

# Modelling Temporality in Person- and Variable-Centred Approaches

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## Abstract

Learning analytics needs to pay more attention to the temporal aspect of learning processes, especially in self-regulated learning (SRL) research. In doing so, learning analytics models should incorporate both the duration and frequency of learning activities, the passage of time, and the temporal order of learning activities. However, where this exhortation is widely supported, there is less agreement on its consequences. Does paying tribute to temporal aspects of learning processes necessarily imply that event-based models are to replace variable-based models, and analytic discovery methods substitute traditional statistical methods? We do not necessarily require such a paradigm shift to give temporal aspects their position. First, temporal aspects can be integrated into variable-based models that apply statistical methods by carefully choosing appropriate time windows and granularity levels. Second, in addressing temporality in learning analytic models that describe authentic learning settings, heterogeneity is of crucial importance in both variable- and event-based models. Variable-based person-centred modelling, where a heterogeneous sample is split into homogeneous subsamples, is suggested as a solution. Our conjecture is illustrated by an application of dispositional learning analytics, describing authentic learning processes over an eight-week full module of 2,360 students.

## Notes for Practice

- Both variable-based and event-based models are well suited to describe temporal aspects of learning processes.
- The key to including temporality is a meticulous specification of both time window and granularity level.
- In authentic settings with strong sample heterogeneity, person-centred methods provide a way out by homogenizing into subsamples.
- Variable-based models lend themselves better to learning interventions based on LA feedback.

## Keywords

Temporal analysis, learning analytics, dispositional learning analytics, time, event-based models

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## 1. Introduction

The call for a paradigm shift (Saint et al., 2022) in applications of learning analytics (LA) follows an earlier call for strengthening the role of temporality in LA applications (Chen et al., 2018; Knight et al., 2017). Paying more attention to the time dimension in LA models and using appropriate LA methods incorporating time dimensions are a widely welcomed in the LA community. The appeal is primarily aimed at achieving more balance in the state of contemporary LA research, where static models seem to be dominant. The suggestion by Reimann (2009) to improve the balance by integrating temporal aspects in existing working methods and combining variable-centred methods — which investigate relationships between independent

and dependent variables — and event-centred methods that model whether, when, and for how long events take place, found their way into LA-based studies such as Han et al. (2020), Pardo et al. (2017), and Rizvi et al. (2022).

In contrast, the paradigm shift proposed by Saint et al. (2022) as a conclusion to their systematic literature review of temporally focused analytics of self-regulated learning (SRL), introduces such a radical change that it can only be seen as a call for an opposite imbalance. The proposed “framework of directives and questions to aid researchers” (Saint et al., 2022, p. 1) steers the LA user, in a context where time plays a crucial role, inevitably toward the use of analytic discovery methods as process or sequence mining with learning events rather than learning-related variables acting as the subjects of these models. There is no escaping the impression that taking this route is better described as creating a new imbalance in the opposite direction rather than restoring balance. Refer to Reimann’s (2009) call: “I argue in this paper that an event-based view of process and change is an important addition to the variable-centric approach” (p. 242). The power is clearly in the combination of the two, not in the individual components themselves.

In this paper, we shall argue, and support with an empirical example, that the renunciation of traditional, variable-oriented statistical methods in favour of discovery methods based on event data is by no means necessary to give the time aspect a proper place in LA modelling. Nor is it in line with the original analyses about the inadequate role of time in our models, as put forward in Reimann (2009), Reimann et al. (2014), and Molenaar and Wise (2022), that seek the incorporation of temporality in existing explanatory theories: “In the absence of explanatory theory, using sequence and process mining methods for exploratory purposes on learning data is helpful for detecting potential regularities worth explaining. However, patterns of regular event sequences are only conceptually interesting if they are sufficiently explained in theoretical terms” (Reimann et al., 2014, p. 538).

## 2. Temporality in Learning Analytics

### 2.1. The Role of Time

The notion that learning is fundamentally a temporal process — that “learning unfolds over time” — is the departure point of Reimann’s (2009) critique of the state of educational modelling. Models that are predominantly variable-centred typically ignore the process characteristics of learning. To appreciate these process characteristics, Reimann calls us to pay better tribute to the fact that “time is precious” and allows for different conceptualizations. First, the notion of temporality as the “passage of time” refers to the duration and frequency of learning activities (Knight et al., 2017; Molenaar, 2014; Molenaar & Wise, 2022). How often do activities take place, and how long is the time-on-task? A second conceptualization relates to the temporal order of learning activities: what comes first, and what follows (Nguyen et al., 2018)? Concerning both perspectives, Reimann observes that empirical research into learning processes (so not only practices of LA) understates the role of temporality: “researchers have privileged access to process data, the theoretical constructs and methods employed in research practice frequently neglect to make full use of information relating to time and order” (Reimann, 2009, p. 239; see also Knight et al., 2017, p. 7).

When matters of temporality are brought to the forefront, both data collection and methodological choices may require a shift. Where LA research is often based on variable-oriented modelling, the introduction of time and specific temporal ordering can profit from event-oriented modelling (Molenaar, 2014; Reimann et al., 2014). Analytical methods best suited for these contexts may require temporal data mining or sequential pattern mining techniques (Reimann et al., 2014; Rizvi et al., 2022).

Two articles by Uzir and co-authors (2019; 2020) are leading examples of investigating temporal facets of SRL. Both focus on estimating student time management tactics using trace data. The four different time management tactics discovered — learning ahead, learning just in time, catching-up, and revisiting — all refer to the timing of student learning for the topic of the specific week, thus, are based on the design of the module. In Uzir et al. (2020), time-management tactics are combined with learning tactic components of learning strategies, applying automatic detection based on traces. Saint et al. (2022) provide another example of investigating the temporal facets of SRL, where the focus is not time management relative to an educational design-based schedule but the allocation of learning activities over the stages of planning and forethought, performance and monitoring, and reflection and evaluation.

### 2.2. Seeking Balance

A nuanced approach characterized the earliest calls for more focus on the temporal aspect. After introducing event-centred analysis, Reimann (2009) states, “I argue in this paper that an event-based view of process and change is an important addition to the variable-centric approach” (p. 242). The complementary nature of the two approaches is made explicit in Reimann’s proposal to combine variable-centred and event-centred methods in computer-supported collaborative learning (CSCL) research. Reimann et al. (2014) explain why such a combination is essential, warning about the “major ontological constraints of solely event-focused theoretical explanations of learning phenomena” (p. 529). Since learning often takes place in so-called open systems that have external interactions, the authors infer that “[a]ccounting for events, such as human learning activities,

solely in terms of other events — what we call ‘a flat event ontology’ — is not a strategy that can lead to the identification of learning mechanisms” (Reimann et al., 2014, p. 535). A dilemma that can be solved by “including other levels that provide certain theoretical account of a mechanism and context. Dispositional accounts, such as those based on aptitude, are good candidates for explanations in [SRL] research” (Reimann et al., 2014, p. 536). A last balance to restore is that of investigating authentic learning contexts versus short learning episodes in laboratory settings by investigating “perceptually and experientially richer problem-solving environments that provide for more authentic learning experiences” (Reimann et al., 2014, p. 537).

However, much of this nuance is lost in more recent work on the role of time in LA. An example of a full-paradigm shift from variables-only to events-only modelling is the systematic literature review of temporally focused analytics of SRL by Saint et al. (2022). Arguing that the sequential dynamics of processes of SRL “could not be articulated using traditional count-based statistical methods,” the authors decided to use, as one of the exclusion criteria for the review, “studies which relied heavily or solely on traditional statistical methods” (Saint et al., 2022, p. 2). By restricting the focus on research to applying analytic discovery methods only, such as process and sequence mining, there is little left for combining events with variables to ground the modelling in educational theories of SRL, as in the optimal balance suggested by Reimann (2009).

