzy Miner but the lines between one process and the next one show a measure of the likelihood of transition between the processes, that is, the transition probability. Visual interpretations can be conducted from the thickness of the lines but more formal analyses rely on interpreting the actual transition probability values. pMineR has been used in SRL studies to explore time management [1] and learning strategies [17], and in conjunction with the Trace-SRL framework [25] to explore the use of SRL micro-level processes across groups of students who followed different learning strategies.

2.3 Research Questions

It is clear that the use of PM has a presence in the study of SRL. As such it is important that the choice of PM algorithm is informed by considerations of the suitability of the associated metrics to solve specific research questions and to achieve specific analytic objectives. In addition, the promise of combining PM metrics in SRL settings is one which has rarely been explored. Utilising the Trace-SRL framework [25] for coding *micro-level processes* of SRL from raw trace data collected by a learning management system, we present a systematic comparison of prominent PM algorithms to model sequential and temporal relations between *micro-level processes* of SRL. We also explore the promise of combining PM metrics from the PM algorithms to explore meaningful patterns of SRL. We seek to answer these questions:

- RQ1 What insights can be obtained from commonly used process mining algorithms when applied in the analysis of temporal and sequential relationships of micro-level processes of SRL extracted from digital trace data?
- RQ2 What insights can be obtained from interpreting a combination of metrics from the commonly used PM algorithms in the analysis of micro-level processes of SRL extracted from digital trace data?

3 METHODOLOGY

3.1 Data Collection and Preparation

The data for this study were collected from a Moodle learning management system (LMS) created to support a Python coding course at an Australian university. The source trace data were generated by as single cohort of 726 students over the course of a 13-week term. General LMS engagement data were additionally augmented with reading and annotation data generated from student engagement with the integrated eTextbooks. The annotation data were generated from a novel web-based annotation tool called *Hypothes.is* [28]. Using this tool, students were able to generate, categorise, edit and delete tag-based annotations within the pages of the texts. As such, these kinds of annotation events could be viewed as expressions of a certain control of learning, or more specifically SRL. For each instance of learner engagement with the LMS, raw event data were recorded. Over the course of the term, 571,718 raw trace events were generated.

In order to transform the raw trace events into micro-level SRL processes, we first needed to segment streams of events into learning sessions and then label theses events into learning actions (as shown in Figure 1). In several previous studies, the "unreasonable long dwell times" between two events were often used as markers for separating learning sessions. For example, in the Matcha et al. [17] study, a 45 minute period of inactivity indicated that the learner had already left this learning task and ended the corresponding learning session. However, after initial analysis of the trace data in our study, we discovered that learners usually needed to login several times in one day to finish the whole pre-class task, that is, several short sessions (terminated after 45 minutes of inactivity) in one day. We also received feedback from teachers that, based on their observation and experience, the learners usually needed several such short sessions to complete pre-class tasks in the course. Since we aimed to look at micro-level processes related to completion of learning tasks, a sequence of daily events was more appropriate as a session in our study. Considering that learners often studied very late at night, we chose 4AM as the starting and ending points for 24-hour sessions. Once the learning sessions were defined, an action library was derived in order to provide initial transformation of the raw event data in each session into descriptively meaningful learning actions. This resulted in the creation of 24 learning action descriptions, allocated to 7 categories. The detailed action library can be found at LAK21SM.

3.2 Data Processing

We adapted the Siadaty et al. [26] basic framework for micro-level analysis of SRL to reflect *micro-level processes* of SRL derived from trace data recorded in authentic LMS settings. There are three parts to this sequence: i) micro-level SRL framework definition; ii) SRL process library creation; and iii) SRL micro-level process generation. The final step, in which the raw trace data were parsed into SRL *processes* (micro- and macro-levels), was achieved running a REGEX Python script. The learning action sequences were transformed into micro-level SRL processes in order to provide the required SRL characterisation (the first step in Figure 1). For more details on this approach, refer to the studies by Siadaty et al. [26] and Saint et al. [25]. The generated process library (LAK21SM) comprises three macro-level processes of SRL, which correspond to the three constructs of the our model of SRL: 1) Planning; 2) Engagement; and 3) Evaluation. Categorised within these macro-level processes, we adapted a set of micro-level processes from the Siadaty et al. [26] framework. Within these categories, we labelled a set of *processes*. For example, a three-step *process*, such as

Reading → *HomePage_Viewed* → *Forum_Post* was categorised as *CLTS.Interaction*, where *CLTS* refers to the Coordinating Learning Task Sequences micro-level process. The *CLTS* micro-level process is one of the elements that make up the macro-level process, *Engagement*. In this sense, the raw data were actually coarsened, in terms of grain, through this transformation approach. This produced a final micro-level process dataset of 156,586 records.

3.3 Data Analysis

3.3.1 Building the Process Models. PM has mandatory requirements of its event trace. The key elements are: 1) an activity – a well-defined step in a broader process; 2) a case – a process instance; and 3) a timestamp. These three PM roles were populated thus: micro-level process → Activity; Day Timestamp → Timestamp; User Learning Session → Case.

3.3.2 Evaluating the PM Algorithms. To address **RQ1**, we supplied identical event data to the four chosen PM algorithms. In presenting the algorithms, we cover four key metrics when discussing the process models. In this context, our *processes* are the *micro-level processes* (as opposed to the raw learner actions from which they had been parsed), as described in the process library. When collectively referring to the relationship between *micro-level processes*, the term 'transition' is used. Fuzzy Miner and Inductive Miner can provide frequency and time metrics, while Heuristics Miner can provide frequency and dependency metrics. pMineR uniquely provides probability transition metrics. To avoid duplication of metric interpretation, we present the following PM algorithms and associated metrics: Inductive Miner (process frequency); Fuzzy Miner (process and transition frequency, transition median time); Heuristics Miner (dependency); and pMineR (transition probability). For each PM algorithm, we use this three-paragraph structure: 1) An overview of the process model and insights provided for the algorithm analysed; 2) An interpretation of transitional behaviour between a specific subset of the micro-level processes in the context of SRL – *TA.Overview*, *Eval.Learning Processes*, and *Eval.Learning Outcomes*; and 3) An appraisal of the algorithm in this context. The three chosen *micro-level processes* represent key SRL relationships in the model, and also provide an optimal mix of metrics to explore the method.

3.3.3 Comparing the PM Algorithm Metrics. To address **RQ2**, the key transition metrics, frequency and time from Fuzzy Miner, and and probability from pMineR, are interpreted in combination. The Inductive Miner model does not provide transition metrics between *processes*, and the Heuristic Miner dependency metric was determined not to be suitable for a combined interpretation, due to its non-intuitive construction. We used the three micro-level processes highlighted in the previous section to provide this combined interpretation of the relationships between the processes, as articulated through the three chosen metrics.

4 RESULTS

4.1 RQ1: Analysis by Algorithm

For the purposes of this analysis, we briefly discuss the concept of process model soundness. In conventional process mining, unlike LA processing, the goal is to provide the best approximation of process flows of a particular system. As such there are four dimensions of process model soundness: 1) replay fitness – how accurately can the model reproduce the process combinations; 2) simplicity – how cleanly can the process map be rendered and how easily can it be interpreted; 3) precision – the fraction of the behavior allowed by the model which is not seen in the source event trace; and 4) generalisation – how well can the model reproduce future process behaviour [6]. Whilst these dimensions are not applicable to Fuzzy and pMineR, they do inform our treatment of Inductive Miner and Heuristics Miner.

4.1.1 Inductive Miner. The focus of Inductive Miner is model soundness, that is, to accurately reflect all possible event paths throughout a process life-cycle. As such, multiple case paths are presented as completely as possible. Moving from the left to the right of Figure 2, we start with 48,907 cases (i.e., learning sessions). The first major branching in our model is parallel. This is indicated by an icon resembling a diamond with a plus sign, and also by the metrics for the outgoing branches from the + diamond, which are unchanged at 48,907. This indicates that any of these paths is taken at any given point in the overall flow.

We can trace a path of 48,907 sessions from the beginning of the process flow (the small green node at the left of the figure). This path can then split into a number of directions, one of which tells us that in 20,704 cases, *TA.Overview* is engaged. In 7,628 cases, we see this flow loop back on itself. This means that on 7,628 occasions, there were transitions to the same *micro-level* process, within a single learning session, making a total engagement frequency of 28,332. It is unclear how we articulate the relationship of *TA.Overview* with the other *micro-level processes*. As with *TA.Overview*, *Eval.Learning Processes* and *Eval.Learning Outcomes* are presented in the terms of frequency of cases, but with seemingly non-joined paths. In essence, each instance of these two *micro-level processes* simply tells us that learners can engage with the *micro-level process*, or not engage. The metrics show us process frequency engagement, but not in the sense that there is a transition between the *micro-level processes*. As such, we can interpret *micro-level process* frequency. In terms of SRL, it provides some sense about relative engagement with task analysis and evaluation of learning.

That we cannot easily see the multiple transitions between the processes is not a failing of the algorithm, but an expression of its unsuitability in the research of SRL. For the purposes of SRL, the process model visualisation is problematic in that it does not show transitions between *micro-level processes*. We know from the data, and from the other PM visualisations, that there were transitions between many of these *micro-level processes* but this is difficult to interpret in the model extracted by Inductive Miner. The branch types — parallel or choice — are employed to service model soundness, not to articulate the dynamics of a model of learning and its many variations. Inductive Miner works well when the learning sequence is more structured and shaped relatively strictly by a learning or course design. For example, the study reported in Bogarín et al. [5] presented useful results obtained with the use of Inductive Miner and demonstrated good soundness in context of the four dimensions of process model soundness [6]. However, the SRL behaviours captured in our study are more fluid in nature, and

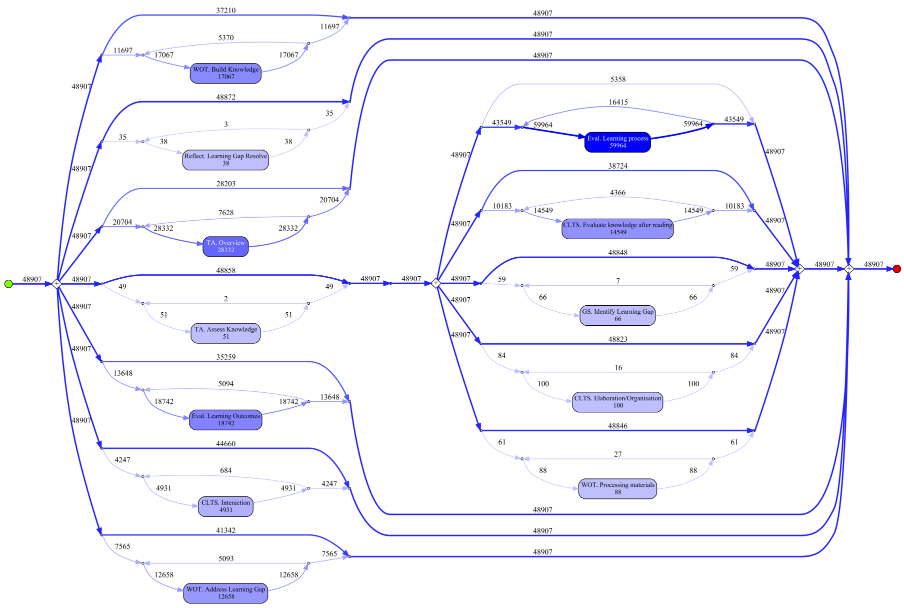

Figure 2: Inductive Miner Process Map

Inductive Miner struggled to articulate transitions between micro-level phases. We can derive an interpretation from the frequency metrics presented in the process model, but not much else. Inductive Miner is more suitable for traditional business process modelling where the exact type of notation (OR, XOR, and AND) is extensively used. However, such structured processes are not so common in SRL where learners continuously exercise their agency and adapt to the changing internal and external conditions [36].

4.1.2 Fuzzy Miner. The Fuzzy Miner process model, as rendered in Fluxicon Disco, provides an immediate snapshot of the relative prominence of the *micro-level processes* and the measure of the relationships between them, that is, the transitions. A quick overview (see Figure 3) identifies *Eval.Learning Process* as the most heavily engaged. This is indicated by the frequency metric (59,964) of the *micro-level process* and also its colour, which is the darkest in the process map. The colour grade lightens for *micro-level processes* that are less frequently engaged. The edges between the nodes also have frequency and temporal metrics, indicating the absolute count of transitions between the two joined processes and the median lag time. Disco also provides visual cues in the form of relative thickness of the edges. In event data where *start* and *end* date-timestamps are available, the median time-on-process (i.e., median time spent engaging on an *micro-level process*) would be present. In an event log with a single timestamp, such as the one used in the current study, this is not available.

We can interpret frequent transitions between *TA.Overview*, *Eval.Learning Processes*, and *Eval.Learning Outcomes*. We can also make an informed choice as to the starting point of our interpretation of the Fuzzy Miner process model; we know that *TA.Overview* is the most frequently engaged *micro-level process* at the start of a session (18,519). Transition from *TA.Overview* to *Eval.Learning Process*, is common, with a frequency metric of 13,037. We see transition from *Eval.Learning Process* to *Eval.Learning Outcomes*, is less common, with edge frequency of 8,984. The transition between *Eval.Learning Outcomes* and *Eval.Learning Process* even less frequent (2847). We interpret the temporal association in the transition from *Eval.Learning Outcomes* to *TA.Overview*, with median lag time of 105 seconds. This is the shortest lag time in the process model. There is a longer median lag time from *TA.Overview* to *Eval.Learning Process* (7.7 minutes). The lag time from *Eval.Learning Process* to *Eval.Learning Outcomes* is 3.6 minutes. This gives us a sense of transition between the *micro-level processes* in temporal space. We could interpret the short lag time between evaluating assessment results (*Eval.Learning Process*) and assessing the learning tasks (*TA.Overview*) as positive expression of SRL.

Fuzzy Miner allows practical interpretation of *micro-level processes* transitions in terms of frequency and time. In our model, strong *micro-level processes* relationships can be articulated both from the transition metrics and the visual cues; the colour and shading of the *micro-level processes*, and the the thickness of the transition edges between the *micro-level processes*. Frequency and time are universally known measures and easy to interpret. This being said, a reliance is placed on the researcher if they want to compare metrics from different *micro-level processes*. It may be difficult to get a sense of dominant transitions without a broader analysis of the other *micro-level process* metrics in the model. Also, the time metric can be deceptive if: 1) the original trace data collection method does not contain start and end timestamps of every event in the log data; and 2) the engagement timestamps are subject to skewing from, for example, learners clicking a page of the LMS and then leaving the page open while doing some other task.