### 2.3. Authentic Settings and Variable Approaches: Inter-Individual, Intra-Individual, and Person-Centred

Another methodological debate concerning the design of empirical models of learning processes is the merits of inter-individual analyses versus intra-individual analyses. Inter-individual differences are observed between people, whereas intra-individual differences are observed in the same person assessed at different times or in different situations. The plea for greater application of within-person, intra-individual research in educational psychology is derived from Molenaar’s contribution to system theory (2004; Molenaar & Campbell, 2009; Voelkle et al., 2014). That contribution focuses on the ergodic theorems of dynamic systems. Ergodicity addresses the question under what conditions the analysis of inter-individual or between-person variation results in the same outcomes as the analysis of intra-individual or within-person variation. The answer is given by the two ergodic conditions: 1) homogeneity, where each subject in the population obeys the same statistical model, and 2) stationarity, where the statistical model is constant over time (Molenaar, 2004; Molenaar & Campbell, 2009).

According to Howard and Hoffman (2018), both inter-individual analysis (variable-centred approaches) and intra-individual analysis (person-specific approaches) are two poles of a continuum of methodological approaches. They characterize these methodological approaches with two attributes: specificity and parsimony. In that continuum ranging from relative parsimony (the variable-centred pole) to relative richness (the person-specific pole), Howard and Hoffman (2018) position a third approach in the middle: the person-centred approach. In this approach, unobserved heterogeneity in the population is acknowledged and solved by classifying subjects into homogeneous subpopulations. The analysis aims to understand relations with antecedents and consequences on the subpopulation level, just as one would do in the variable-centred approach when the population is homogeneous. Person-centred approaches fall into the middle of the continuum: their solutions are richer but less parsimonious than variable-centred outcomes — describing subpopulations by different models — but are less rich and more parsimonious than person-specific solutions that create models for each subject.

Indeed, LA studies taking place in authentic learning settings, as compared to laboratory-based research, are often plagued by the strong heterogeneity of learners (Pardo et al., 2017; Rizvi et al., 2022; Tempelaar et al., 2020a). In each class, one can expect both novice learners and those with prior knowledge; in lab research, one can choose the topic to minimize any prior knowledge. Next, authentic settings will prevent repeatedly measuring parts of the learning process, as is common in laboratory research. Heterogeneity asks for analyses of the intra-individual type, but a lack of repeated measures will generally exclude such approaches. Therefore, in this study, we argue that in these cases a person-centred approach (Malcom-Piqueux, 2015) is not only a good compromise, it is the only possible modelling approach.

### 2.4. Research Objectives

The main objective of this contribution is to recover (some of) that lost nuance in Saint et al. (2022). Recognizing that the call for more focus on the temporal aspect of learning processes is valid in itself, especially when investigating SRL, we aim to demonstrate two things. First, Reimann’s (2009) appeal to combine variable-centred modelling with a focus on the role of events and their temporary ordering can very well be achieved for SRL-related data by carefully operationalizing measurements related to SRL processes, also in authentic learning settings. Second, we extend this objective by demonstrating that “traditional count-based statistical methods” can be used to make temporal aspects of SRL visible, as long as the choice of measured constructs is based on these temporal aspects of self-regulation. Rephrased in the words of Reimann et al. (2014): “(EDM) needs to be applied to data that measures theoretically relevant properties and mechanisms. These are not necessarily found in log files of software that has been designed for practical educational rather than research purposes” (p. 538).

The theoretical relevance of our demonstration is grounded in the instructional context in which it is situated, as well as the socio-cognitive nature of that instructional context. Our case study investigates SRL in the context of problem-based

learning (PBL; Hmelo-Silver, 2004). In line with PBL principles, the learning process is subdivided into three consecutive learning phases. The first is the preparation of the tutorial session in which small groups of students, the tutorial groups, collaboratively try to solve problem tasks. The second follows later the same week when students prepare a so-called quiz session in which they are asked to demonstrate their mastery of topics learned in the weekly learning cycle. The last phase refers to preparing for the final examination at the end of the module, where students demonstrate how well they have integrated the several weekly learning cycles by solving integrated problems. Since each of these learning phases is sharply demarcated by the sequence of tutorial sessions, quizzes, and final exam, an operationalization of log file data that distinguishes student engagement in subsequent learning phases can be implemented. This enables us to include both passage of time measures (Knight et al. 2017), the intensity of engagement in each learning phase, and the order of time measures resulting in the relative allocation of engagement over three learning phases. In other words, as an alternative to detecting sequential, ordering, and temporal patterns in SRL by data-driven discovery methods, resulting in event-based models, this study aims to demonstrate that we can pay tribute to temporality and the sequencing of events using traditional, variable-based statistical methods. Central to this approach is the careful selection of time windows and the size of time units, not by discovery methods but by the educational design (Molenaar et al., 2023).

The second component of grounding measures on relevant theoretical principles stems from the social-cognitive nature of PBL (Hmelo-Silver, 2004). In such instructional philosophy of student-centred learning, a crucial consideration is this: What learning skills do students need to be successful learners in a PBL program? The skill of being a self-regulated learner is generally regarded as a key disposition for PBL (Loyens et al., 2013). This is in line with the recommendation of Reimann et al. (2014) to include aptitudes — the set of student skills, abilities, and willingness to learn — as “other levels” in the form of dispositional accounts to complement event-based data in SRL research. Learning styles, epistemic beliefs, and attitudes are introduced in Reimann et al. (2014) as being crucial for SRL. We agree, but our perspective is slightly broader. To pay tribute to all facets of social constructivism, aptitudes were included that cover a range of affective, behavioural, and cognitive dispositions. These include cognitive learning processing strategies and metacognitive learning regulation strategies, cognitive motivational constructs (of both adaptive and maladaptive types), behavioural engagement constructs (again of adaptive and maladaptive types), and epistemic learning emotions as affective measures. Following Reimann et al. (2014), we regard these aptitudes as sufficiently static over the entire module period. That supposition allows us to measure aptitudes at the very start of the module, and regard these as student entry characteristics.

Incorporating stationary learning aptitudes into a model that describes the evolution of learning events over time is the second main goal of this contribution. Our solution is grounded on variable-based modelling, after transforming event-based measures into variables. That transformation refers to both the passage of time and order of time types of events. To our knowledge, integrating learning aptitudes into event-based models is still unexplored.

The solutions that compose this contribution aim to provide confirmative answers to the following research questions:

RQ1: Can we design models of learning processes that incorporate temporal facets using time windows and granularity derived from the educational design?

RQ2: Do these models need to be event-based or are variable-based models fit for incorporating temporal facets?

RQ3: If we opt for creating learning profiles that enable learning feedback or educational interventions framed in terms of essential aptitudes for SRL, what are the perspectives of event-based and variable-based solutions?

## 3. Methods

### 3.1. Context and Setting

This study took place in a large-scale introductory mathematics and statistics module for first-year undergraduate students in a business/economics program in the Netherlands, with a study load of 20 hours per week, for a period of eight weeks. This is a compulsory first module for all first-year students and is often an obstacle for students with limited mathematics affinity. The course design is best described as “blended” or “hybrid” according to the principles of the flipped classroom. The main component was face-to-face: PBL, where students learn in small groups (14 students), coached by a content expert tutor. Participation in tutorial groups was required and constituted around  $2 \times 2$  hours per week. Weekly, pre-recorded online lectures introduce the key concepts of that week. The remaining 14 hours were self-study, which was supported by printed materials (i.e., textbooks) and two interactive e-tutorials: Sowiso (<https://sowiso.nl/>) and MyStatLab (Nguyen et al., 2016; Rienties et al., 2019; Tempelaar et al., 2015, 2017, 2020a, 2020b). This design was based on the philosophy of student-centred education, placing the responsibility for making educational choices primarily on the student. In line with the principles of PBL, feedback from our LA applications was shared with students and tutors. In their bilateral contact with the students of their tutorial groups, the tutors also take care of the “prompting” when needed: they discuss the consequences of the feedback and options to improve. Since this prompting takes place in tutorial sessions, it remains unobserved.