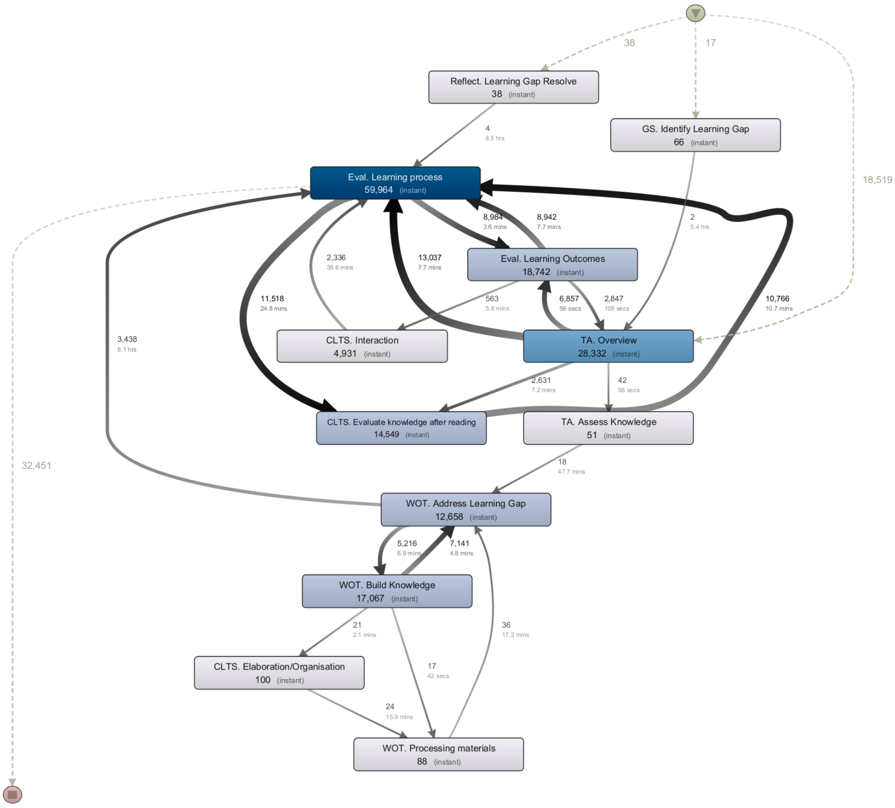

Figure 3: Fuzzy Miner Process Map

4.1.3 Heuristics Miner. This algorithm is designed to produce a *sound* process model, that is, one that measures against the four dimensions of process model soundness [6]. Looking at the process model discovered by Heuristic Miner (Figure 4), we can get some sense of the connection between the *micro-level processes*; it does not, however, display the full set of transitions we know to exist between the *micro-level processes.* To recap, the dependency metric, it is a value between -1 and +1, where a value closer to 1 indicates a strong dependency relationship.

In assessing a selection of the dependency metrics in this model, we see there is a strong dependency relationship between *TA. Overview* and *Eval.Learning Process*, with a the dependency metric of 0.824. This indicates that *Eval.Learning Process* followed *TA.Overview* on a large number occasions and whilst there was a transition back, it was less frequent. The dependency metric from *Eval.Learning Process* to *Eval.Learning Outcomes* is 0.0002, indicating that no dependency exists. It should not not be interpreted as infrequent transition. In this model, it means that there was a similar level of transition both ways between *Eval.Learning Process* and *Eval.Learning Outcomes.*

The dependency metrics provide useful insights but their interpretation is somewhat counter-intuitive in terms of typical interpretation of SRL. In more conventional measures of transition, such as frequency or time, we can easily determine some sort of meaning, such as when two *micro-level processes* frequently transition to each other, or follow each other with a long or short time lag. This is not immediately obvious on initial viewing of Heuristic Miner models; to an untrained eye, small value metrics may infer a lack of association between *micro-level processes.* This is not necessarily the case, as can be seen in our Heuristics model.

4.1.4 pMineR. The interpretation of pMineR's first order Markov models lies in assessing the transition probabilities between the (*micro-level processes*). The emphasis, therefore, is on the likely learning paths between *micro-level processes.* In Figure 5, we see the arrangement of *micro-level processes* within the bounds of BEGIN and END processes. The *BEGIN* process is positioned in the process model to allow us to describe the transition probabilities from the beginning of a session to the first *micro-level processes.* It allows us to interpret the most probable *micro-level processes* engaged at the beginning of a session. The *END* process allows us to interpret the probability of a *micro-level process* transitioning to the end of the session.

In assessing the transition probabilities in this model, we see that learners engaging with *TA.Overview* were more likely to engage next to *Eval.Learning Process* than any other *micro-level process*, with a transition probability of 0.57. This describes an emphatic

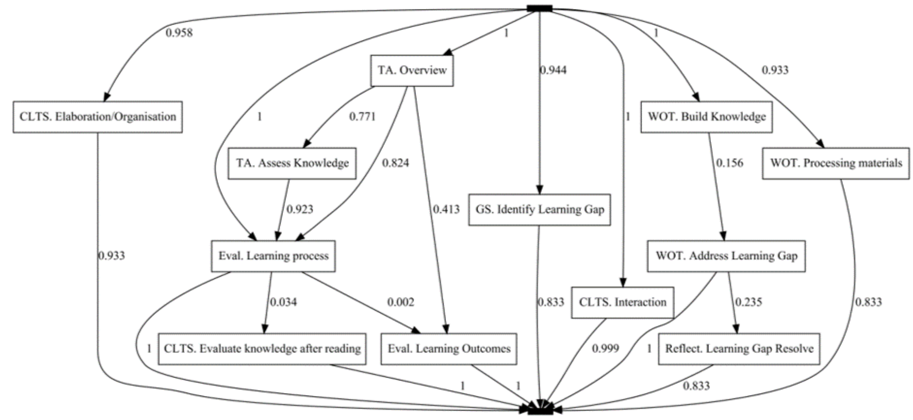

Figure 4: Heuristics Miner Process Map

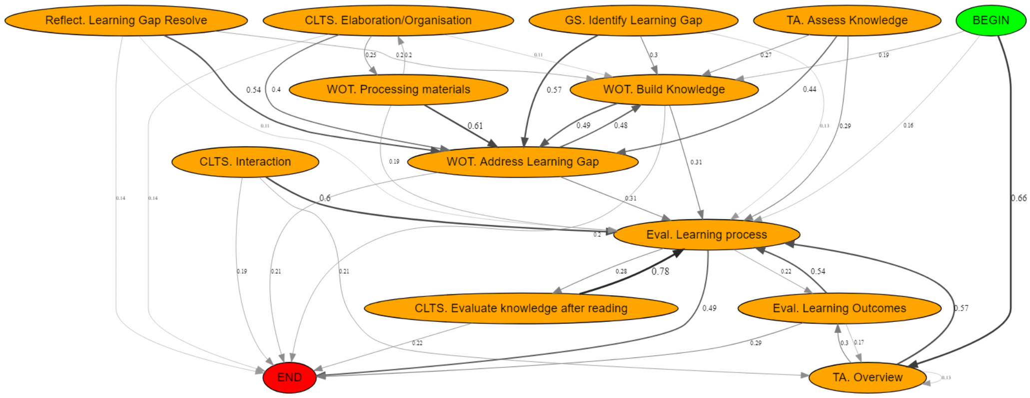

Figure 5: pMiner FOMM Process Map

probabilistic link. From *Eval.Learning Process*, there was a 0.22 probability of transition to *Eval.Learning Outcomes* and the transition probability from *Eval.Learning Outcomes* to *TA.Overview* was 0.17. This provides us with sense of the likely movement between these *micro-level processes*. We see that *Eval.Learning Process* seems to have been a likely transition from *TA.Overview*. In the other transitions, this likelihood was less.

Transition probability metrics are useful, as they allows an easy interpretation of *micro-level process* relationships in a measurement scale with which most researchers and practitioners are familiar. They provide a means of articulating the dynamics of SRL in terms of probabilistic likelihood. We can glean important insights from transition pairings of learners who exhibits SRL behaviours. For example, we could identify optimal SRL as a learner starting a session by assessing the learning tasks in hand (*TA.Overview*), then moves to a reading *micro-level process*, that is, (*WOT.Knowledge Build*), then maybe to engagement with other learning processes such as *Eval.Learning Process*. The transition probabilities between these processes provide a useful insight into probable movements of such learners. One shortcoming of transition probabilities is they offer no sense of absolute frequency; only relative frequency. A high transition probability may genuinely represent a probable transition, but it may also represent a transition from a very low frequency *micro-level process*. In Figure 5, *GS.Identify Learning Gap* appears to have a strong relationship with *WOT.Address Learning Gap*, with a transition probability of 0.57. In reality, this *micro-level process* had a very low frequency and a low transition frequency, rendering the transition probability largely meaningless.

4.2 RQ2: Algorithm Consolidation

The PM algorithms assessed in this study can provide valuable insights if used individually, but it is useful to consider what researchers could gain in combining insights from more than one algorithm, or, more specifically, from the metrics they provide. In considering a combined set of metrics, we need to establish which metrics are the easiest to interpret individually, and as a group. Assessing Inductive Miner, the first thing to note is that it does not provide transition metrics between the *micro-level processes* in the model. For example, we know that transitions from *TA.Overview* to *Eval.Learning Process* occurred on 13,037 occasions. This cannot be interpreted from the process model provided by Inductive Miner. In summary, Inductive Miner does not provide the edge metrics in the form that is suitable for SRL analysis. Assessing Heuristics Miner's dependency metric, we see that it does provide an indication of dependency between the *micro-level processes*. Its interpretation, however, is not immediately intuitive (as outlined in RQ1), and is at odds with the other PM metric measurement scales, which are based on frequency and probability. A combination of frequency, time and transition probability, holds some promise. Consider the visualisation in Figure 6.

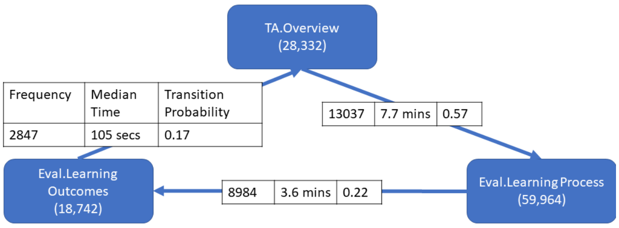

Figure 6: Combined PM Metric Visualisation

The strong linkage from *TA.Overview* to *Eval.Learning Process* is emphatically articulated. More importantly, the frequency metric (Fuzzy, Inductive) is given a probabilistic context by the transition probability (pMineR). So we can say that, not only is this a frequent *micro-level process* transition, but it is the most likely transition from the *TA.Overview*. If we look at the transition from *Eval.Learning Process* to *Eval.Learning Outcomes*, the frequency metric (13,037) tells us something, but the transition probability immediately articulates the likelihood of this transition (0.57). This provides a useful complementary interpretation. Frequency of transition provides an absolute transition measure and articulates a clear sense of *micro-level process* association. Without interpreting some other connected transition frequencies, a comparative sense of frequency may not be immediately clear. The transition probability metric provides an immediate sense of context. In models where there are varying frequencies of occurrences of *micro-level processes*, this probabilistic insight provides a standardised measure, that is, one that is independent of absolute frequency. Conversely, we know (from RQ1) that high transition probabilities can be generated from *micro-level processes* of low frequency. A large transition probability may be the effect of a genuinely strong association, or it may just be the effect of transition from a very infrequently engaged *micro-level process*. Combining these metrics would help mitigate spurious interpretations of transition probabilities. Infrequent transitions could be easily identified, such as those seen around the *micro-level process* comprised of text annotations, that is, *GS.Identify Learning Gap* or *Eval.Learning Gap Resolve*. The time metric (Fuzzy), that is, the median lag time between *micro-level processes*, provides another layer. In Figure 6, we see a less probable transition from *Eval.Learning Outcomes* to *TA.Overview* but the median lag time is the shortest in the model. In this way, we can further articulate the dynamics of the transition. Certain SRL behaviour maybe typified by variations in frequency, transition probability and median lag time between *micro-level processes*.

5 DISCUSSION

5.1 Discussion of Results

PM provides insights into SRL that cannot be obtained using conventional statistical modelling that typically use counts and duration of occurrences of micro-level SRL processes. If we accept that SRL is a process that unfolds over time [7], then we must also accept that there are certain ontological limitations that statistical modelling imposes. PM algorithms provide a means of capturing a learning dynamic that is not possible using conventional frequency measures alone [22]. The suitability of PM in the research of SRL is demonstrated by the body of studies currently published [1, 3, 8, 9, 15–17, 24, 25, 29].

In this study, we assessed the value of four PM algorithms used in previous SRL studies. Firstly, using a common dataset coded with the instances of the use of micro-level SRL processes, we conducted an empirical study to systematically explore the insights provided by the different process models, using key PM metrics generated from these models. In Table 1, we summarised the high-level findings from six dimensions. Secondly, we explored the promise of combining the metrics from the various models in a unified interpretation to explore the extent to which different PM metrics — frequency, time, and probability — complement each other. We assessed Inductive Miner for process frequency metric, Heuristics Miner for transition dependency metrics, Fuzzy Miner for transition and process frequency and time metrics, and pMiner for transition probability metrics

In addressing **RQ1**, our research showed that the PM algorithms fall into two broad categories: algorithms to seek process model soundness (i.e., Inductive Miner and Heuristics Miner) and those that focus on simplified model generation (i.e., Fuzzy Miner and pMineR). This finding informs the choice of algorithms for researchers who seek to study how SRL unfolds over time [7]. The process model generated from Inductive Miner proved quite difficult to interpret. The process flows articulated in its visualisations were presented in an unwieldy parallel configuration which did not convey the various transitions that we know exist between the SRL micro-level processes. This algorithm was successfully used in two studies of SRL [5, 8], which were conducted in the context of a more structured set of learning paths. The Heuristics Miner dependency metric provided some promising insights in certain pairs of micro-level processes. We were able to glean a sense of process directional process dependency, that is, a sense of when one micro-process follows another and whether the transition was often reversed. The Heuristics dependency metric is, however, not immediately intuitive to interpret. The SRL studies in which Heuristic Miner has been used did not systematically interpret the dependency metric, although those studies did identify relationships between the learning processes that were modelled [9, 29]. We gleaned richer results from Fuzzy Miner, whose metrics are easy to interpret. The transition frequencies and lag times provided clear insights into the relationships between between micro-level processes in the context of SRL. This clarity of insight is seen in a number of SRL studies that use Fuzzy Miner [15, 16]. Interpreting the absolute frequency of a specific process measure, particularly in a process model with numerous processes, can put responsibility on the researcher to assess other process frequency measures to get a sense of relative

Table 1: Summary and comparison of the four process mining algorithms

	Inductive Miner	Fuzzy Miner	Heuristics Miner	pMineR
Metrics	Frequency, time	Frequency, time	Dependency, frequency	Transition probability
Package/Toolkit	ProM, BupaR	Fluxicon Disco, Celonis, ProM	ProM, BupaR	pMineR R package
Key features	Process model soundness	Simplified models	Process model soundness	First order Markov models
Study examples	[5, 8]	[15, 16]	[9, 29]	[1, 17, 25]
Advantages	Model soundness	Ease of interpretation for SRL	Unique dependency metric	Ease of interpretation, Unique probability metric
Limitations	Not useful for unstructured models in SRL	No relative scale for frequency and time	Dependency metric not intuitive	No absolute scale

scale. pMineR also provided clear insights in the context of probable transitions between micro-level processes, addressing the issue of relative scale by providing probability as a measure. Conversely, we need to be mindful when interpreting high transition probabilities, as they may be due to small process frequencies, as opposed to probable transitions.

The main finding obtained in addressing **RQ1** was that none of the metrics provided by a single PM algorithm provided a complete picture of SRL. To provide a complete picture, in **RQ2**, we presented a novel method of combining and comparing PM metrics to form a joint interpretation. Our results show that combining and comparing the metrics from different PM algorithms provides a level of nuance that cannot be gleaned from the interpretation of single models. Combining frequency and probability provided a complementary interpretation of transitions between micro-level processes, which articulates both relative (i.e., transition probability) and absolute scales (i.e., transition dependency, transition frequency, and time lag). The addition of time provides another dimension through which we can interpret SRL. For example, we may see strong evidence of transition between an SRL phase of *Planning* to an SRL phase of *Engagement*, but also evidence of long time lags between these two phases. Shorter lag times may indicate a more pro-active self-regulated learner. As a counterpoint, these results also show that combining and analysing multiple algorithm metrics requires a deeper consideration of the nuances of the metrics available to each algorithm, and the resources to train and generate multiple process models.

5.2 Implications for Future Research

If the use of PM algorithms in SRL research is to move from exploratory work to more impactful studies, greater consideration must be given to their selection and deployment. The use of Inductive Miner or Heuristics Miner may not be suitable in environments where SRL processes are subject to the nuances of the learning design and the learners who enact it. In these scenarios, a more forgiving process model, such as Fuzzy Miner or pMineR, would be more viable. A combined interpretation of relative and absolute metrics provided by different PM algorithms should also be considered in the future studies of SRL. To that end, a significant benefit could be gained by developing a unified tool for analysis of SRL that combines inputs from the various PM metrics, or a new unified process miner that provides native support for multiple metrics beyond what is currently available in the four PM algorithms commonly used in SRL research.

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REFERENCES

[1] Nora'ayu Ahmad Uzir, Dragan Gašević, Wannisa Matcha, Jelena Jovanović, and Abelardo Pardo. 2020. Analytics of time management strategies in a flipped classroom. *Journal of Computer Assisted Learning* 36, 1 (2020), 70–88. https://doi.org/10.1111/jcal.12392 _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/jcal.12392.

[2] Roger Azevedo, Daniel C. Moos, Amy M. Johnson, and Amber D. Chauncey. 2010. Measuring Cognitive and Metacognitive Regulatory Processes During Hypermedia Learning: Issues and Challenges. *Educational Psychologist* 45, 4 (Oct. 2010), 210–223. https://doi.org/10.1080/00461520.2010.515934 Publisher: Routledge _eprint: https://doi.org/10.1080/00461520.2010.515934.

[3] Maria Bannert, Peter Reimann, and Christoph Sonnenberg. 2014. Process mining techniques for analysing patterns and strategies in students' self-regulated learning. *Metacognition and Learning* 9, 2 (Aug. 2014), 161–185. https://doi.org/10.1007/s11409-013-9107-6

[4] Monique Boekaerts. 1996. Coping with stress in childhood and adolescence. In *Handbook of coping: Theory, research, applications.* John Wiley & Sons, Oxford, England, 452–484.

[5] Alejandro Bogarín, Rebeca Cerezo, and Cristóbal Romero. 2018. Discovering learning processes using Inductive Miner: A case study with Learning Management Systems (LMSs). *Psicothema* 30.3 (Aug. 2018), 322–329. https://doi.org/10.7334/psicothema2018.116

[6] Joos C. A. M. Buijs, Boudewijn F. van Dongen, and Wil M. P. van der Aalst. 2012. On the Role of Fitness, Precision, Generalization and Simplicity in Process Discovery. In *On the Move to Meaningful Internet Systems: OTM 2012 (Lecture Notes in Computer Science)*, Robert Meersman, Hervé Panetto, Tharam Dillon, Stefanie Rinderle-Ma, Peter Dadam, Xiaofang Zhou, Siani Pearson, Alois Ferscha, Sonia Bergamaschi, and Isabel F. Cruz (Eds.). Springer, Berlin, Heidelberg, 305–322. https://doi.org/10.1007/978-3-642-33606-5_19

[7] Deborah L. Butler and Philip H. Winne. 1995. Feedback and Self-Regulated Learning: A Theoretical Synthesis. *Review of Educational Research* 65, 3 (Sept. 1995), 245–281. https://doi.org/10.2307/1170684 Publisher: [Sage Publications, Inc., American Educational Research Association].

[8] Rebeca Cerezo, Alejandro Bogarín, María Esteban, and Cristóbal Romero. 2020. Process mining for self-regulated learning assessment in e-learning. *Journal of Computing in Higher Education* 32, 1 (April 2020), 74–88. https://doi.org/10.1007/s12528-019-09225-y

[9] Katharina Engelmann and Maria Bannert. 2019. Analyzing temporal data for understanding the learning process induced by metacognitive prompts. *Learning and Instruction* (May 2019), 101205. https://doi.org/10.1016/j.learninstruc.2019.05.002

[10] Roberto Gatta, Jacopo Lenkowicz, Mauro Vallati, Alessandro Stefanini, Nicola Dinapoli, Berardino De Bari, and Lucia Sacchi. 2017. pMineR: Processes Mining in Medicine. https://CRAN.R-project.org/package=pMineR

[11] Roberto Gatta, Mauro Vallati, Jacopo Lenkowicz, Eric Rojas, Andrea Damiani, Lucia Sacchi, Berardino De Bari, Arianna Dagliati, Carlos Fernandez-Llatas, Matteo Montesi, Antonio Marchetti, Maurizio Castellano, and Vincenzo Valentini. 2017. Generating and Comparing Knowledge Graphs of Medical Processes Using pMineR. In *Proceedings of the Knowledge Capture Conference (K-CAP 2017)*. Association for Computing Machinery, Austin, TX, USA, 1–4. https://doi.org/10.1145/3148011.3154464

[12] Jeffrey Alan Greene and Roger Azevedo. 2009. A macro-level analysis of SRL processes and their relations to the acquisition of a sophisticated mental model of a complex system. *Contemporary Educational Psychology* 34, 1 (Jan. 2009), 18–29. https://doi.org/10.1016/j.cedpsych.2008.05.006

[13] Christian W. Günther and Wil M. P. van der Aalst. 2007. Fuzzy Mining – Adaptive Process Simplification Based on Multi-perspective Metrics. In *Business Process Management (Lecture Notes in Computer Science)*, Gustavo Alonso, Peter Dadam, and Michael Rosemann (Eds.). Springer, Berlin, Heidelberg, 328–343. https://doi.org/10.1007/978-3-540-75183-0_24

[14] S. J. J. Leemans, D. Fahland, and Van Der W. M.P. Aalst. 2014. Process and deviation exploration with Inductive visual Miner. In *BPM Demo Sessions 2014 (co-located with BPM 2014, Eindhoven, The Netherlands, September 20, 2014)*. CEUR-WS.org, 46–50. https://research.tue.nl/en/publications/process-and-deviation-exploration-with-inductive-visual-miner

[15] Jorge Maldonado-Mahauad, Mar Pérez-Sanagustín, René F. Kizilcec, Nicolás Morales, and Jorge Munoz-Gama. 2018. Mining theory-based patterns from Big data: Identifying self-regulated learning strategies in Massive Open Online Courses. *Computers in Human Behavior* 80 (March 2018), 179–196. https://doi.org/10.1016/j.chb.2017.11.011

[16] Jonna Malmberg, Sanna Järvelä, Hanna Järvenoja, and Ernesto Panadero. 2015. Promoting socially shared regulation of learning in CSCL: Progress of socially shared regulation among high- and low-performing groups. *Computers in Human Behavior* 52 (Nov. 2015), 562–572. https://doi.org/10.1016/j.chb.2015.03.082

[17] Wannisa Matcha, Dragan Gašević, Nora'ayu Ahmad Uzir, Jelena Jovanović, and Abelardo Pardo. 2019. Analytics of Learning Strategies: Associations with Academic Performance and Feedback. In *Proceedings of the 9th International Conference on Learning Analytics and Knowledge (LAK19)*. Association for Computing Machinery, Tempe, AZ, USA, 461–470. https://doi.org/10.1145/3303772.3303787

[18] Inge Molenaar. 2014. Advances in temporal analysis in learning and instruction. *Frontline Learning Research* 2, 4 (Dec. 2014), 15–24. https://doi.org/10.14786/flr.v2i4.118 Number: 4.

[19] Ernesto Panadero. 2017. A Review of Self-regulated Learning: Six Models and Four Directions for Research. *Frontiers in Psychology* 8 (April 2017), 1–28. https://doi.org/10.3389/fpsyg.2017.00422

[20] Paul R. Pintrich. 2000. Chapter 14 - The Role of Goal Orientation in Self-Regulated Learning. In *Handbook of Self-Regulation*, Monique Boekaerts, Paul R. Pintrich, and Moshe Zeidner (Eds.). Academic Press, San Diego, 451–502.

[21] Paul R. Pintrich. 2002. The Role of Metacognitive Knowledge in Learning, Teaching, and Assessing. *Theory Into Practice* 41, 4 (Nov. 2002), 219–225. https://doi.org/10.1207/s15430421tip4104_3 Publisher: Routledge _eprint: https://doi.org/10.1207/s15430421tip4104_3.

[22] Peter Reimann. 2009. Time is precious: Variable- and event-centred approaches to process analysis in CSCL research. *International Journal of Computer-Supported Collaborative Learning* 4, 3 (Sept. 2009), 239–257. https://doi.org/10.1007/s11412-009-9070-z

[23] Peter Reimann, Lina Markauskaite, and Maria Bannert. 2014. e-Research and learning theory: What do sequence and process mining methods contribute? *British Journal of Educational Technology* 45, 3 (Feb. 2014), 528–540. https://doi.org/10.1111/bjet.12146 _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/bjet.12146.

[24] John Saint, Dragan Gašević, Wannisa Matcha, Nora'Ayu Ahmad Uzir, and Abelardo Pardo. 2020. Combining analytic methods to unlock sequential and temporal patterns of self-regulated learning. In *Proceedings of the Tenth International Conference on Learning Analytics & Knowledge (LAK '20)*. Association for Computing Machinery, Frankfurt, Germany, 402–411. https://doi.org/10.1145/3375462.3375487

[25] John Saint, Alexander Whitelock-Wainwright, Dragan Gašević, and Abelardo Pardo. 2020. Trace-SRL: A Framework for Analysis of Microlevel Processes of Self-Regulated Learning From Trace Data. *IEEE Transactions on Learning Technologies* 13, 4 (Oct. 2020), 861–877. https://doi.org/10.1109/TLT.2020.3027496 Conference Name: IEEE Transactions on Learning Technologies.

[26] Melody Siadaty, Dragan Gasevic, and Marek Hatala. 2016. Trace-based Microanalytic Measurement of Self-Regulated Learning Processes. *Journal of Learning Analytics* 3, 1 (April 2016), 183–214. https://doi.org/10.18608/jla.2016.31.11

[27] Melody Siadaty, Dragan Gašević, and Marek Hatala. 2016. Measuring the impact of technological scaffolding interventions on micro-level processes of self-regulated workplace learning. *Computers in Human Behavior* 59 (June 2016), 469–482. https://doi.org/10.1016/j.chb.2016.02.025

[28] Shaveen Singh and Bernd Meyer. 2019. Using Social Annotations to Augment the Learning Space and Learner Experience. In *Proceedings of the 2019 ACM Conference on Innovation and Technology in Computer Science Education (ITiCSE '19)*. Association for Computing Machinery, New York, NY, USA, 527–533. https://doi.org/10.1145/3304221.3319767

[29] Márta Sobocinski, Jonna Malmberg, and Sanna Järvelä. 2017. Exploring temporal sequences of regulatory phases and associated interactions in low- and high-challenge collaborative learning sessions. *Metacognition and Learning* 12, 2 (Aug. 2017), 275–294. https://doi.org/10.1007/s11409-016-9167-5

[30] Christoph Sonnenberg and Maria Bannert. 2016. Evaluating the Impact of Instructional Support Using Data Mining and Process Mining: A Micro-Level Analysis of the Effectiveness of Metacognitive Prompts. *JEDM | Journal of Educational Data Mining* 8, 2 (Dec. 2016), 51–83. https://doi.org/10.5281/zenodo.3554597 Number: 2.

[31] Wil van der Aalst. 2016. *Process Mining: Data Science in Action* (2 ed.). Springer-Verlag, Berlin Heidelberg. https://doi.org/10.1007/978-3-662-49851-4

[32] Van Der W. M.P. Aalst, A. J. M. M. Weijters, and L. Maruster. 2004. Workflow mining: Discovering process models from event logs. *IEEE Transactions on Knowledge and Data Engineering* 16, 9 (2004), 1128–1142. https://doi.org/10.1109/TKDE.2004.47 Publisher: IEEE Computer Society.

[33] A. J. M. M. Weijters, Van Der W. M.P. Aalst, and A. K. Alves De Medeiros. 2006. *Process mining with the HeuristicsMiner algorithm*. Technische Universiteit Eindhoven. https://research.tue.nl/en/publications/process-mining-with-the-heuristicsminer-algorithm

[34] Philip H. Winne. 2006. How Software Technologies Can Improve Research on Learning and Bolster School Reform. *Educational Psychologist* 41, 1 (March 2006), 5–17. https://doi.org/10.1207/s15326985ep4101_3 Publisher: Routledge _eprint: https://doi.org/10.1207/s15326985ep4101_3.

[35] Philip H. Winne. 2018. Theorizing and researching levels of processing in self-regulated learning. *British Journal of Educational Psychology* 88, 1 (2018), 9–20. https://doi.org/10.1111/bjep.12173

[36] Philip H. Winne and Allyson F. Hadwin. 1998. Studying as self-regulated learning. In *Metacognition in educational theory and practice*. Lawrence Erlbaum Associates Publishers, Mahwah, NJ, US, 277–304.

[37] Philip H Winne and Dianne Jamieson-Noel. 2002. Exploring students' calibration of self reports about study tactics and achievement. *Contemporary Educational Psychology* 27, 4 (Oct. 2002), 551–572. https://doi.org/10.1016/S0361-476X(02)00006-1

[38] Philip H. Winne and Nancy E. Perry. 2000. Chapter 16 - Measuring Self-Regulated Learning. In *Handbook of Self-Regulation*, Monique Boekaerts, Paul R. Pintrich, and Moshe Zeidner (Eds.). Academic Press, San Diego, 531–566. https://doi.org/10.1016/B978-012109890-2/50045-7

[39] K. A. Young. 2005. Direct from the source: The value of 'think-aloud' data in understanding learning. 6, 1 (Oct. 2005), 19–33. https://opus.lib.uts.edu.au/handle/10453/6348

[40] Barry J. Zimmerman. 1986. Becoming a self-regulated learner: Which are the key subprocesses? *Contemporary Educational Psychology* 11, 4 (Oct. 1986), 307–313. https://doi.org/10.1016/0361-476X(86)90027-5

[41] Barry J. Zimmerman. 2000. Chapter 2 - Attaining Self-Regulation: A Social Cognitive Perspective. In *Handbook of Self-Regulation*, Monique Boekaerts, Paul R. Pintrich, and Moshe Zeidner (Eds.). Academic Press, San Diego, 13–39. http://www.sciencedirect.com/science/article/pii/B9780121098902500317

6.3 Summary

The study presented in this chapter builds on the aspirations of Chapter five in the sense we explored the output from multiple methods on a common SRL-informed dataset. There were, however, a number of key developments. In this chapter we emphasised a more systematic comparison, which was possible due to the specific targeting of process mining algorithms. This decision was informed by the broader analysis of temporally focused SRL in Chapter two, in which it became clear that process mining was one of the most commonly used techniques in this area, and as such demanded a sharper focus. One important factor to note is that process mining algorithms were born in the sectors of industry and corporate logistics, and were designed to capture more rigidly designed process flows than those of SRL. Two of the algorithms analysed in our study—Heuristics Miner and Inductive Miner—are manifestations of this design, and, as such, did not provide satisfactory process maps when applied to our SRL data. To our knowledge, only the studies by Bogarín et al. (2018) and Cerezo et al. (2020) made satisfactory use of Inductive Miner, due to the specific and structured nature of the learner data. Previous studies that used Heuristics Miner tended to be vague in their interpretation of its metrics; our study highlighted their counter-intuitive nature in the context of SRL data. The first conception of Fuzzy Miner (Günther & van der Aalst, 2007), in which the attainment of process model soundness was relegated in favour of more immediate interpretability, was a key development. It provided the possibility of the use of process mining in less structured settings, such as those typified by SRL; a possibility that was explored by Bannert et al. (2014) in their seminal study. In our study, we found that the Fuzzy-informed Disco platform produced a set of rich and interpretable insights, which aligned with the fluid nature of SRL. This richness was also afforded by the probabilistic outcomes produced by pMineR (Gatta, Vallati, et al., 2017). The key contribution here is that our analysis forces a more specific conversation about the choice of process mining platform, algorithm, and metric(s) (and a sense that all three are not always synonymous); one which we feel is more critical if the LA community want to push this type of SRL research beyond the exploratory.