As stated before, this study distinguished three relatively distinct learning phases in terms of the timing of learning. In phase 1, students prepare for the first tutorial session of the week. The face-to-face time of tutorial sessions was used to discuss solving “advanced” mathematical and statistical problems and required preceding self-study by students to enable participation in the discussion. Phase 1 was not formally assessed, other than that such preparation allowed students to actively participate in discussing the problems in the tutorial session. Phase 2 was preparing the quiz session at the end of every week, except the first week. Those quizzes were primarily formative in nature, providing feedback on student mastery of the mathematical and statistical topics covered that week. However, to stimulate students to participate in the quizzes, they also contained a summative component, contributing 17.5% of the total score. Quizzes, administered online, consisted of test items drawn from the same question pools applied in the practise mode. This approach was chosen to encourage students with limited prior knowledge to make intensive use of the e-tutorials. Phase 3 consisted of preparing for the final exam, in the eighth week of the module. Phase 3 included formal, graded assessments. Therefore, student timing decisions related to the amount of preparation in each of the three phases.

### 3.2. Participants

We included 2,360 first-year students from academic years 2020–2021 and 2021–2022 who had been active in at least one digital platform. Of these students, 39% were female, 61% male; 21% had a Dutch high school diploma, and 79% were international students. Amongst the international students, neighbouring countries of Germany (31.5%) and Belgium (13.3%) were well represented, as well as other European countries. In addition, 5.1% of the students were from outside of Europe. High school systems in Europe differ greatly, most notably in the teaching of mathematics and statistics (i.e., the Dutch high school system has a strong focus on statistics, whereas this topic is completely missing in high school programs of many other countries). Next, all countries distinguish between several levels of math education in high school: preparing for sciences, social sciences, or humanities. To enter this international business program, prior mathematics education in preparing for social sciences is required. At the same time, 35.7% of the students followed the highest mathematics track in high school, adding to the diversity in prior knowledge in the current sample. Therefore, it was crucial that the first module offered to these students was flexible and allowed for individual learning paths with frequent, interactive feedback on student learning strategies and tasks.

Beyond a final written exam, student assessment included a student project in which students analyzed personal learning disposition data statistically. To this end, students administered several questionnaires addressing affective, behavioural, and cognitive aspects of aptitudes at the start of the module, and received personal datasets for their project work some weeks later.

Both modules were delivered under COVID-19 conditions. In the 2020–2021 module, no on-campus meetings could take place, so all sessions took place online. In the 2021–2022 module, the COVID-19 regime was less severe, and sessions were hybrid, with synchronous in-class as well as online participation. Data from both modules were aggregated into one overall dataset.

### 3.3. E-Tutorial Trace Data

Trace data were collected from both e-tutorial systems (Sowiso, mathematics, and MyStatLab, statistics), and Canvas, which was used as the university-wide generic learning management system to provide general information and links to Sowiso and MyStatLab. Both Sowiso and MyStatLab are e-tutorials based on the instructional method of mastery learning (Tempelaar et al., 2017). However, the two systems do differ strongly regarding the possibilities to collect trace data. MyStatLab offers students and instructors several dashboards that summarize student progress in terms of mastery of individual exercises and chapters, but does not provide time-stamped use data. In contrast, Sowiso provides time-stamps for every individual event initiated by the student and mastery data, allowing for full integration of temporality in the design of learning models. In this study, we therefore restricted the analysis to Sowiso event data: 1,360,756 individual events by 2,360 students.

The building blocks of the e-tutorial are assignments or exercises that students are expected to solve. These assignments are grouped in packages, and packages are grouped in topics. The order of assignments within packages, and the order of packages within topics, are fixed, determined by the logic of the discipline, calculus. Assignments are parametrized: calling an assignment a second time will generate an equivalent problem with different parameters. Students can call two different learning aids: solutions and hints. A solution is a fully worked-out example of the assignment. It does not bring any mastery, but after learning from the worked example, students can repeat the attempt to solve an equivalent assignment. Hints provide support in a single solution step. The events distinguished in Sowiso are as follows:

*Attempt:* Starting a new assignment

*Mastered Attempt:* Successful finishing an assignment, achieving full mastery

*Finished Package:* Successful finishing a complete package of assignments, achieving full mastery

*Solution:* Calling a worked example for an assignment

*Hint:* Calling a hint for a single solution step in an assignment

Figure 1 provides an impression of one of the attempts, an assignment about multivariate functions. At the lower end of the graph are the follow-up steps: *Check* the given solution, consult a *Theory* page, call a *Solution*, or call a *Hint*.

The respective time window and granularity are entirely determined by the instructional design. There are seven weekly topics — like functions of one variable, derivatives, functions of two variables, and optimization — which are hierarchically ordered. Every topic consists of about ten packages each containing five to ten assignments. Within each topic, we distinguish three subsequent learning phases demarcated by the moment of the tutorial session, quiz session, and final exam. This way, the trace database contains 21 measurements for *Attempts: AttWk1TG, AttWk1Qz, and AttWk1Ex* for the three learning phases of the week 1 topic, *AttWk2TG, AttWk2Qz, and AttWk2Ex* for the three learning phases of the week 2 topic, and so on. Similarly, 21 measures for *Mastered Attempts, Finished Packages, Solutions, and Hints* can be distinguished.

Week6: Functions of two variables: Basic notions

Visualizing bivariate functions (exercise id: 1549)

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Consider the function

$$f(x, y) = e^{-x^2 - y^2}.$$

Its graph is displayed in the figure below.

At a particular point  $[a, b]$  the level curve going through that point is the unit circle. What is the value  $f(a, b)$ ?

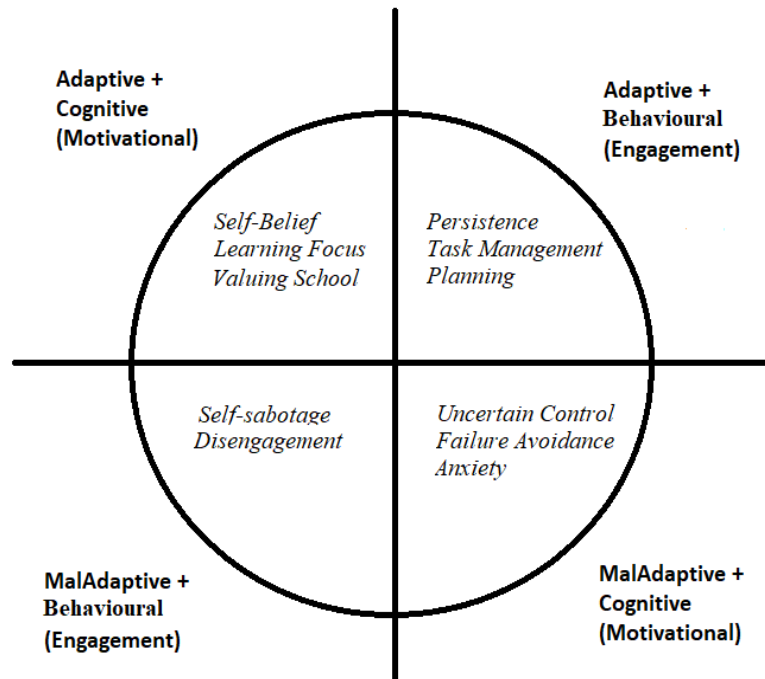
$f(a, b) =$

Figure 1. Example of an attempt of an assignment in SOWISO.