The other key contribution is the promise of combining the metrics from various algorithms into a unified visualisation. Given that these metrics can be proprietary (such as the dependency metric from Heuristics Miner) or universal (such as frequency, time, or probability), and can be absolute or relative, the use of each metric provides its own view of the SRL processes and the relationships between them. Each view necessarily has strengths and limitations in terms of temporally and sequentially-informed SRL analysis. An awareness of this factor is not only key to choosing the most appropriate metric for a study, but also to the consideration how they can be combined and interpreted in unison. This combined view was presented in our study and is prototypical; it requires some finessing in order to provide more immediate actionable insights, but the promise of developing a unified and configurable multi-metric discovery algorithm is an intriguing one. For example, we noted that we may see strong evidence of transition between an SRL phase of Planning to an SRL phase of Engagement, but also evidence of long time lags between these two phases. Could shorter lag times indicate more pro-active self-regulated learners? If the relationship is weak, what does this indicate? These are dimensions of interpretation not possible from single metrics. We acknowledge that several packages, such as Fluxicon Disco, provide the option to display secondary metrics, but we are unaware of one that provides probabilistic, frequency, and time-based metrics, and we have seen few SRL studies that make full use of the variety of metrics available. Another key contribution is the deployment of the *Trace-SRL* framework on a new data source (Moodle) which allowed us to test its utility in the context of different learner actions. Up to now, we have stressed the importance of data transformation to reduce dimensionality and provide theoretical underpinning, but the other key demand is the ability to apply it in different contexts.

7 Conclusions and Future Directions

> There is no end to education. It is not that you read a book, pass an examination, and finish with education. The whole of life, from the moment you are born to the moment you die, is a process of learning
>
> — Jiddu Krishnamurti, *Krishnamurti on Education*

THE overarching theme of this thesis is the use of analytic methods to unlock patterns of self-regulated learning from trace data collected in authentic digital learning environments. More specifically, it seeks to explore how these methods can be used: i) to embed analyses in recognised models of self-regulated learning; ii) to unlock the temporal and sequential dynamics of self-regulated learning that cannot be detected using conventional statistical methods; and iii) in unison, to provide richer analytical insights. As such, we presented the findings of multiple studies in which we explore these areas, contextualised by a systematic review of the research area.

In this chapter, we briefly summarise the main findings and contributions of the work presented in this thesis according to the key research goals and questions stated in Section 1.1. Next, we focus the impact of the present work and its implications, both for research and practice, and posit a number of directions for future work. Finally, we provide some concluding remarks.

7.1 Impact of the present work

7.1.1 RQ1: Self-regulated Learning, time, and sequence

In Chapter two, we presented a systematic review of the literature on self-regulated learning as viewed through the lenses of temporality and sequence. This was inspired by the notion, first hinted at by Winne and Perry (2000) and developed by Reimann (2009) and Molenaar (2014), that learning is a process that unfolds in sequences over time. In accepting this conceptualisation in the context of self-regulated learning, we subscribe to the notion that conventional statistical and variable-centric methods are limited in this context. The review systematically analysed studies whose authors also subscribed to this notion. As such, we revealed a variety of insightful and novel explorations of temporally focused self-regulated learning. More importantly, we posited a set of perspectives that we feel future researchers should consider before embarking on studies in this area.

Methodological: We argue that the choice of analytic method should be approached with greater consideration than is generally articulated in many of the studies. We suggest that on the basis of the excellent work undertaken in these studies, researchers are now in a stronger position to make explicit assessments of available methods, as opposed to choosing them by convenience, curiosity, or familiarity.

Theoretical: SRL model usage is subject to much nuance. Some researchers demonstrate a clear and definable use of a recognised model of SRL; for others, SRL has a lighter presence, and is more of a contextual backdrop for the study. We would not prescribe an alignment in one specific direction, and acknowledge that there are many other positions on the spectrum of SRL model usage, but we would suggest a greater clarity of purpose in the use of learning theory. As stated, we hope this inspires a response to the call by Gašević et al. (2015) to embed LA research in recognised theories of learning.

Validity-focused: Whilst we cannot claim to address the many challenging issues around validity, the review does point to a number of ways in which researchers augment the robustness of their work. We argue that the greatest empirical gains can be made in employing *multi-channel* analysis (in which the same SRL phenomena are analysed from different data sources), whilst acknowledging the demand on skills and resources needed to deploy this. Nonetheless, there are measures, linked to decisions around method and theory, that can be addressed.

Temporal: In a sense, considerations of how researchers approach temporality are interlinked with methodological considerations. The review provides insights into some of the ways in which researchers can more readily consider the alignment between method and temporal insights.

To provide a more actionable framework, the review outlines a series of 26 questions, categorised by the four perspectives outlined above, which, we argue, will force a more explicit conversation around the conceptualisation and implementation of temporally focused SRL projects.

7.1.2 RQ2: The measurement of temporal dynamics

As stated repeatedly throughout this thesis and the incorporated studies, the conception of learning as an unfolding sequence of events (Molenaar, 2014; Reimann, 2009; Winne & Perry, 2000) is a major conceptual inspiration. The capture and analysis of the temporal and sequential dynamics of learner engagement is a research goal which underpins all of the studies reported on in chapters 3 to 6, although its emphasis does shift from study to study. Chen et al. (2018) conceptualised two broad temporal features: i) The *passage of time*, pertaining to event duration or frequency; and ii) temporality as a dynamic of how events are ordered and how they relate in terms of sequence. Whilst the first feature is important, it is the second feature that we sought to capture and articulate in addressing this research question.

That the study reported on in Chapter three (Saint et al., 2018) made use of a (then) novel process mining algorithm (Gatta, Lenkowicz, et al., 2017) is important but its true importance derives from the interpretation of its process mining metrics, which are transition probabilities. More specifically, in viewing the relationships between learning events in probabilistic terms, we articulated likelihoods of the occurrences of learning sequences. This allowed us to view learning in a temporal and sequential context not achievable using variable-centric methods. Although the use of process mining is not novel in and of itself, our deployment of stochastic process mining allowed us to take a set of learner groups, already extracted in the Jovanović et al. (2017) study, and provide an arguably richer and more sequentially dynamic characterisation of their learning behaviours. This is a key implication of the work. Another aspect of this analysis was the systematic interpretation of the process model metrics. Although there were a selection of relevant studies using process mining in learning contexts (see the outcomes of Chapter two), metric choice and interpretation generally stopped short of being systematic, being more general in nature (notable exceptions being the work undertaken by Ahmad Uzir et al. (2020) and Matcha, Gašević, Ahmad Uzir, Jovanović, and Pardo (2019)). We deployed a similar level of forensic interpretation to the remaining studies in order to further address the demands of RQ2 in differing contexts, using different process and network analytic algorithms.

Another key element of these interpretations was the use of pairwise model comparison, as demonstrated in all studies except the one reported on in Chapter six. In these studies, we compared different learner groups, mainly through pMineR "compare" plots as represented by their trained process models. This allowed us to directly assess the differences in specific temporal sequences, in context of likelihood, based on the differences between their respective event transition probabilities. This provided key insight into well-formed and malformed learning behaviours that may have gone unseen if analysed in isolation.

Our explorations of RQ2 outlined a robust and systematic way of capturing and visualising learner data, providing a dynamic view of its temporal and sequential nature, one which we hope is more widely adopted.

7.1.3 RQ3: A framework for embedding SRL

Transforming or coding raw data provides a means of viewing and analysing it through a lens which is better aligned to the demands of the given research scope. In effect, it translates data into a language that researchers can more readily understand and communicate, and with this comes other benefits, such as reduction of noise and dimensionality. Whilst these benefits are of great importance, we argue that they are undermined without the use of recognised models or theories of SRL to inform the coding process. The call to embed learning theory more explicitly in LA research has been made repeatedly (Dawson et al., 2015; Gašević et al., 2015; Gašević et al., 2017) and it is this call that we sought to answer in addressing this research question, and one which is deployed in the studies reported on in Chapter four, Chapter five, and Chapter six.

The work of Greene and Azevedo (2009) is of key importance as they provided a formalised method of interpreting raw learner data into categorised codes whilst aligning it with a recognised SRL model. Siadaty et al. (2016) formulated a means of implementing the Greene and Azevedo (2009) micro-level process analysis method using trace data in semi-experimental settings. We further expanded the method by deploying it using authentic LMS data, which allowed us to explore learner engagement in the context of SRL. Our "Trace-SRL" framework represents a cohesive theoretical and methodological process which can be deployed in different learning contexts. In our deployment, we used a Zimmerman-inspired SRL model, REGEX, and various process analytic techniques, but in reality, researchers are not bound to all theoretical and methodological elements. In the three studies which utilise the framework, two different REGEX scripts are used, and multiple analytic discovery methods. The key implication here is that the framework can be adjusted to fit multiple contexts, as long as adherence to SRL theory is not abandoned.

The key overarching implication here is that we have outlined a way of bridging the gap between macro-level SRL constructs and the micro-level learner events that are typically generated from authentic LMSs. It is in the bridging of this gap, highlighted by Molenaar (2014), that researchers are forced to have explicit conversations about the robustness and validity of their analyses.

7.1.4 RQ4: Comparing and combining analytic methods

The comparison of analytic methods is one which has been explored in a small number of SRL-related studies (see Chapter two). The Matcha, Gašević, Ahmad Uzir, Jovanović, Pardo, et al. (2019) study, for example, employed a systematic comparison of process, sequence, and network analytic methods, in assessing the different dimensions that each approach emphasises. The combining of analytic methods was explored, for example, in the Ahmad Uzir et al. (2020) study. The final two studies in this thesis (Chapter five and Chapter six) build on the methodological explorations of the previous chapters to provide both comparative and consolidated analyses of the dynamics of SRL. There are broad synergies between the two studies, so it is worth analysing implications of each study and the key differences.

The study reported on in Chapter five (Saint, Gašević, Matcha, et al., 2020) provided a comparison of techniques from a broad selection: frequency analysis, epistemic network analysis, and process mining. In this selection, the ontology of the phenomena observed effectively changes from method to method: the frequency analyses provided count-based aggregations on SRL engagement; epistemic network analysis provided insights into SRL event co-occurrence; and processing mining provided a more sequential and cyclical view. As such, they provided very distinct analytical perspectives, which we compared and consolidated. In doing so, we presented potential SRL researchers with a systematic view of each method's insights, and a qualitative example of a consolidated view. The study reported on in Chapter six followed the same comparison/consolidation trajectory but placed a more specific focus on various process mining algorithms, which intrinsically share a similar temporal and sequential ontological aspect. There are other key differences, which are also key implications: in undertaking a systematic assessment of the various process mining metrics available, we make explicit statements about their respective suitability for the analysis of SRL; and we demonstrate how these metrics could be combined to provide a richer, more ontologically complete view of SRL phenomena.

Perhaps the most important message, and one which chimes with the outcomes of the systematic review of Chapter two, is the call for researchers to formulate a more explicit assessment of process analytic methods, given the current level of maturity of SRL research.

7.2 Directions for future research

The work undertaken in this thesis paves the way for the exploration of some promising ideas and techniques. The focus of this work could be directed on the theoretical considerations around the conceptualisation of models of SRL and the methodological challenges of embedding the model in applied analytical settings. The focus could also be directed towards the conceptual considerations of representing SRL as a temporal entity and the methodological challenges of enacting it. We hope that any meaningful research in this encompasses all of these aspects.

In general, the conceptualisation of SRL models is well researched. In the context of its analysis in a temporal and sequential context, its deployment is subject to much nuance. Whilst we stop short of prescribing a specific direction, we suggest that the explicit and cohesive way in which we deployed our chosen SRL model should provide an impetus for researchers who seek to explore insights into the dynamics of SRL. One important factor is the alignment of SRL models to data collection methods. For example, self-report and specialised trace data capture allows the deployment of sophisticated models of SRL, such as the Winne and Hadwin (1998) model. Conversely, the challenges presented in capturing SRL processes from authentic trace data may mean some facets of this model would be necessarily underused, if deployed in this context. Authentic trace data capture may align more fully with a simpler, cyclical model of SRL, whose elements are common to most major models (Panadero, 2017). Much benefit could be derived from a conceptual study of the delineation of SRL models in context of data collection methods, with specific focus on the positioning of the constructs: i) as processes in an ongoing cycle of SRL, for example, preparation, engagement, and reflection, which can, if necessary, be further characterised as meta-cognitive or cognitive (e.g., the studies undertaken in chapters 4 to 6), or; ii) as overt categorisations of metacognition, cognition, and motivation, in which processes are subcategories (e.g., Bannert et al. (2014) and associated researchers).

Building on this conceptual work but focusing more on the capture of SRL from authentic trace data, we suggest that the deployment of REGEX in our "Trace-SRL" framework should be further developed and enhanced to make it more transferable (notwithstanding the need to improve validity robustness, discussed later in this section). Due to its novel and exploratory positioning in our studies, the REGEX routine must be seen as contextual to its data sources, which somewhat inhibits its immediate transfer to different settings. One direction may be to develop a configurable version of the routine in which parameters such as model choice, constructs, action sequences, amongst others, could be supplied and calibrated to generate SRL process data. The use of REGEX itself could be challenged; it is powerful but challenging to deploy in the context of more nuanced SRL sequences. A more transparent and procedural method would encourage more engagement with trace data coding, which is still relatively underexplored beyond the studies in this thesis.

Another promising avenue, as touched upon in the study reported on Chapter six, is the development of discovery algorithms that i) synergise more closely with with theoretical frameworks of learning, and ii) allow multi-metric consolidation. Multiple metrics can be configured in most process mining algorithms but we have yet to see one which combines probabilistic, temporal, and frequency metrics. Thought should be given to innovative ways of visually communicating multiple metrics in this context. This raises the broader question of the development of process analytic tools in educational contexts. Process mining as a tool was developed to serve the needs of commerce and industry and although it has been deployed successfully in several LA studies, it has been suboptimally used in others (see Chapter two). As far as we are aware, the only discovery tool specifically developed to analyse cognitive behaviours in educational and/or collaborative settings is ENA (Shaffer et al., 2009), which, in its original form, does not reflect the dynamics of order and sequence that are key to our temporal view of SRL. It is encouraging to see that the new version of ENA, dENA (Fogel et al., 2021), has been designed to articulate a sense of directional sequence, and employs a set of intuitive visuals to communicate the relationships between it activities/states. This kind of methodological evolution is critical to the advancement of research areas that seek to explore learner process dynamics.