### 3.4. Disposition Data

*Motivation and Engagement Wheel Measures.* The Motivation and Engagement Survey (MES), based on the Motivation and Engagement Wheel framework (Martin, 2007), breaks down learning cognitions and learning behaviours into four quadrants of adaptive versus maladaptive types and cognitive (motivational) versus behavioural (engagement) types. *Self-Belief, Learning Focus, and Valuing School* shape the adaptive, cognitive factors or positive motivations. *Persistence, Task Management, and Planning* shape the adaptive, behavioural factors or positive engagement. The maladaptive cognitive factors or negative motivations are *Uncertain Control, Failure Avoidance, and Anxiety*, while *Self-sabotage and Disengagement* are the maladaptive behavioural factors or negative engagement. Figure 2 gives insight into the four quadrants of learning motivation and engagement.

*Learning Attitudes.* Attitudes and beliefs toward learning quantitative topics were assessed with the SATS instrument (Tempelaar et al., 2007). This instrument, based on the Expectancy X Value Theory (EVT), distinguishes *Affect*, cognitive competence (*CognCompetence*), *Value*, expected difficulty in learning, reversed (*NoDifficulty*), *Interest*, and planned *Effort*.



**Figure 2.** Adaptive and maladaptive learning cognitions and behaviours.

*Learning Process and Regulation Strategies.* Learning processing and regulation strategies, shaping SRL, were based on Vermunt’s (1996) student learning pattern (ILS) instrument. Our study focused on the two domains of cognitive processing strategies and metacognitive regulation strategies, each composed of five scales. The five processing strategies were ordered in line with the SAL research framework (see Han et al., 2020): from deep approaches to learning at the one pole (students aim toward understanding) to stepwise or surface approaches at the opposite pole (students aim to reproduce material rather than actually understanding it):

1. *Critical Processing:* Students form their own opinions when learning
2. *Relating and Structuring:* Students look for connections, make diagrams
3. *Concrete Processing:* Students focus on making new knowledge concrete, applying it
4. *Analyzing:* Students investigate step by step
5. *Memorizing:* Students learn by heart

The first two components shape the deep approach, the last two the stepwise approach. Likewise, the following five metacognitive regulation strategies describe how students regulate their learning processes and allow for positioning students in the spectrum from self-regulation as the main mechanism to external regulation:

1. *SRL Process:* Self-regulation of learning processes
2. *SRL Content:* Self-regulation of learning content
3. *ERL Process:* External regulation of learning processes
4. *ERL Content:* External regulation of learning results
5. *Lack Regulation:* Lack of regulation

*Achievement Emotions.* The Control-Value Theory of Achievement Emotions (CVTAE; Pekrun, 2006) postulates that achievement emotions differ in valence, focus, and activation. From the Achievement Emotions Questionnaire (AEQ; Pekrun et al., 2011), an instrument based on the CVTAE, we selected the four emotion scales most strongly related to academic performance: positive activating *Enjoyment*, negative activating *Anxiety*, and negative deactivating *Boredom* and *Hopelessness*.

### 3.5. Statistical Analyses

Building on person-centred modelling approaches (Malcom-Piqueux, 2015), using cluster analysis techniques to distinguish “unique” and common profiles of learners based on actual engagement and behaviour that satisfy the requirements of homogeneity (Howard & Hoffman, 2018), the analysis was carried out using k-means clustering. Input variables were the five times 21 Sowiso trace variables representing attempts, mastered attempts, finished packages, solutions, and hints in each of the three learning phases, preparing the tutorial sessions, the quiz sessions, and the final exam, and each of the seven weekly

topics. Although disposition data could have been included in the cluster analysis step, we opted to cluster on trace data only to isolate its role from all other data, allowing for comparison with Saint et al. (2022) and Pardo et al. (Han et al., 2020; Pardo et al., 2017). Grouping students into clusters of different learning orientations using learning behaviour only means that we can distinguish and investigate the relationships of learning orientations based on learning activities versus self-reported aptitudes (Han et al., 2020). If not for the demonstration of commonalities of learning orientations derived in these two different ways, a more natural choice would have been to combine behavioural and dispositional measures as the basis for clustering, as in Zamecnik et al. (2022) and Tempelaar et al. (2020b). In that case, profiles of students, the outcome of the clustering operation, represent a mixture of actual learning activities and self-perceptions of learning dispositions. A third option, focusing on the role of dispositions in learning behaviours, is to base clusters on disposition data only and investigate differences in the learning behaviours of clusters. An example is (Tempelaar et al., 2021), which aims to demonstrate characteristic differences in learning behaviours of students in different mindset profiles, a specific learning aptitude.

The number of clusters was chosen to have maximum profile variability without going into small clusters (with less than 5% of the students). We opted for an eight-cluster solution containing five “real” clusters (three clusters contained a single outlier and were excluded from further analysis; all three were students with abnormally high levels of trace data but strongly differing in their temporal patterns of intensive use of the e-tutorial system). Solutions with higher dimensions did not strongly change the characteristics of the clusters and were more complex to interpret. As a next step in the analysis, shaping the variable-centred analysis, differences between profiles were investigated with ANOVA. All these analyses were done using IBM SPSS statistical package. The event-based structural equation model of observed traces was estimated in MPLus. Ethics approval was obtained by the Ethical Review Committee Inner City faculties of Maastricht University (ERCIC\_044\_14\_07\_2017).

## 4. Results

### 4.1. Student Engagement Profiles by Clustering Log Data

As with most LA applications based on authentic settings, trace data exhibited right skewness; in particular regarding the learning aid data, with standard deviation to mean ratios of two or even higher. Next, a few outlying cases are present, such as the student who submitted 2,185 worked-out solutions in the eight-week module, about tenfold of the average of 222 for all students. Rather than addressing skewed data distributions and high outliers with data transforms and case deletion, we opted to address data heterogeneity by creating more homogeneous student profiles by applying cluster analysis. The choice of the number of clusters was primarily based on the presence of a simple, intuitive interpretation of the several profiles, preferring more parsimonious solutions. The five-cluster solution has that characteristic, with the clusters representing five different profiles of learning approaches. These profiles are best interpreted with the timelines of four categories of traces (see Figures 3 and 4).

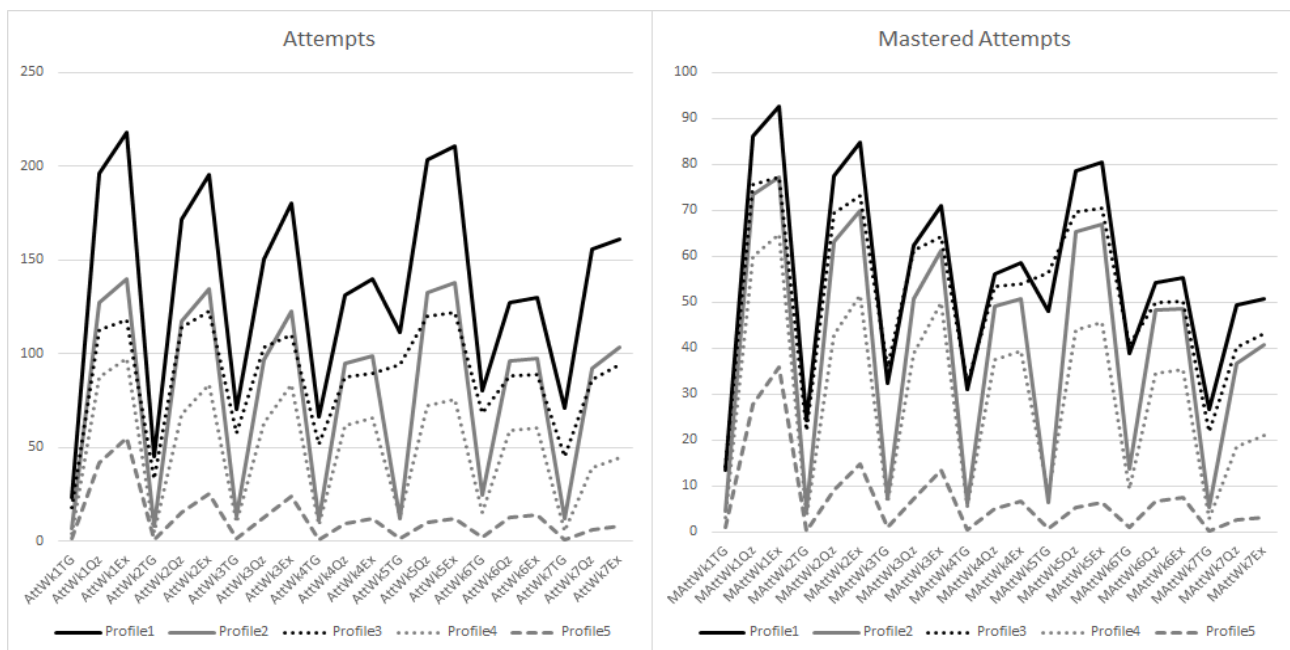


Figure 3. Activity trace data of five profiles of learning approaches: Attempts and Mastered Attempts.

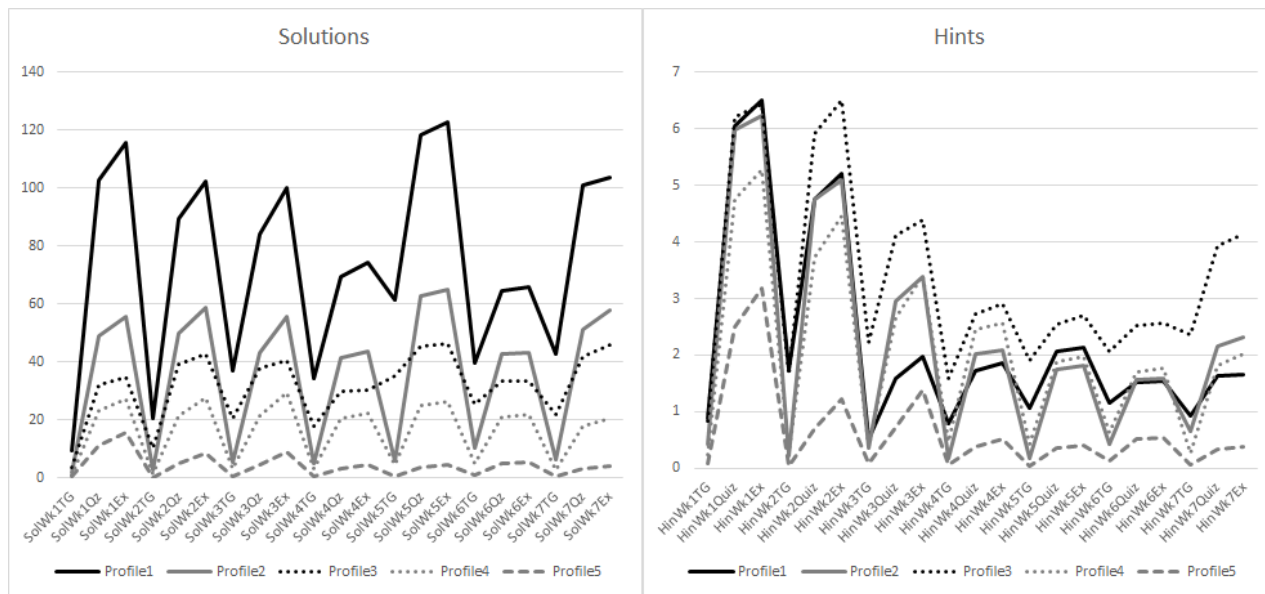


A saw-tooth gradient characterizes both figures. That gradient was determined by the seven cycles of three subsequent learning phases. Most students, in all profiles, concentrated on the second learning phase, where more activity took place than in the first and third. Therefore, the cumulative number of attempts made a modest start in learning phase one, a large jump in learning phase two, and a modest further increase in the last learning phase. In short, most students went relatively unprepared to the tutorial sessions, focused their learning on preparing for the quizzes, and did not need extra preparation for the final exam. This pattern was repeated seven times for all weekly topics.

The exception to this course of action are the students in Profile 1, the smallest profile, containing 146 students. They are the most active students and they study the earliest, with more balance between learning activities in the first two phases (except the very first cycle, where the module starts with a tutorial meeting, leaving students little time to prepare). Aggregated over all weeks, Profile 1 students made 120 attempts in the first phase, 367 in the second phase, and 57 in the last phase. Differences between weekly topics were caused by differences in the number of topic exercises.

Comparing the two panels of Figure 3 clarifies that Profile 1 students are not the most efficient learners; learners from Profile 2 (387 students) and Profile 3 (320 students) take many fewer attempts to reach about the same level of mastery. These two profiles differ in that Profile 3 are early learners, distributing learning activities over the first two learning phases, whereas Profile 2 learners concentrate fully on the second phase of quiz preparation. The last two profiles, Profile 4 (the largest with 824 students) and Profile 5 (648 students), mimic the learning approach of Profile 2 learners, putting most effort into the second learning phase, but at lower activity levels. Basically, Profile 5 learners opted-out of using the e-tutorial after the first week.

Figure 4 provides insight into the use of learning aids over the several weekly topics and three learning phases: *Solutions*, or worked-out examples, and *Hints*. Students used the solution functionality more frequently than the hints: on average, 222 *Solutions* and 19 *Hints* per student, mostly in the second learning phase.



**Figure 4.** Activity trace data of five profiles of learning approaches: Solutions and Hints.

Figure 4 clarifies a large gap between *Attempts* and *Mastered Attempts* in Figure 3 for Profile 1 students: they exceed in worked Solutions. But because calling a solution renders the attempt as one of un-mastered type, there is a gap between *Attempts* and *Mastered Attempts*. From the right panel of Figure 4 describing *Hints*, we observe that Profile 3 students are the most frequent users of this functionality, although their general activity level is below that of the Profile 1 students. These students appear to performing better; in general, they do not need the full exposé of a worked example but suffice with a partial, directed hint.

**4.2. Relevance of Clustering-Based Profiles for Module Performance and Learning Dispositions**

The fundamental question in any LA application is to what extent the profiling of students using trace-based engagement data is predictive for module performance. Figure 5 provides a straightforward answer to this question. There were apparent average performance differences between the five profiles in terms of their final module grade (*Grade*; eta squared effect size equal to 14.0%) and the component scores of final grade, exam scores for mathematics (*ExamMath*; eta squared effect size equal to 7.4%), and quiz scores for mathematics (*QuizMath*; eta squared effect size equal to 7.0%). As Figure 3 describes, the highest

scores were achieved by Profile 3 students, the lowest scores by Profile 5 students, with basically equal scores for the other three profiles. Cluster differences are substantive from a consequential point of view: the grade benchmark to pass the module is 5.5, so with an average grade of 5.4, a large number of Profile 5 students will not pass, in contrast to the other profiles.