Although the studies in this thesis are driven by single-source trace data collection, we recognise the import of exploring multi-channel data capture in order to improve measures of validity within this field of research. Although utilising a model of SRL contributes to sense of validity, there are still major challenges around the validation of cognitive and, especially, metacognitive expressions of SRL, as derived from trace data sources. To establish a more robust ground truth, the triangulation of multiple data sources (channels) in the capture of the same phenomena is critical. The triangulation of SRL self-report and trace data, as being currently explored by the researchers of the FLoRA project, van der Graaf et al. (2021) *and featured in* Pelletier et al. (2021), is a major step in the direction of construct and content validity (Messick, 1987); the holy grail of analytics research.

We hope that the LA research community will take heed of the framework of considerations presented in our systematic review of literature (Chapter two) and move toward a more transparent articulation of research in the exploration of the dynamics of SRL. Ultimately, we hope that the final outcome of our research is the development of mechanisms which combine effective SRL analytic techniques in combination with automated personalised feedback tools, such as advocated by Pardo (2018). In combining these technologies, we can provide support not just for learning designers and analysts, but for the most important stakeholder; the student.

Bibliography

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. https://doi.org/10.1111/jcal.12392 (cited on pp. 5, 8, 48, 88, 120, 121)

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 M. Scheffel, J. Broisin, V. Pammer-Schindler, A. Ioannou, & J. Schneider (Eds.), *Transforming Learning with Meaningful Technologies* (pp. 555–569). Springer International Publishing. (Cited on pp. 3, 48).

Bannert, M., Reimann, P., & Sonnenberg, C. (2014). Process mining techniques for analysing patterns and strategies in students' self-regulated learning. *Metacognition and Learning*, *9*(2), 161–185. https://doi.org/10.1007/s11409-013-9107-6 (cited on pp. 3, 4, 49, 67, 116, 122)

Bjork, R. A., Dunlosky, J., & Kornell, N. (2013). Self-Regulated Learning: Beliefs, Techniques, and Illusions [_eprint: https://doi.org/10.1146/annurev-psych-113011-143823]. *Annual Review of Psychology*, *64*(1), 417–444. https://doi.org/10.1146/annurev-psych-113011-143823 (cited on pp. 4, 49)

Boekaerts, M. (1996). Coping with stress in childhood and adolescence. *Handbook of coping: Theory, research, applications* (pp. 452–484). John Wiley & Sons. (Cited on p. 2).

Boekaerts, M. (2011). *Emotions, Emotion Regulation, and Self-Regulation of Learning*. Routledge Handbooks Online. https://doi.org/10.4324/9780203839010.ch26. (Cited on p. 68)

Bogarín, A., Cerezo, R., & Romero, C. (2018). Discovering learning processes using Inductive Miner: A case study with Learning Management Systems (LMSs). *Psicothema*, (30.3), 322–329. https://doi.org/10.7334/psicothema2018.116 (cited on p. 116)

Brown, T. A. (2015). *Confirmatory factor analysis for applied research, 2nd ed* [Pages: xvii, 462]. The Guilford Press. (Cited on p. 67).

Buijs, J. C. A. M., van Dongen, B. F., & van der Aalst, W. M. P. (2012). On the Role of Fitness, Precision, Generalization and Simplicity in Process Discovery. In R. Meersman, H. Panetto, T. Dillon, S. Rinderle-Ma, P. Dadam, X. Zhou, S. Pearson, A. Ferscha, S. Bergamaschi, & I. F. Cruz

(Eds.), *On the Move to Meaningful Internet Systems: OTM 2012* (pp. 305–322). Springer. https://doi.org/10.1007/978-3-642-33606-5_19. (Cited on p. 103)

Butler, D. L., & Winne, P. H. (1995). Feedback and Self-Regulated Learning: A Theoretical Synthesis [Publisher: [Sage Publications, Inc., American Educational Research Association]]. *Review of Educational Research*, *65*(3), 245–281. https://doi.org/10.2307/1170684 (cited on p. 3)

Cerezo, R., Bogarín, A., Esteban, M., & Romero, C. (2020). Process mining for self-regulated learning assessment in e-learning. *Journal of Computing in Higher Education*, *32*(1), 74–88. https://doi.org/10.1007/s12528-019-09225-y (cited on p. 116)

Cerón, J., Baldiris, S., Quintero, J., García, R. R., Saldarriaga, G. L. V., Graf, S., & Valentin, L. D. L. F. (2021). Self-Regulated Learning in Massive Online Open Courses: A State-of-the-Art Review [Conference Name: IEEE Access]. *IEEE Access*, *9*, 511–528. https://doi.org/10.1109/ACCESS.2020.3045913 (cited on p. 2)

Chen, B., Knight, S., & Wise, A. F. (2018). Critical Issues in Designing and Implementing Temporal Analytics [Number: 1]. *Journal of Learning Analytics*, *5*(1), 1–9. https://doi.org/10.18608/jla.2018.53.1 (cited on pp. 2, 14, 47, 49, 119)

Dawson, S., Mirriahi, N., & Gasevic, D. (2015). Importance of Theory in Learning Analytics in Formal and Workplace Settings [Number: 2]. *Journal of Learning Analytics*, *2*(2), 1–4. https://doi.org/10.18608/jla.2015.22.1 (cited on p. 120)

Devolder, A., Braak, J. v., & Tondeur, J. (2012). Supporting self-regulated learning in computer-based learning environments: Systematic review of effects of scaffolding in the domain of science education [_eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1365-2729.2011.00476.x]. *Journal of Computer Assisted Learning*, *28*(6), 557–573. https://doi.org/10.1111/j.1365-2729.2011.00476.x (cited on p. 2)

Efklides, A. (2011). Interactions of Metacognition With Motivation and Affect in Self-Regulated Learning: The MASRL Model [Publisher: Routledge]. *Educational Psychologist*, *46*(1), 6–25. https://doi.org/10.1080/00461520.2011.538645 (cited on p. 2)

Engelmann, K., & Bannert, M. (2021). Analyzing temporal data for understanding the learning process induced by metacognitive prompts. *Learning and Instruction*, *72*, 1–11. https://doi.org/10.1016/j.learninstruc.2019.05.002 (cited on p. 3)

Fan, Y., Saint, J., Singh, S., Jovanovic, J., & Gašević, D. (2021). A learning analytic approach to unveiling self-regulatory processes in learning tactics. *LAK21: 11th International Learning Analytics and Knowledge Conference*, 184–195. https://doi.org/10.1145/3448139.3448211 (cited on pp. 48, 88)

Fincham, E., Gasevic, D., Jovanović, J., & Pardo, A. (2019). From Study Tactics to Learning Strategies: An Analytical Method for Extracting Interpretable Representations [Publisher: IEEE]. *IEEE Transactions on Learning Technologies*, *12*(1), 59–72. https://doi.org/10.1109/TLT.2018.2823317 (cited on p. 49)

Fogel, A., Swiecki, Z., Marquart, C., Cai, Z., Wang, Y., Brohinsky, J., Siebert-Evenstone, A., Eagan, B., Ruis, A. R., & Shaffer, D. W. (2021). Directed Epistemic Network Analysis. In A. R. Ruis & S. B. Lee (Eds.), *Advances in Quantitative Ethnography* (pp. 122–136). Springer International Publishing. https://doi.org/10.1007/978-3-030-67788-6_9. (Cited on pp. 47, 123)

Gašević, D., Dawson, S., & Siemens, G. (2015). Let's not forget: Learning analytics are about learning. *TechTrends: Linking Research & Practice to Improve Learning*, *59*(1), 64–71. https://doi.org/10.1007/s11528-014-0822-x (cited on pp. 2, 4, 46, 67, 68, 119, 120)

Gašević, D., Kovanović, V., & Joksimović, S. (2017). Piecing the learning analytics puzzle: A consolidated model of a field of research and practice. *Learning: Research and Practice*, *3*(1), 63–78. https://doi.org/10.1080/23735082.2017.1286142 (cited on p. 120)

Gatta, R., Lenkowicz, J., Vallati, M., Stefanini, A., Dinapoli, N., Bari, B. D., & Sacchi, L. (2017). pMineR: Processes Mining in Medicine. Retrieved Sept. 16, 2019, from https://CRAN.R-project.org/package=pMineR. (Cited on pp. 9, 10, 50, 89, 103, 120)

Gatta, R., Vallati, M., Lenkowicz, J., Rojas, E., Damiani, A., Sacchi, L., De Bari, B., Dagliati, A., Fernandez-Llatas, C., Montesi, M., Marchetti, A., Castellano, M., & Valentini, V. (2017). Generating and Comparing Knowledge Graphs of Medical Processes Using pMineR. *Proceedings of the Knowledge Capture Conference*, 1–4. https://doi.org/10.1145/3148011.3154464 (cited on p. 116)

Greene, J. A., & Azevedo, R. (2009). A macro-level analysis of SRL processes and their relations to the acquisition of a sophisticated mental model of a complex system. *Contemporary Educational Psychology*, *34*(1), 18–29. https://doi.org/10.1016/j.cedpsych.2008.05.006 (cited on pp. 4, 7, 9, 46, 48, 68, 69, 87, 121)

Greene, J. A., Plumley, R. D., Urban, C. J., Bernacki, M. L., Gates, K. M., Hogan, K. A., Demetriou, C., & Panter, A. T. (2019). Modeling temporal self-regulatory processing in a higher education biology course. *Learning and Instruction*, 101201. https://doi.org/10.1016/j.learninstruc.2019.04.002 (cited on p. 2)

Greene, J. A., Robertson, J., & Costa, L.-J. C. (2011). Assessing self-regulated learning using think-aloud methods. *Handbook of self-regulation of learning and performance* (pp. 313–328). Routledge/Taylor & Francis Group. (Cited on p. 67).

Günther, C. W., & Rozinat, A. (2012). Disco: Discover your processes. *Proceedings of the Demonstration Track of the 10th International Conference on Business Process Management (BPM 2012)*, 40–44. Retrieved Mar. 31, 2020, from https://research.tue.nl/en/publications/disco-discover-your-processes (cited on p. 103)

Günther, C. W., & van der Aalst, W. M. P. (2007). Fuzzy Mining – Adaptive Process Simplification Based on Multi-perspective Metrics. In G. Alonso, P. Dadam, & M. Rosemann (Eds.), *Business*

Process Management (pp. 328–343). Springer. https://doi.org/10.1007/978-3-540-75183-0_24. (Cited on pp. 103, 116)

Heirweg, S., De Smul, M., Merchie, E., Devos, G., & Van Keer, H. (2020). Mine the process: Investigating the cyclical nature of upper primary school students' self-regulated learning. *Instructional Science*, *48*(4), 337–369. https://doi.org/10.1007/s11251-020-09519-0 (cited on pp. 3, 67)

Janssenswillen, G., Depaire, B., Swennen, M., Jans, M., & Vanhoof, K. (2019). bupaR: Enabling reproducible business process analysis. *Knowledge-Based Systems*, *163*, 927–930. https://doi.org/10.1016/j.knosys.2018.10.018 (cited on pp. 10, 89)

Järvelä, S., Järvenoja, H., Malmberg, J., & Hadwin, A. F. (2013). Exploring Socially Shared Regulation in the Context of Collaboration [Publisher: Springer Section: Part 1: Underexplored Contexts and Populations in Self-Regulated Learning]. *Journal of Cognitive Education and Psychology*, *12*(3), 267–286. https://doi.org/10.1891/1945-8959.12.3.267 (cited on p. 1)

Johnson, R. B., Onwuegbuzie, A. J., & Turner, L. A. (2007). Toward a Definition of Mixed Methods Research [Publisher: SAGE Publications]. *Journal of Mixed Methods Research*, *1*(2), 112–133. https://doi.org/10.1177/1558689806298224 (cited on p. 88)

Jolliffe, I. T. (2002). *Principal Component Analysis* (2nd ed.). Springer-Verlag. https://doi.org/10.1007/b98835. (Cited on p. 67)

Jovanović, J., Gašević, D., Dawson, S., Pardo, A., & Mirriahi, N. (2017). Learning analytics to unveil learning strategies in a flipped classroom [Place: US Publisher: JAI Press, Inc.]. *The Internet and Higher Education*, *33*, 74–85. https://doi.org/10.1016/j.iheduc.2017.02.001 (cited on pp. 3, 9, 49, 50, 66, 120)

Kinnebrew, J. S., & Biswas, G. (2012). *Identifying Learning Behaviors by Contextualizing Differential Sequence Mining with Action Features and Performance Evolution* [Publication Title: International Educational Data Mining Society]. International Educational Data Mining Society. Retrieved Sept. 15, 2021, from https://eric.ed.gov/?id=ED537192. (Cited on p. 49)

Kizilcec, R. F., Pérez-Sanagustín, M., & Maldonado, J. J. (2017). Self-regulated learning strategies predict learner behavior and goal attainment in Massive Open Online Courses. *Computers & Education*, *104*, 18–33. https://doi.org/10.1016/j.compedu.2016.10.001 (cited on p. 46)

Knight, S., & Buckingham Shum, S. (2017). Theory and Learning Analytics. In C. Lang, G. Siemens, A. F. Wise, & D. Gaševic (Eds.), *The Handbook of Learning Analytics* (1st ed., pp. 17–22). Society for Learning Analytics Research (SoLAR). http://solaresearch.org/hla-17/hla17-chapter1. (Cited on p. 1)

Knight, S., Wise, A. F., & Chen, B. (2017). Time for Change: Why Learning Analytics Needs Temporal Analysis [Number: 3]. *Journal of Learning Analytics*, *4*(3), 7–17. https://doi.org/10.18608/jla.2017.43.2 (cited on pp. 2, 14)

Leemans, S. J. J., Fahland, D., & van der Aalst, W. M. P. (2014). Process and deviation exploration with Inductive visual Miner. *BPM Demo Sessions 2014 (co-located with BPM 2014, Eindhoven, The Netherlands, September 20, 2014)*, 46–50. Retrieved Oct. 17, 2020, from https://research.tue.nl/en/publications/process-and-deviation-exploration-with-inductive-visual-miner (cited on p. 103)

Lust, G., Elen, J., & Clarebout, G. (2013). Regulation of tool-use within a blended course: Student differences and performance effects. *Computers & Education*, *60*(1), 385–395. https://doi.org/10.1016/j.compedu.2012.09.001 (cited on p. 49)

Mahzoon, M. J., Maher, M. L., Eltayeby, O., Dou, W., & Grace, K. (2018). A Sequence Data Model for Analyzing Temporal Patterns of Student Data. *Journal of Learning Analytics*, *5*(1), 55–74–55–74. https://doi.org/10.18608/jla.2018.51.5 (cited on p. 47)

Malmberg, J., Järvelä, S., Järvenoja, H., & Panadero, E. (2015). Promoting socially shared regulation of learning in CSCL: Progress of socially shared regulation among high- and low-performing groups. *Computers in Human Behavior*, *52*, 562–572. https://doi.org/10.1016/j.chb.2015.03.082 (cited on p. 49)

Malmberg, J., Järvelä, S., & Kirschner, P. A. (2014). Elementary school students' strategic learning: Does task-type matter? *Metacognition and Learning*, *9*(2), 113–136. https://doi.org/10.1007/s11409-013-9108-5 (cited on p. 4)

Matcha, W., Gašević, D., Ahmad Uzir, N., Jovanović, J., & Pardo, A. (2019). Analytics of Learning Strategies: Associations with Academic Performance and Feedback. *Proceedings of the 9th International Conference on Learning Analytics and Knowledge*, 461–470. https://doi.org/10.1145/3303772.3303787 (cited on pp. 48, 120)

Matcha, W., Gašević, D., Ahmad Uzir, N., Jovanović, J., Pardo, A., Maldonado-Mahauad, J., & Pérez-Sanagustín, M. (2019). Detection of Learning Strategies: A Comparison of Process, Sequence and Network Analytic Approaches. In M. Scheffel, J. Broisin, V. Pammer-Schindler, A. Ioannou, & J. Schneider (Eds.), *Transforming Learning with Meaningful Technologies* (pp. 525–540). Springer International Publishing. https://doi.org/10.1007/978-3-030-29736-7_39. (Cited on pp. 8, 48, 102, 121)

Messick, S. (1987). Validity. *ETS Research Report Series*, *1987*(2), i–208. https://doi.org/10.1002/j.2330-8516.1987.tb00244.x (cited on p. 123)

Molenaar, I. (2014). Advances in temporal analysis in learning and instruction [Number: 4]. *Frontline Learning Research*, *2*(4), 15–24. https://doi.org/10.14786/flr.v2i4.118 (cited on pp. 2, 4, 7, 14, 69, 118, 119, 121)

Morse, J. (2003). Principles of Mixed Methods and Multimethod Research Design [Journal Abbreviation: Handbook of mixed methods in social and behavioral research]. *Handbook of mixed methods in social and behavioral research*. (Cited on p. 88).