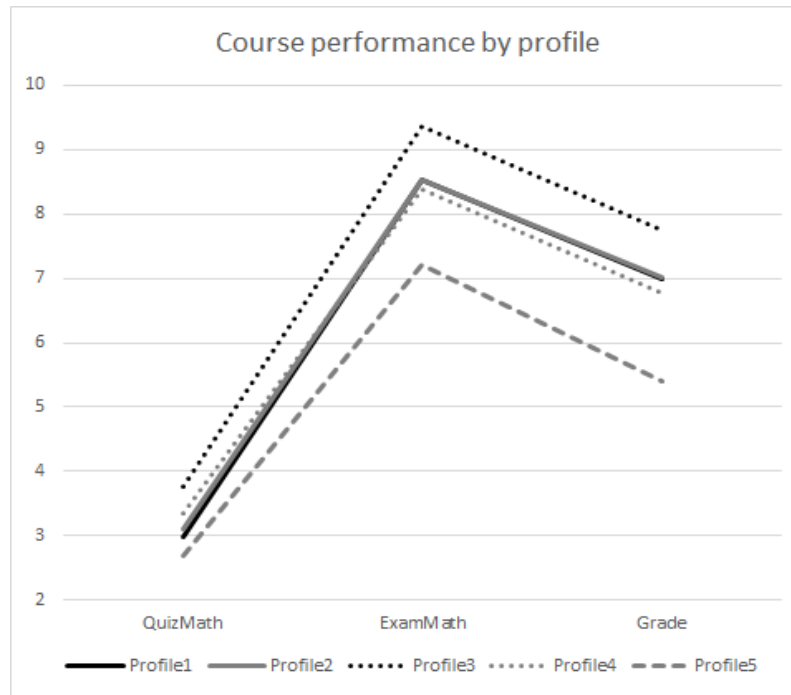


Figure 5. Average module performance of students in different profiles.

Profiting from the availability of disposition data of student aptitudes, we were finally interested in how the five profiles related to our “static” measurements of student motivation and engagement, their approaches to learning — expressed as cognitive processing strategies and metacognitive regulation strategies — their attitudes toward learning and their tendency to postpone, all measured at the start of the module, and their learning activity emotions, measured halfway through the module. ANOVA tests pointed toward all profile differences being statistically significant beyond the .01 level, with one exception: students in different profiles do not differ on their assessment of the difficulty of the module (*NoDifficulty*). Given the large sample sizes, the practical significance of profile differences is, however, more important than statistical significance.

In the adaptive motivations and engagement scales, we find small differences in the cognitive, motivational constructs, but larger differences for the behavioural, engagement constructs, with highest effect size for *Planning* (eta squared equals 6.6%). The first five scales of Figure 6 shows these adaptive scales. We see a similar pattern for the maladaptive scales, depicted in the second panel: no practically significant profile differences for the cognitive, motivational factors, but larger differences for the behavioural, engagement constructs *Disengagement* and *Self-Sabotage*, up to effect sizes of 4.3%. Profile differences follow the pattern that Profile 1 students demonstrate the better scores (higher adaptive scores, lower maladaptive scores), Profile 5 students demonstrate adverse scores, and other profiles take intermediate positions.

Concerning learning processing and learning regulation scales, we observe that Profile 1 students champion all scales: deep processing and stepwise processing, self-regulation and external regulation, with again Profile 5 students in the mirror position. Effects are modest in size, up to 4.0% for stepwise processing and 3.7% for external regulation.

This pattern of profile differences continues in the learning attitudes, with the far-largest effect size noted for planned learning Effort (6.3%). The largest overall effect is the tendency to *Postpone* (6.8%), where Profile 5 students score considerably higher than students in other profiles.

Amongst the learning activity emotions, less a disposition but more an outcome of performing learning activities, the score for learning *Boredom* is remarkable: again, a high score for Profile 5 students (effect size 6.4%).

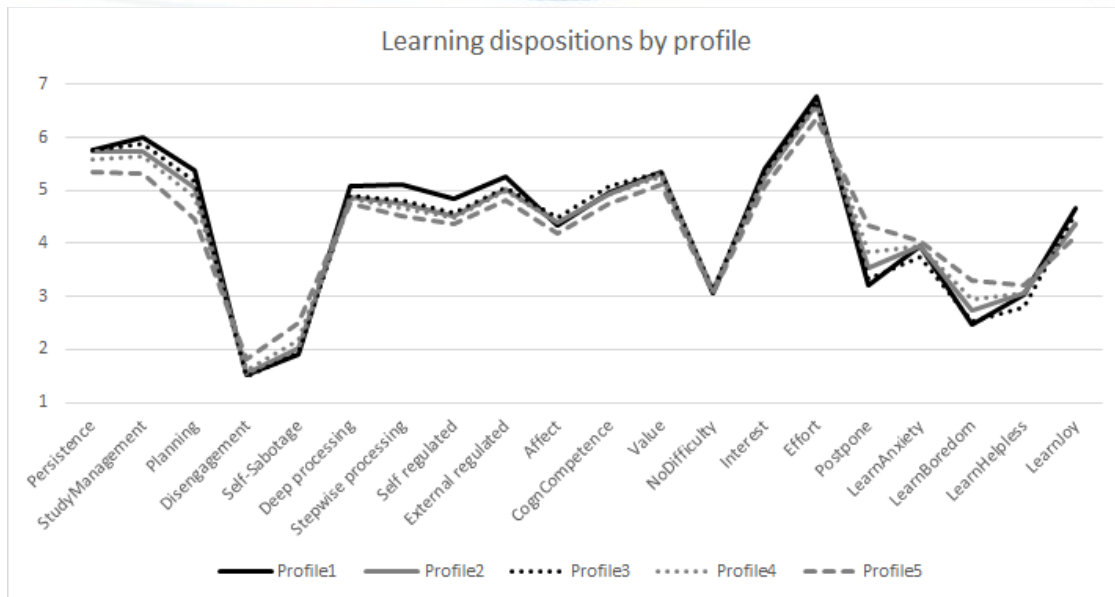


Figure 6. Average regulation and processing levels of students in different profiles.

### 4.3. An Event-Based Model of Trace Data

The database of event data contains 1,360,756 individual learning events by 2,360 students. Since data are collected in an authentic learning context, these events demonstrate timing differences between students, necessitating an aggregation step. From the instructional design perspective, individual timing differences within learning phases are non-essential and may be subject to aggregation, whereas individual differences in timing between learning phases are essential and should not be aggregated. The same logic refers to the seven learning cycles: aggregation can take place for events belonging to the same learning cycle but not for events based on different learning cycles.

Aggregating all event data along this logic gave rise to a complex event model consisting of seven sub-models: one for each learning cycle. Figure 7 provides the theoretical event model for one sub-model, with arrows on the left and right sides indicating the hypothesized behavioural relationships between the levels of events in subsequent learning cycles.

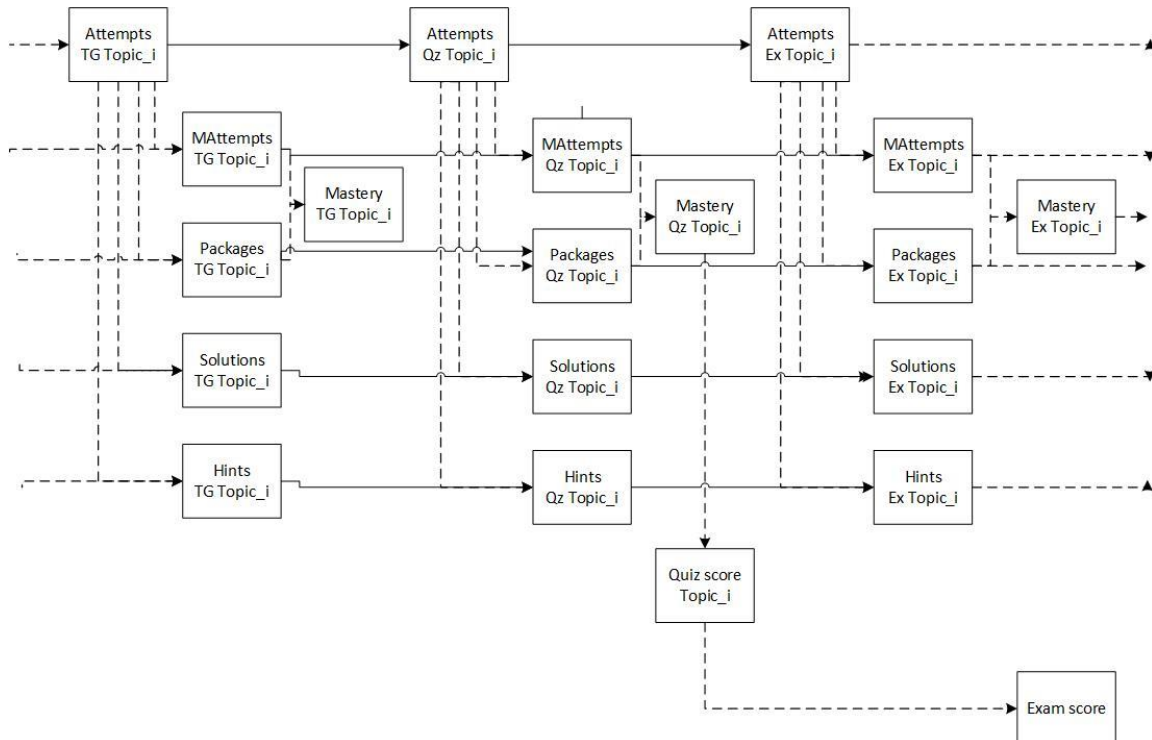


Figure 7. Event sub-model for one learning cycle distinguishing three learning phases.

Within each sub-model, the three phases of learning are demarcated: *TG* for preparing for the tutorial group session, *Qz* for preparing for the quiz session, and *Ex* for preparing for the exam writing. In addition, within each learning phase, the following types of events are distinguished: an *Attempt*, a *Mastered Attempt*, finishing a complete *Package*, calling a *Solution*, and calling a *Hint*.

The arrows in Figure 7 represent predictive relationships, where dashed arrows indicate the behavioural type, and straight arrows represent both a behavioural component and the outcome of an instructional design choice. Thus, *Mastered Attempts*, finished *Packages*, *Solutions*, and *Hints* are predicted as a proportion of *Attempts* in any learning phase or cycle, *Mastery* achieved by a student is predicted by *Mastered Attempts* and finished *Packages*, *Quiz* score is predicted by *Mastery* achieved in the second learning phase, and all seven *Quiz* scores predict the *Exam* score.

Structural equation methods (SEM) can be applied to estimate this path model. However, although the model fit is reasonable (not illustrated), there is a conceptual issue that prevents the use of the model. We can illustrate that by looking at the very first relationship in this model — the relationship between attempts in the first learning phase (*Attempts TG*) and attempts in the second (*Attempts Qz*) for all weekly topics, both for all students together and for the individual profiles. Those relationships are summarized in Table 1.

**Table 1.** Prediction Equations of *Attempts Qz* by *Attempts TG* Per Profile and Topic

	<i>All</i>	<i>Profile 1</i>	<i>Profile 2</i>	<i>Profile 3</i>	<i>Profile 4</i>	<i>Profile 5</i>
Topic 1	85.8+0.857*** <i>x</i>	192.0+0.118 <i>x</i>	125.6+0.267** <i>x</i>	109.5+0.183*** <i>x</i>	86.0+0.346*** <i>x</i>	40.3+0.993*** <i>x</i>
Topic 2	64.8+0.882*** <i>x</i>	159.8+0.265** <i>x</i>	114.0+0.415*** <i>x</i>	105.6+0.253*** <i>x</i>	65.2+0.495*** <i>x</i>	14.3+1.340*** <i>x</i>
Topic 3	52.8+0.698*** <i>x</i>	134.2+0.228** <i>x</i>	92.7+0.328*** <i>x</i>	89.5+0.384*** <i>x</i>	59.8+0.187*** <i>x</i>	10.7+1.028*** <i>x</i>
Topic 4	49.7+0.644*** <i>x</i>	115.7+0.229*** <i>x</i>	92.8+0.154* <i>x</i>	79.7+0.157*** <i>x</i>	58.8+0.291*** <i>x</i>	8.3+1.121*** <i>x</i>
Topic 5	60.3+0.725*** <i>x</i>	190.8+0.115 <i>x</i>	131.7+0.091 <i>x</i>	75.2+0.475*** <i>x</i>	69.2+0.231*** <i>x</i>	8.3+1.213*** <i>x</i>
Topic 6	44.0+0.675*** <i>x</i>	116.1+0.135* <i>x</i>	93.1+0.110** <i>x</i>	62.7+0.372*** <i>x</i>	54.3+0.306*** <i>x</i>	10.4+1.039*** <i>x</i>
Topic 7	40.0+0.881*** <i>x</i>	134.6+0.301*** <i>x</i>	87.8+0.382** <i>x</i>	65.0+0.470*** <i>x</i>	35.6+0.600*** <i>x</i>	5.8+1.115*** <i>x</i>
All Topics	349+1.143*** <i>x</i>	1074+0.131* <i>x</i>	728+0.329*** <i>x</i>	584+0.346*** <i>x</i>	438+0.185*** <i>x</i>	93+1.670*** <i>x</i>

*Notes: Attempts TG is represented as x; \*=*p*-value<.05; \*\*=*p*-value<.01; \*\*\*=*p*-value<.001*

Prediction equations exhibit strong variability, both over the several topics as well as over the profiles. More specifically, this profile variability is large. A second observation from Table 1 is that prediction equations for the full population of students tend to have higher path coefficient estimates than the prediction equations in the individual profiles, except the last profile. Explained variation, not reported here, is also much higher in the prediction equations for the full population than for any individual profile (for example,  $R^2=42.5\%$  for all students for all topics aggregated, but ranging between  $R^2=1.8\%$  and  $R^2=17.8\%$  for the profiles).

The cause of profile-specific relationships being different from all student relationships is again best illustrated with graphical means. Figure 8 provides the prediction equations both per profile and based on the full sample of all students. Next, it contains the line that best fits the means of the six profiles: the inter-profile relationship, whereas the profile-specific prediction equation represents the intra-profile relationships. The full sample prediction equation takes both these sources of variation into account, thus the path coefficient is expected to be between the coefficient of the full sample estimate and the five profile-specific estimates.

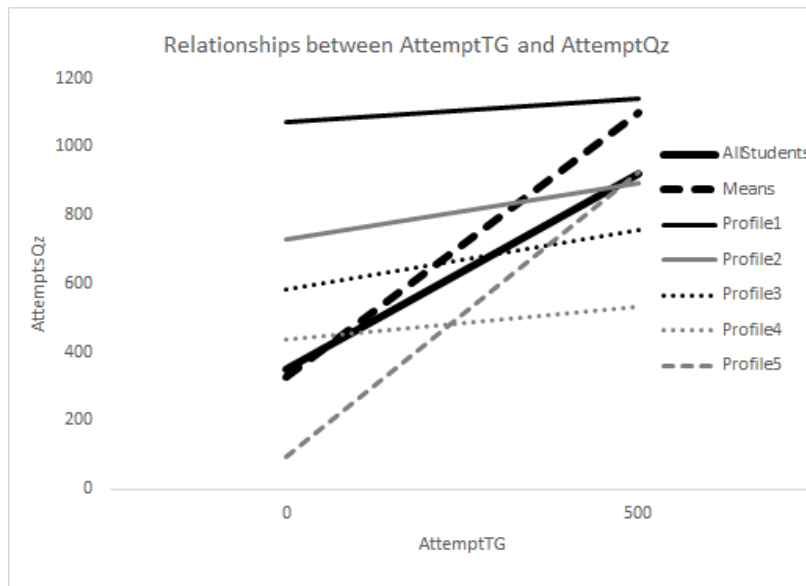


Figure 8. Prediction equation of *AttemptQz* on *AttemptTG*, for full sample, profiles, and means of profiles.