Munshi, A., Rajendran, R., Ocumpaugh, J., Biswas, G., Baker, R. S., & Paquette, L. (2018). Modeling Learners' Cognitive and Affective States to Scaffold SRL in Open-Ended Learning Environments [event-place: Singapore, Singapore]. *Proceedings of the 26th Conference on User Modeling, Adaptation and Personalization*, 131–138. https://doi.org/10.1145/3209219.3209241 (cited on p. 67)

Paans, C., Molenaar, I., Segers, E., & Verhoeven, L. (2019). Temporal variation in children's self-regulated hypermedia learning. *Computers in Human Behavior*, *96*, 246–258. https://doi.org/10.1016/j.chb.2018.04.002 (cited on p. 2)

Panadero, E. (2017). A Review of Self-regulated Learning: Six Models and Four Directions for Research. *Frontiers in Psychology*, *8*, 1–28. https://doi.org/10.3389/fpsyg.2017.00422 (cited on pp. 2, 46, 68, 122)

Pardo, A. (2018). A feedback model for data-rich learning experiences [Publisher: Routledge _eprint: https://doi.org/10.1080/02602938.2017.1356905]. *Assessment & Evaluation in Higher Education*, *43*(3), 428–438. https://doi.org/10.1080/02602938.2017.1356905 (cited on p. 124)

Paris, S. G., & Paris, A. H. (2001). Classroom applications of research on self-regulated learning [Place: US Publisher: Lawrence Erlbaum]. *Educational Psychologist*, *36*(2), 89–101. https://doi.org/10.1207/S15326985EP3602_4 (cited on p. 14)

Pelletier, K., Brown, M., Brooks, D. C., McCormack, M., Reeves, J., Arbino, N., Bozkurt, A., Crawford, S., Czerniewicz, L., Gibson, R., Linder, K., Mason, J., & Mondelli, V. (2021). *2021 EDUCAUSE Horizon Report Teaching and Learning Edition* [Pages: 2-50]. EDU. Retrieved Sept. 1, 2021, from https://www.learntechlib.org/p/219489/. (Cited on p. 123)

Piaget, J. (1972). *Psychology and Epistemology: Towards a Theory of Knowledge* [Google-Books-ID: 7DkdAQAAMAAJ]. Allen Lane. (Cited on p. 1).

Pintrich, P. R. (2000). Chapter 14 - The Role of Goal Orientation in Self-Regulated Learning. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of Self-Regulation* (pp. 451–502). Academic Press. (Cited on pp. 2, 4, 68).

Pintrich, P. R., & de Groot, E. V. (1990). Motivational and self-regulated learning components of classroom academic performance [Place: US Publisher: American Psychological Association]. *Journal of Educational Psychology*, *82*(1), 33–40. https://doi.org/10.1037/0022-0663.82.1.33 (cited on pp. 2, 14)

Reimann, P. (2009). Time is precious: Variable- and event-centred approaches to process analysis in CSCL research. *International Journal of Computer-Supported Collaborative Learning*, *4*(3), 239–257. https://doi.org/10.1007/s11412-009-9070-z (cited on pp. 2, 3, 7, 14, 46, 47, 49, 118, 119)

Roll, I., & Winne, P. H. (2015). Understanding, evaluating, and supporting self-regulated learning using learning analytics [Number: 1]. *Journal of Learning Analytics*, *2*(1), 7–12. https://doi.org/10.18608/jla.2015.21.2 (cited on p. 1)

Saint, J., Fan, Y., Gašević, D., & Pardo, A. (2021). Temporally focused Self-regulated Learning: A Systematic Review of Literature (cited on pp. viii, 11, 16).

Saint, J., Fan, Y., Singh, S., Gasevic, D., & Pardo, A. (2021). Using process mining to analyse self-regulated learning: A systematic analysis of four algorithms. *LAK21: 11th International Learning Analytics and Knowledge Conference*, 333–343. https://doi.org/10.1145/3448139.3448171 (cited on pp. viii, 13, 104)

Saint, J., Gašević, D., Matcha, W., Ahmad Uzir, N., & Pardo, A. (2020). Combining analytic methods to unlock sequential and temporal patterns of self-regulated learning. *Proceedings of the Tenth International Conference on Learning Analytics & Knowledge*, 402–411. https://doi.org/10.1145/3375462.3375487 (cited on pp. viii, 12, 90, 121)

Saint, J., Gašević, D., & Pardo, A. (2018). Detecting Learning Strategies Through Process Mining. In V. Pammer-Schindler, M. Pérez-Sanagustín, H. Drachsler, R. Elferink, & M. Scheffel (Eds.), *Lifelong Technology-Enhanced Learning* (pp. 385–398). Springer International Publishing. https://doi.org/10.1007/978-3-319-98572-5_29. (Cited on pp. viii, 11, 51, 120)

Saint, J., Whitelock-Wainwright, A., Gašević, D., & Pardo, A. (2020). Trace-SRL: A Framework for Analysis of Microlevel Processes of Self-Regulated Learning From Trace Data [Conference Name: IEEE Transactions on Learning Technologies]. *IEEE Transactions on Learning Technologies*, *13*(4), 861–877. https://doi.org/10.1109/TLT.2020.3027496 (cited on pp. viii, 12, 69)

Sedrakyan, G., De Weerdt, J., & Snoeck, M. (2016). Process-mining enabled feedback: "Tell me what I did wrong" vs. "tell me how to do it right". *Computers in Human Behavior*, *57*, 352–376. https://doi.org/10.1016/j.chb.2015.12.040 (cited on p. 88)

Shaffer, D. W., Collier, W., & Ruis, A. R. (2016). A Tutorial on Epistemic Network Analysis: Analyzing the Structure of Connections in Cognitive, Social, and Interaction Data. *Journal of Learning Analytics*, *3*(3), 9–45. Retrieved Aug. 19, 2019, from https://eric.ed.gov/?id=EJ1126800 (cited on pp. 5, 10, 89)

Shaffer, D. W., Hatfield, D., Svarovsky, G. N., Nash, P., Nulty, A., Bagley, E., Frank, K., Rupp, A. A., & Mislevy, R. (2009). Epistemic Network Analysis: A Prototype for 21st-Century Assessment of Learning. *International Journal of Learning and Media*, *1*(2), 33–53. https://doi.org/10.1162/ijlm.2009.0013 (cited on p. 123)

Siadaty, M., Gašević, D., & Hatala, M. (2016). Measuring the impact of technological scaffolding interventions on micro-level processes of self-regulated workplace learning. *Computers in Human Behavior*, *59*, 469–482. https://doi.org/10.1016/j.chb.2016.02.025 (cited on pp. 4, 7, 9, 46, 48, 68, 69, 87, 121)

Sonnenberg, C., & Bannert, M. (2015). Discovering the Effects of Metacognitive Prompts on the Sequential Structure of SRL-Processes Using Process Mining Techniques [Number: 1]. *Journal of Learning Analytics*, *2*(1), 72–100. https://doi.org/10.18608/jla.2015.21.5 (cited on pp. 3, 49, 67)

Sonnenberg, C., & Bannert, M. (2016). Evaluating the Impact of Instructional Support Using Data Mining and Process Mining: A Micro-Level Analysis of the Effectiveness of Metacognitive Prompts [Number: 2]. *JEDM | Journal of Educational Data Mining*, *8*(2), 51–83. https://doi.org/10.5281/zenodo.3554597 (cited on p. 88)

Swiecki, Z., Lian, Z., Ruis, A. R., & Shaffer, D. W. (2019). Does Order Matter? Investigating Sequential and Cotemporal Models of Collaboration. *Proceeding of the 13th International Conference on Computer-Supported Collaborative Learning*, *2*, 112–120 (cited on pp. 48, 102).

van der Aalst, W. M. P. (2016). *Process Mining: Data Science in Action* (2nd ed.). Springer-Verlag. https://doi.org/10.1007/978-3-662-49851-4. (Cited on p. 5)

van der Aalst, W. M. P., & Weijters, A. J. M. M. (2004). Process mining: A research agenda. *Computers in Industry*, *53*(3), 231–244. https://doi.org/10.1016/j.compind.2003.10.001 (cited on p. 103)

van der Graaf, J., Lim, L., Fan, Y., Kilgour, J., Moore, J., Bannert, M., Gasevic, D., & Molenaar, I. (2021). Do Instrumentation Tools Capture Self-Regulated Learning? *LAK21: 11th International Learning Analytics and Knowledge Conference*, 438–448. https://doi.org/10.1145/3448139.3448181 (cited on p. 123)

Viberg, O., Hatakka, M., Bälter, O., & Mavroudi, A. (2018). The current landscape of learning analytics in higher education. *Computers in Human Behavior*, *89*, 98–110. https://doi.org/10.1016/j.chb.2018.07.027 (cited on p. 1)

Weijters, A. J. M. M., van der Aalst, W. M. P., & Medeiros, A. K. A. D. (2006). *Process mining with the HeuristicsMiner algorithm*. Technische Universiteit Eindhoven. Retrieved July 21, 2020, from https://research.tue.nl/en/publications/process-mining-with-the-heuristicsminer-algorithm. (Cited on p. 103)

Winne, P. H. (2010). Improving Measurements of Self-Regulated Learning [Publisher: Routledge _eprint: https://doi.org/10.1080/00461520.2010.517150]. *Educational Psychologist*, *45*(4), 267–276. https://doi.org/10.1080/00461520.2010.517150 (cited on pp. 3, 47)

Winne, P. H. (2014). Issues in researching self-regulated learning as patterns of events. *Metacognition and Learning*, *9*(2), 229–237. https://doi.org/10.1007/s11409-014-9113-3 (cited on p. 3)

Winne, P. H. (2017). Learning Analytics for Self-Regulated Learning. In C. Lang, G. Siemens, A. Wise, & D. Gasevic (Eds.), *Handbook of Learning Analytics* (First, pp. 241–249). Society for Learning Analytics Research (SoLAR). https://doi.org/10.18608/hla17.021. (Cited on p. 14)

Winne, P. H., & Hadwin, A. F. (1998). Studying as self-regulated learning. *Metacognition in educational theory and practice* (pp. 277–304). Lawrence Erlbaum Associates Publishers. (Cited on pp. 2, 4, 122).

Winne, P. H., & Hadwin, A. F. (2013). nStudy: Tracing and Supporting Self-Regulated Learning in the Internet. In R. Azevedo & V. Aleven (Eds.), *International Handbook of Metacognition and Learning Technologies* (pp. 293–308). Springer New York. https://doi.org/10.1007/978-1-4419-5546-3_20. (Cited on p. 1)

Winne, P. H., Hadwin, A. F., & Gress, C. (2010). The learning kit project: Software tools for supporting and researching regulation of collaborative learning. *Computers in Human Behavior*, *26*(5), 787–793. https://doi.org/10.1016/j.chb.2007.09.009 (cited on p. 1)

Winne, P. H., & Jamieson-Noel, D. (2002). Exploring students' calibration of self reports about study tactics and achievement. *Contemporary Educational Psychology*, *27*(4), 551–572. https://doi.org/10.1016/S0361-476X(02)00006-1 (cited on pp. 3, 49)

Winne, P. H., & Perry, N. E. (2000). Chapter 16 - Measuring Self-Regulated Learning. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of Self-Regulation* (pp. 531–566). Academic Press. https://doi.org/10.1016/B978-012109890-2/50045-7. (Cited on pp. 1, 2, 14, 68, 118, 119)

Wong, J., Baars, M., Davis, D., Zee, T. V. D., Houben, G.-J., & Paas, F. (2019). Supporting Self-Regulated Learning in Online Learning Environments and MOOCs: A Systematic Review [Publisher: Taylor & Francis _eprint: https://doi.org/10.1080/10447318.2018.1543084]. *International Journal of Human–Computer Interaction*, *35*(4-5), 356–373. https://doi.org/10.1080/10447318.2018.1543084 (cited on p. 2)

Zhou, M., & Winne, P. H. (2012). Modeling academic achievement by self-reported versus traced goal orientation. *Learning and Instruction*, *22*(6), 413–419. https://doi.org/10.1016/j.learninstruc.2012.03.004 (cited on pp. 4, 49)

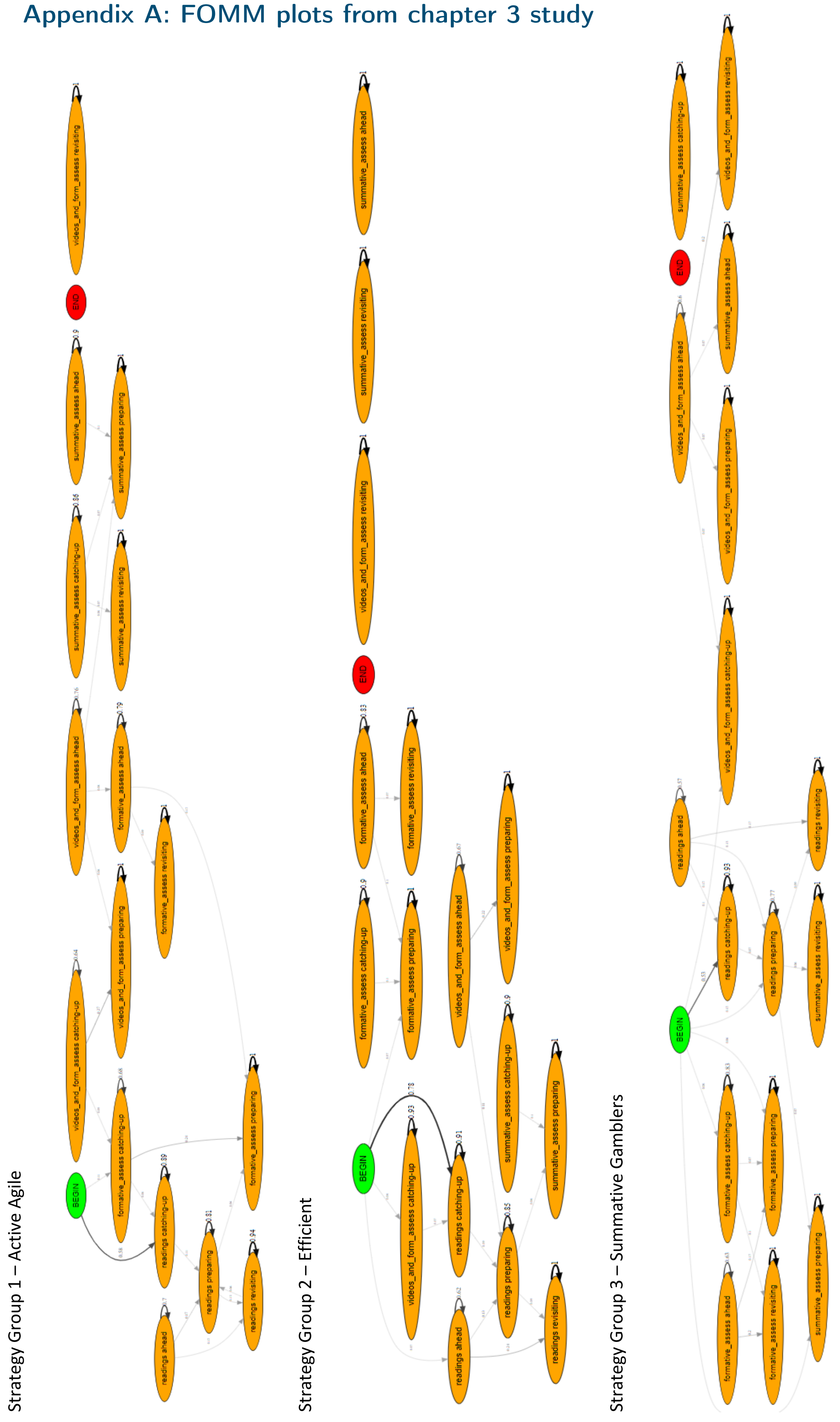
Zimmerman, B. J. (1986). Becoming a self-regulated learner: Which are the key subprocesses? *Contemporary Educational Psychology*, *11*(4), 307–313. https://doi.org/10.1016/0361-476X(86)90027-5 (cited on p. 14)