## 5. Discussion and Conclusion

Empirical research into the temporal aspect of SRL is predominantly based on laboratory research taking short learning episodes as their subject; the example presented in Reimann et al. (2014) of a 1.5-hour session in hypermedia learning is representative. At the same time, there is the wish to go beyond laboratory settings and investigate “perceptually and experientially richer problem-solving environments” that “provide for more authentic learning experiences” (Reimann et al., 2014, p. 537). Without doubt, our case that stretches over an eight-week period of SRL is such an environment par excellence. In many ways, this complicates the analysis because of the “open systems” characteristic of any authentic learning setting (Reimann et al., 2014).

A main complication of investigating learning in an authentic context rather than in experimental research taking place in a laboratory (see Molenaar et al., 2023, for examples) is the heterogeneity of the learners. In the lab, learning is typically focused on a topic none of the participants is familiar with, guaranteeing that all learners are novices. In an authentic setting, some learners will be novices, but others have substantial prior knowledge. This diversity will create heterogeneity in the data describing the learning by students. Consequently, we cannot assume that patterns derived from trace data represent the typical learning behaviour of all students; in the presence of heterogeneity, variable- and event-based models, both assuming homogeneity, are dysfunctional.

When learners follow individual learning paths that crucially differ from each other, creating heterogeneity, we need an intra-individual analysis of trace data rather than an inter-individual one (Howard & Hoffman, 2018). However, again the authentic setting prevents collecting the repeated measures required for the intra-individual analyses. In this context, person-centred analysis offers the ultimate solution by splitting the heterogeneous sample into homogeneous, or at least more homogeneous, subsamples and designing models for these subsamples. We can observe in Figure 6 how far off LA predictions can be if they are based on multiple types of learners with diverging learning behaviours. The demonstration of prediction errors in Figure 6 uses person-centred prediction models; if models based on intra-individual data had been available, even larger prediction errors would be expected.

Heterogeneity can have different sources, both diverse students and different learning events. To solve this issue, statistical methods such as cluster analysis or latent class analysis, both person-centred methods, serve to identify student profiles. Investigating event heterogeneity takes a different approach. The main aim of any LA application, however, is to provide learning feedback to students, or to enrich instruction by providing student learning-related information. Therefore, a variable-centred approach is prescribed.

Investigating authentic learning settings does not complicate every dimension of an LA application; it may simplify things because of natural choices such as time segmentation, time windows, granularity of time, and the size of time units within the time window (Molenaar et al., 2023). In our case, the time window is determined by the instructional choice of weekly learning cycles. Granularity is induced by the timing of important events — tutorial session, quiz session, and final exam — that divide

each learning cycle into three subsequent learning phases. These characteristics of the authentic learning process enable us to express both the passage and the order of time in terms of measured variables rather than events only: the amount of student engagement in each phase for each cycle and the allocation of engagement over subsequent phases. This finding answers the first research question: the educational design, rather than the outcome of a discovery method, provides the relevant time window. In line with previous work (Nguyen et al., 2016, 2017) we conjecture that most authentic learning settings are characterized by instructional choices that allow for a natural identification of segmentation and granularity of time. In a context where student learning behaviour is primarily steered by instructional design choices, well expressed in terms of time window and granularity, the differences in event- and variable-based modelling to include dimensions of temporality tend to disappear, or even favour design-based choices. For example, discovery methods would struggle to recognize our first learning phase, given that so few students properly prepare for tutorial sessions. From an educational point of view, this outcome represents crucial information.

Turning to the second research question: being able to describe learning events in terms of variables opens the way for integrating trace data with disposition data to measure student aptitudes. The person-oriented modelling, introduced as the first step of our analysis, not only homogenizes the sample but also integrates learning aptitudes and observations of learning episodes into one model — Reimann’s solution of a balanced approach. Variable-centred modelling appears to be, for now, the only approach in which aptitudes can be unified into a single model with trace data of learning events. Studies based on event-centred modelling that apply aptitude data — for instance, Han et al. (2020) — perform cluster analyses on event data only and restrict the role of aptitude data to describe qualitative differences between clusters.

Integrating aptitude variables into the learning process model is also instrumental in designing educational intervention — our third research question. If the provision of LA-based individual learning feedback to students is a necessary but not always sufficient step in addressing learning barriers, an ideal setup would be the introduction of educational interventions for groups of students who face similar learning issues. A natural choice for such grouping is provided in the profiling step: profiles represent students with similar learning behaviours in the e-tutorials, having similar learning challenges (see also Zamecnik et al., 2022, for an overview of learner profiling in shaping personalized learning). The availability of disposition data that measure learning aptitudes is the second step to interventions. In our analysis, we find important differences in the levels of motivation and engagement, learning attitudes, and more general personality characteristics (such as the tendency to postpone) in the five profiles of learning approaches. These dispositions represent aptitudes that can be addressed in well-designed learning skills training. Adding these dispositions to the analysis reduces the risk of fighting the symptoms, rather than the causes, of low academic performance. Furthermore, it might prevent sending reminders to inactive students when learning boredom would suggest a different type of intervention.

Compared to other studies that create profiles based on observed learning behaviour, our five-profiles solution tends to be richer than that of other research. Uzir et al. (2019) find a three-profiles solution — Active, Passive, and Selective. Our first and fifth profiles resemble the Active and Passive profiles, but we find three intermediate clusters. Two causes may explain this difference: 1) the share of students falling into very high or very low activity is much smaller than the 70% found by Uzir et al. (2019), and 2) differences in time window and granularity. In our learning context, the time window differentiates three important moments for learning, leading to three learning phases. Consequently, more distinct patterns can be discerned for time management than when the time window is characterized by a single point of reference. In Uzir et al. (2020), clustering by a combination of time-management and learning tactics generated four profiles that differ in both the timing of learning and the use of learning resources. Han et al. (2020) found four profiles of learning behaviour, differing primarily in learning intensity rather than time management. The advantage of profiles based on a single dimension, such as time management, is that educational interventions will be less complex.

A first obvious limitation of our research design is the unbalanced observation of the learning process. We observed in detail how students are learning in the two e-tutorials. However, all learning taking place outside of these e-tutorials was either unobserved or not recorded (e.g., interactions with students during tutorials). In a student-centred program applying blended learning as in our module, students design their own individual learning paths, and may opt out of the e-tutorials. These students end up in Profile 5 because of our focus on engagement in the trace data, together with students who truly have low activity. This limitation is inextricably linked to the authentic learning setting, where the learning measure is necessarily no more than partial.

A second limitation is found in the “closed nature” of the two e-tutorials, limiting the perspectives of event-based methods. The pattern of events observed in our students is largely an artefact of instructional design choices, rather than preferred student learning behaviour. If instructional design leads, one cannot expect event-based models to reveal “secrets” that cannot be found in variable-based models with optimal specifications for time window and granularity. Extending this type of research to more “open” authentic learning contexts, where the impact of contextual factors on the order and timing of events is much larger, would be an attractive next step.

The implications of this study depend on the context of the learning and the type of learning analytics–based feedback. In our authentic learning setting, the educational design specified time window and granularity in full, enabling the expression of temporality in terms of well-chosen variables. Next, learning feedback was framed in terms of learning dispositions essential for our problem-based learning process. Both premises favour a variable-based approach. We conjecture that these premises are often valid in authentic settings. Event-based discovery methods certainly contribute in situations where little is known about the design, or where the design is so flexible that it does not strongly restrain time window or granularity. In that case, profiling students based on the outcomes of event-based models can be a fruitful start to the learning analytics application. However, the specifications of learning feedback or learning interventions in terms of the learning dispositions that are crucial for the learning process will usher in the stage where variables enter.

## Declaration of Conflicting Interest

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