Zimmerman, B. J. (1989). A social cognitive view of self-regulated academic learning [Place: US Publisher: American Psychological Association]. *Journal of Educational Psychology*, *81*(3), 329–339. https://doi.org/10.1037/0022-0663.81.3.329 (cited on pp. 2, 14)

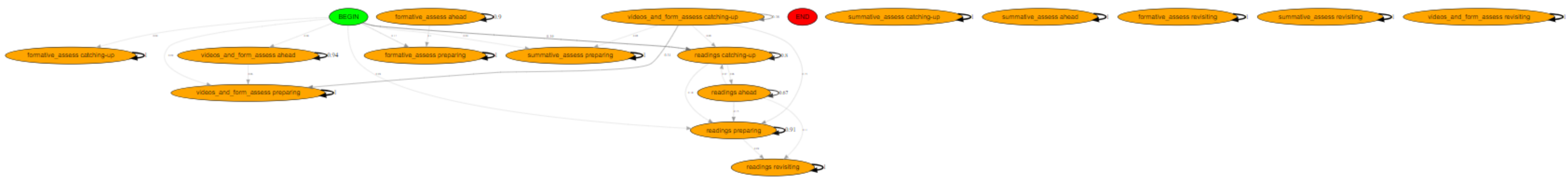
Zimmerman, B. J. (2000). Chapter 2 - Attaining Self-Regulation: A Social Cognitive Perspective. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of Self-Regulation* (pp. 13–39). Academic Press. Retrieved June 3, 2019, from http://www.sciencedirect.com/science/article/pii/B9780121098902500317. (Cited on pp. 1, 2, 4, 68)

Appendices

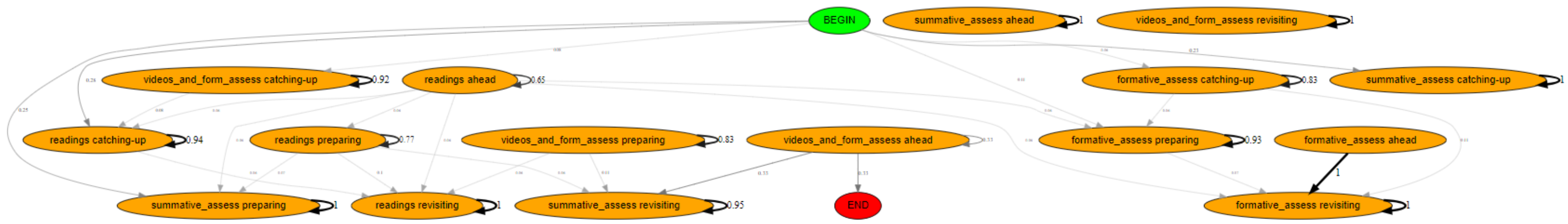
Appendix A: FOMM plots from chapter 3 study



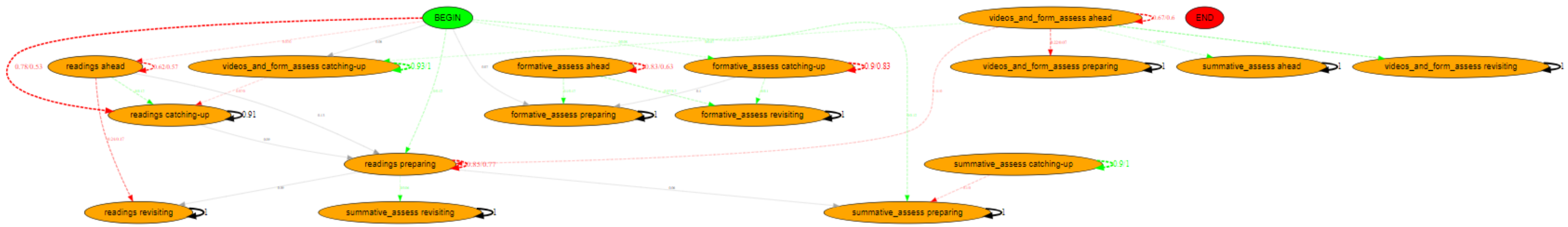
Strategy Group 4 – Active Cohesive



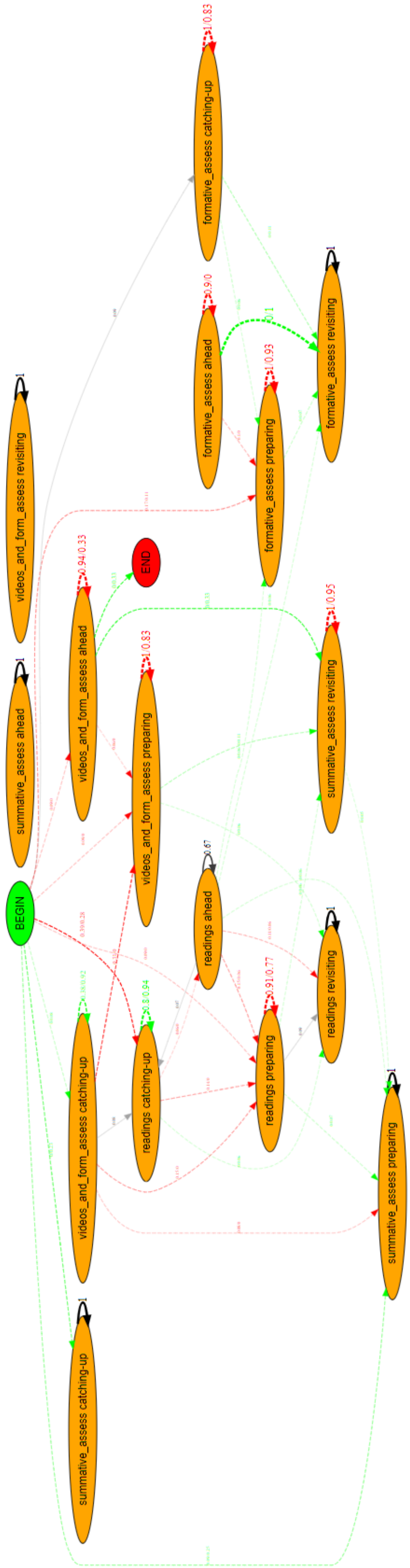
Strategy Group 5 – Extreme Minimalists



Comparative Analysis: Efficient (2) and Summative Gamblers (3)



Comparative Analysis: Active Cohesive (4) and Extreme Minimalist (5)



Appendix B: FOMM plots from chapter 4 study

TLT-2019-07-0220 Supplementary Material

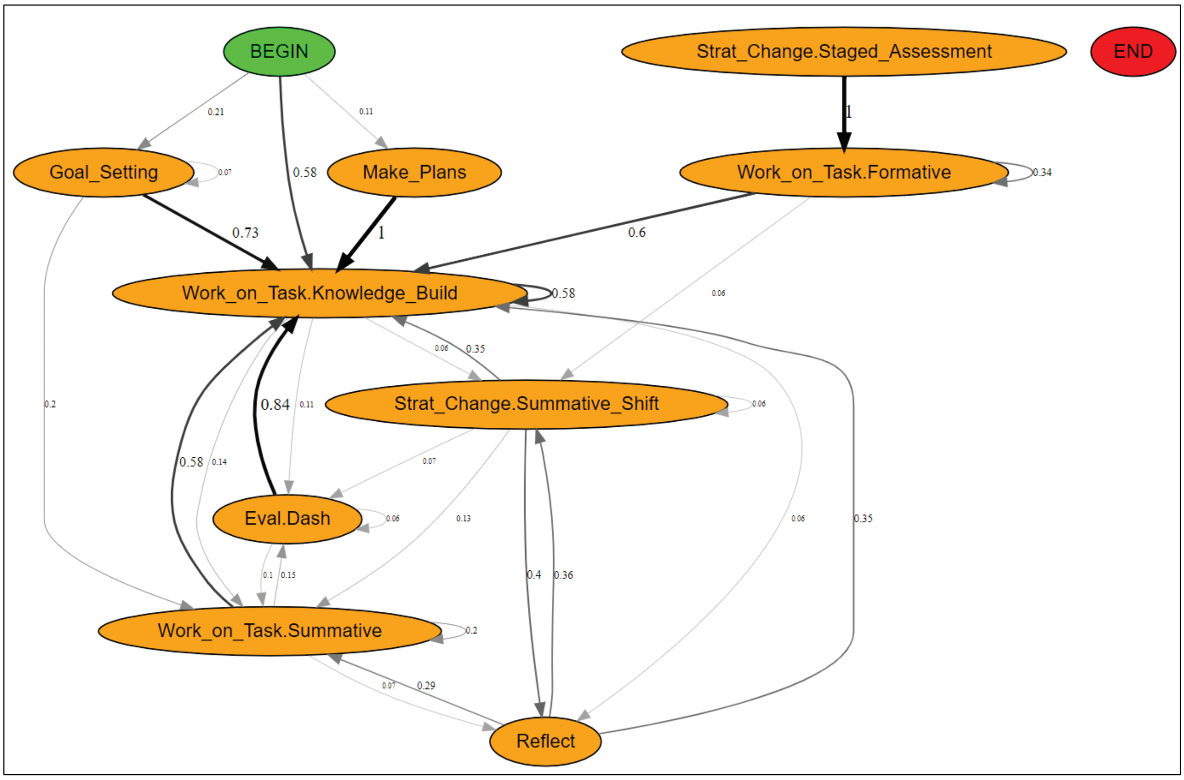


Fig. 2. FOMM diagram for active agile (higher performers).

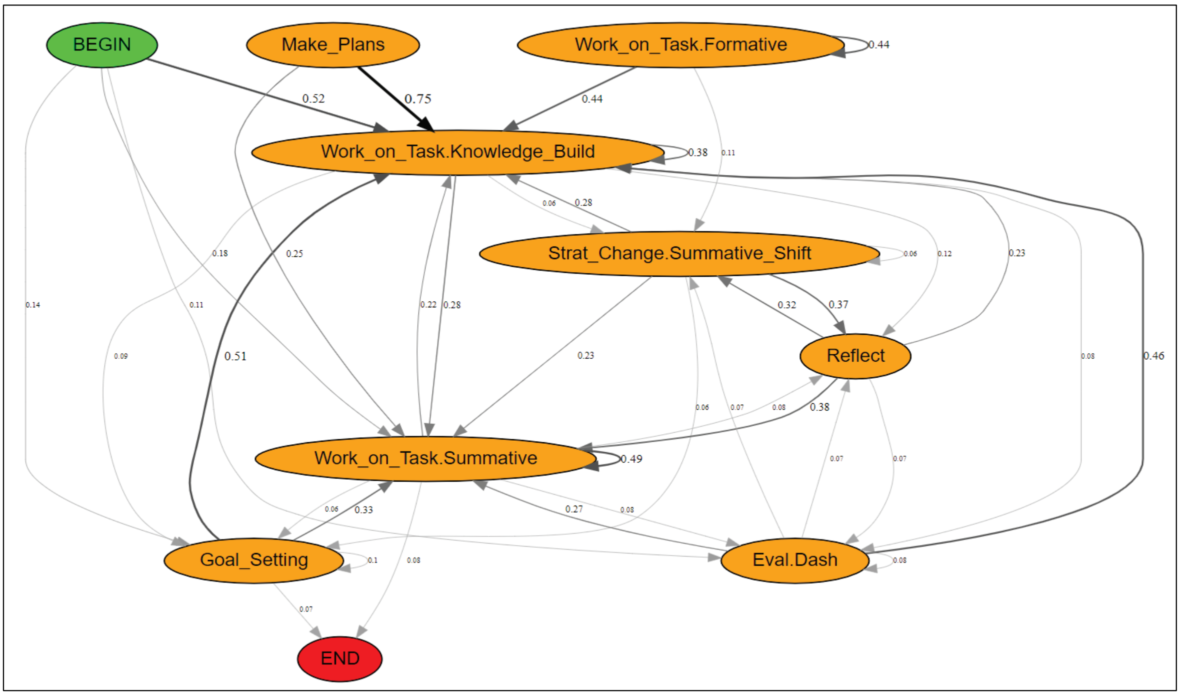


Fig. 1. FOMM diagram for summative gamblers (lower performers).

TLT-2019-07-0220 Supplementary Material

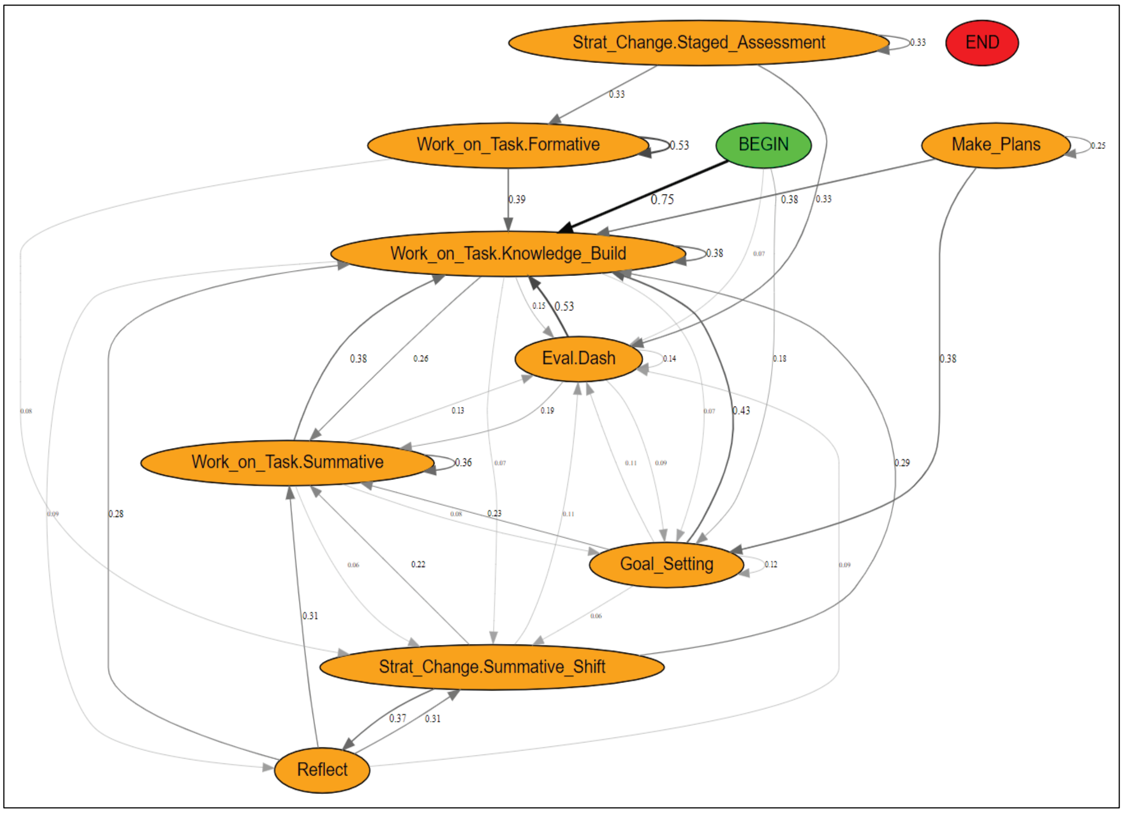


Fig. 3. FOMM diagram for active cohesive (higher performers).

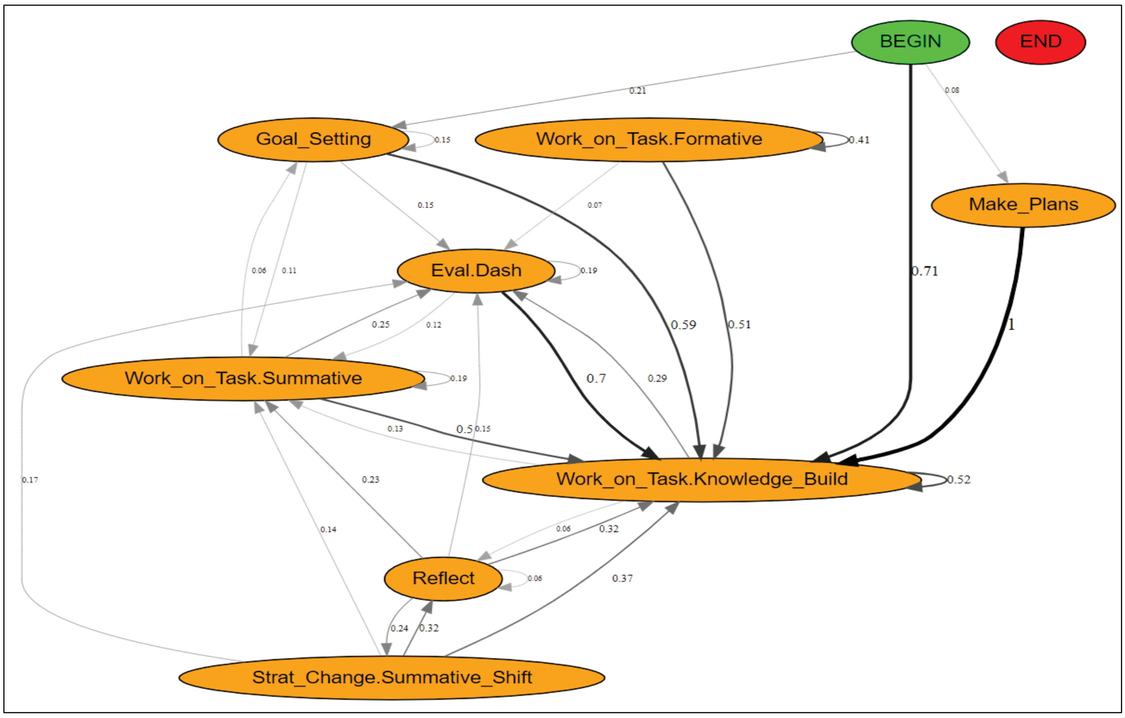


Fig. 4. FOMM diagram for semi-engaged (lower performers).

TLT-2019-07-0220 Supplementary Material

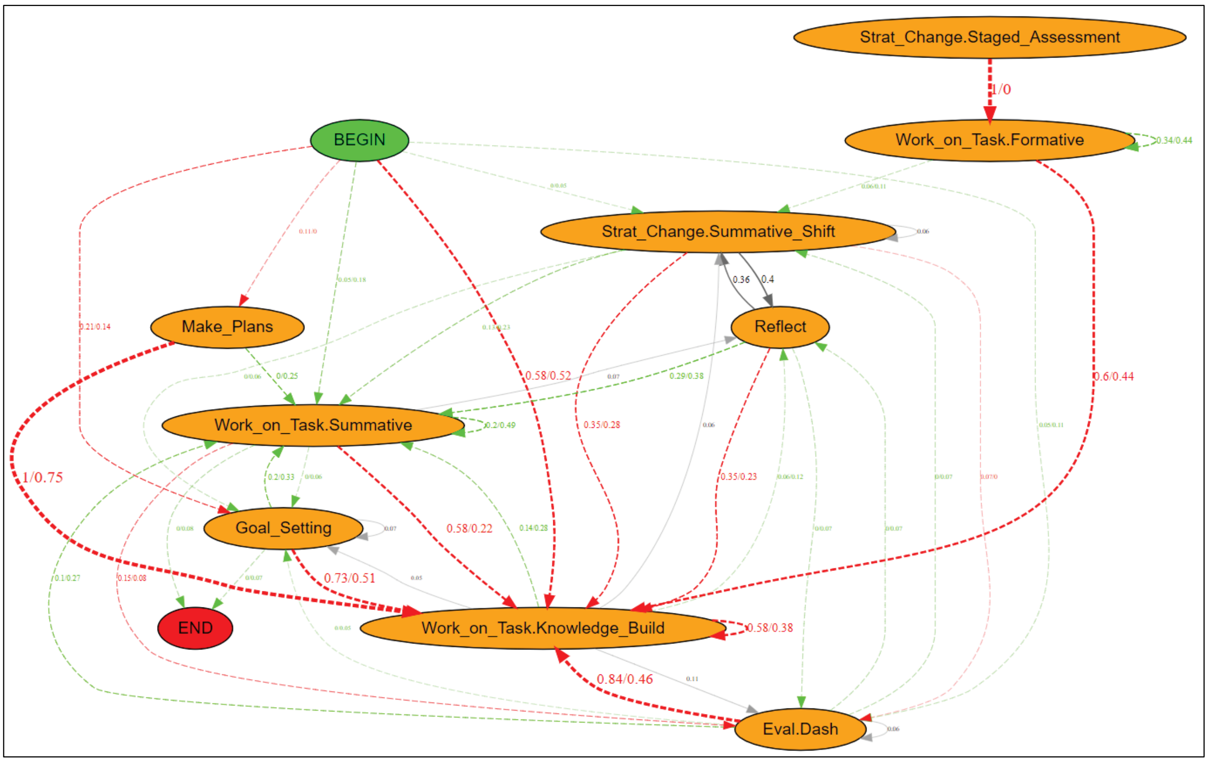


Fig. 5. FOMM Comparison: Active agile and summative gamblers.

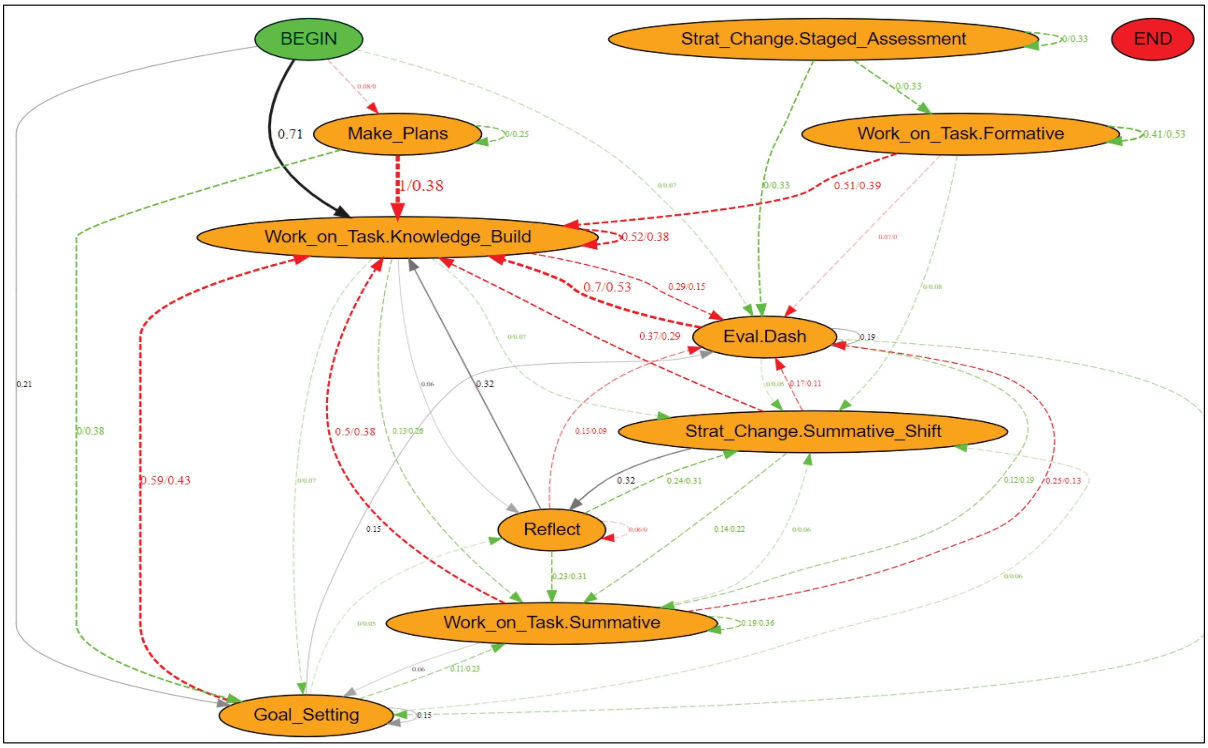


Fig. 6. FOMM Comparison: Active cohesive and semi-engaged.

Appendix C: Action and pattern libraries from chapter 6 study

Using process mining to analyse self-regulated learning: a systematic analysis of four algorithms

Supplementary Materials

Appendix A. The Hierarchical Action Library

Action	Sub_Action	Description
Reading	First_Reading	First time reading of the pre-class reading materials.
	Re_Reading	Re-read some pre-class reading materials within the same learning session.
	Review_Reading	Review some reading materials which learners read in previous learning sessions.
	Expand_Reading	Learners read materials which are not compulsory and not assessed.
	Practical_Reading	Learners read practical class instructions before, in or after class.
Annotation	Annotation_Comment	Learners add comment for certain keywords or sentences in the reading materials.
	Annotation_Confusing	Learners highlight certain keywords or sentences as “Confusing”, or upvote others’ “Confusing” highlights.
	Annotation_Errata	Learners highlight certain keywords or sentences as “Errata” to report some error they found, or upvote others’ “Errata” highlights.
	Annotation_Question	Learners highlight certain keywords or sentences as “Help” to ask questions and seek help from peers or teachers, or upvote others’ “Help” highlights.
	Annotation_Important	Learners highlight certain keywords or sentences as “Important”, or upvote others’ “Important” highlights.
	Annotation_Interesting	Learners highlight certain keywords or sentences as “Interesting”, or upvote others’ “Interesting” highlights.
	Annotation_Deleted	Learners delete annotations made by themselves.
Videos	Videos_Viewed	Learners open and watch videos in Moodle.
	Videos_List	Learners open the list page of videos.
Quiz	Quiz_Attempt	Learners attempt quiz in Moodle, including start a quiz, attempt a quiz, submit a quiz and view a quiz.
	Quiz_List	Learners open the list page of quizzes.
Assignment	Assignment_Attempt	Learners attempt quiz in assignment, including open, attempt and submit an assignment .

	Assignment_Feedback_Viewed	Learners view the teacher's feedback on their submitted assignment.
	Assignment_Submission_Viewed	Learners view their submitted assignment.
	Assignment_List	Learners open the list page of assignment.
Forum	Forum_Post	Learner post something in the forum or view other's posts in the forum.
	Forum_List	Learners open the list page of forum.
Informing	Homepage_Viewed	Learners view or navigate to the LMS homepage.
	Task_Marked_As_Completed	Learners mark something (e.g., reading task, quiz) in the homepage as completed, by click the check boxes.

Note:

1- We labelled actions as Noise if the duration of the actions were less than 5 seconds, then we excluded these Noise actions in the following SRL process detection.

2-There are some other actions logged in the Moodle system, such as search or download slides in the Moodle, which are very infrequent actions, therefore we also excluded them in the following analysis.

Appendix B. The Hierarchical Pattern Library

Macro-level process	Micro-level process	Description	Micro-level action mapping
Planning	Task Analysis (TA)	To get familiar with the learning context of a learning task at hand	**TA. Overview** *HomePage_Viewed/ Quiz_List/ Videos_List (in first half of the whole learning session)* **TA. Assess Knowledge** *Quiz_Attempt*-> (HomePage_Viewed*) -> Reading (in first half of the whole learning session)*
	Goal Setting (GS)	To identify learning gaps and goals	**GS. Identify Learning Gap** *Reading -> Annotation_Confusing/ Annotation_Question*
Engagement	Working on a Learning Task (WOT)	To engage with learning tasks	**WOT. Build Knowledge**: *First_Reading/ Practical_Reading/ Expand_Reading/ Videos_Viewed* **WOT. Processing Materials**: *First_Reading/ Practical_Reading/ Expand_Reading/ -> Annotation_Important/ Annotation_Interesting/ Annotation_Errata* **WOT. Address Learning Gap**: *Re_Reading/ Review_Reading*
	Coordinating Learning Task Sequence(s) (CLTS)	To coordinate task sequences to achieve a learning goal.	**CLTS. Elaboration/Organisation** *Reading -> Annotation_Comment*; *Re_Reading/ Review_Reading -> Annotation_Important/ Annotation_Interesting* **CLTS. Interaction** *(Reading) -> (HomePage_Viewed*) -> Forum_Post** **CLTS. Evaluate Knowledge After Reading** *(Reading) -> (HomePage_Viewed*) -> Quiz_Attempt* (in second half of the whole learning session)*
Evaluation	Evaluating (EVAL)	To evaluate one's learning process and goals	**EVAL. Learning Process** *HomePage_Viewed/ Quiz_List/ Videos_List/ Task_Marked_As_Completed (in second half of the whole learning session)* **EVAL. Learning Outcomes** *Assignment_Submission_Viewed/ Assignment_Feedback_Viewed* **EVAL. Learning Gap Resolve**: *(Re_Reading/Review_Reading) -> Annotation_Deleted*

Note:
1-“->” means a transition from learning action A to learning action B;

2-“()” means a learning action is optional;

3-“*” means one or more consecutive instances of the same learning action;

4-“/” means either learning action A or learning action B;

5-“Reading” means all five sub_actions under the Reading action were included;

6-The processes were terminated by any actions longer than 45 mins;

7-If one action does not belong to any processes in the process library, then this row will be labelled as No_Process and will not be included in the subsequent analysis;

8-The same consecutive processes were merged into one process in the final output.