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Unpacking the intertemporal impact of self-regulation in a blended mathematics environment

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ABSTRACT

With the arrival of fine-grained log-data and the emergence of learning analytics, there may be new avenues to explore how Self-Regulated Learning (SRL) can provide a lens to how students learn in blended and online environments. In particular, recent research has found that the notion of time may be an essential but complex concept through which students make (un)conscious and self-regulated decisions as to when, what, and how to study. This study explores distinct clusters of behavioural engagement in an online e-tutorial called Sowiso at different time points (before tutorials, before quizzes, before exams), and their associations with academic performance, self-regulated learning strategies, epistemic learning emotions, and activity learning emotions. Using a cluster analysis on trace data of 1035 students practicing 429 online exercises in Sowiso, we identified four distinct cluster of students (e.g. early mastery, strategic, exam-driven, and inactive). Further analyses revealed significant differences between the four clusters in their academic performance, step-wise cognitive processing strategies, external self-regulation strategies, epistemic learning emotions and activity learning emotions. Our findings took a step forward towards personalised and actionable feedback in learning analytics by recognizing the complexity of how and when students engage in learning activities over time, and supporting educators to design early and theoretically informed interventions based on learning dispositions.

1. Introduction

It is widely acknowledged that self-regulation is essential for learning, in particular in forms of blended and online learning where there is limited interaction with and guidance from a teacher. Zimmerman (2000) defined self-regulation as “self-generated thoughts, feelings and actions that are planned and cyclically adapted to the attainment of personal learning goals”. When students are learning in blended or online environments (Hadwin, Järvelä, & Miller, 2011; Trevors, Feyzi-Behnagh, Azevedo, & Bouchet, 2016), where students have a range of choices and options as to when, what, how, and with whom to study, with minimal guidance from teachers, “appropriate” Self-Regulated Learning (SRL) strategies are needed for achieving individual learning goals.

Self-regulation theories are based around a range of empirically-derived factors such as goal-setting, motivation, emotion, and academic performance. A growing body of research concludes that these factors are directly and indirectly influenced by positive SRL. For example, one of the early meta-analyses on success factors for online and distance learning by Lou, Bernard, and Abrami (2006) found that self-regulation was an important factor explaining persistence and learning outcomes. Indeed, research conducted by European (Järvelä & Hadwin, 2013; Järvelä, Hurme, & Järvenoja, 2011; Malmberg, Järvelä, & Järvenoja, 2017; Panadero, Klug, & Järvelä, 2016; Pekrun, Goetz, Frenzel, Barchfeld, & Perry, 2011; Vermunt, 1996) and American researchers (Greene & Azevedo, 2009; Hadwin et al., 2011; Moos & Azevedo, 2008; Trevors et al., 2016) have found that self-regulation is an important driver for effective learning regulation, which in turn impacts learning processes, and learning outcomes.

Typically, many SRL researchers used a mix of fine-grained observational instruments (Järvenoja & Järvelä, 2005) with psychometric instruments (Panadero, 2017; Panadero et al., 2016; Tempelaar et al., 2017) derived from SRL theories to explore how students' self-regulation relate to how students regulate their behaviour and learning outcomes, mostly in large-scale quantitative studies. Yet many of the well-established SRL theories (e.g., Boekaerts, 1997; Pintrich & De Groot, 1990; Vermunt, 1996; Winne, 1995; Zimmerman, 2000) were developed and tested in an era where fine-grained computer-based learning

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process and outcome data were not as readily available as they are nowadays.

With the arrival of fine-grained log-data and the emergence of learning analytics there are potentially more, and perhaps new, opportunities to map how students with different self-regulation strategies actually engage over time beyond an experimental lab environment (Winne, 2017; Tempelaar, Rienties, Nguyen, 2018). With trace data on students' affect (e.g., emotional expression in text, eye gaze, self-reported dispositions), behaviour (e.g., engagement, time on task, clicks), and cognition (e.g., how to work through a task, mastery of task, problem-solving techniques), researchers are able to potentially test and critically examine SRL theories on a micro as well as macro-level (D'Mello, Dieterle, & Duckworth, 2017; Panadero et al., 2016).

Indeed, recent research has found that the notion of time is an essential but complex concept, whereby students make (un)conscious and self-regulated decisions when and how to study (Jovanović, Gašević, Dawson, Pardo, & Mirriahi, 2017; Kovanovic et al., 2015; Littlejohn et al., 2016; Malmberg et al., 2017; Nguyen et al., 2017). For example, in two implementations of the same online environmental management course at the Open University UK (Nguyen et al., 2018) our recent research used fine-grained data of what and when 387 students were actually engaging over a period of 32 weeks as they carried out particular learning activities. Perhaps in contrast to prior expectations, many students made conscious decisions not to follow the course schedule, by either studying well in advance, or catching up after the course schedule (Nguyen et al., 2018). While most students were found to complete specific assignments at the prescribed due date, many students did not necessarily stick to the course schedule for other learning activities (e.g., reading, discussing, watching), and appear to have been self-regulating their learning, rather than choosing to be regulated by the course structure or tutor. Similar findings were reported in a flipped classroom context amongst 290 engineering students (Jovanović et al., 2017), where, using cluster analysis techniques, five unique student profiles were identified that describe how students engaged with the course over time.

To the best of our knowledge, no empirical study has linked how and when students make decisions to study over a substantial period of time in a naturalistic setting, or whether (or not) these decisions are related specifically to SRL. Although the research described above indicates that students make complex, self-regulated decisions over time, based upon behavioural trace-data, no study has linked these trace-data with how and when students engage with learning resources (e.g., using a worked example to solve, say, Math exercise 45 before a tutorial, quiz, or immediately before an exam), and how these are related to SRL measurements and learning outcomes. Therefore, given that this special issue focusses on SRL and learning analytics, we will contrast how and when 1035 students following a blended business module on quantitative methods are studying in Sowiso, a Mathematics e-tutorial platform, over a period of seven weeks, and how this might be related to (self-reported) learning dispositions of learning processing and regulation strategies by Vermunt (1996), Epistemic Emotions Scales (Pekrun & Meier, 2011), and Control-Value Theory of Achievement Emotions (Pekrun, 2000).

2. Self-regulation and learning analytics

2.1. Self-regulation, engagement, and measurement

Since the early 1990s a range of SRL theories have been developed, tested, implemented, and fine-tuned on a large scale in primary, secondary, and higher education. As identified by a recent critical review of six key theories of SRL (e.g., Boekaerts, 1997; Hadwin et al., 2011; Zimmerman, 2000) by Panadero (2017), learners will typically go through three phases when studying in a formal learning context. In the preparatory phase, learners are planning and goal-setting their activities based upon the task at hand, the environment, etc. In the performance phase learners are simultaneously performing the task and monitoring and controlling their own cognition. In the appraisal phase, learners are regulating their SRL and reflecting and adapting on their process, either as part of self-reflection, by peers, by a computer, or via a teacher or third-party (e.g., parent). As argued by SRL theorists (Winne, 1995; Zimmerman, 2000), learners will typically go through these phases and sub-phases in a cyclical manner.

Several meta-analyses (e.g., Dignath & Büttner, 2008; Sitzmann & Ely, 2011) have found that appropriate self-regulation often has a positive impact on learning behaviour and academic performance. For example, in a review of 430 studies consisting of 90 K + students Sitzmann and Ely (2011) found that goal level, persistence, effort, and self-efficacy accounted for 17% of variation in learning when controlling for ability and prior knowledge. Similarly, Panadero (2017, p. 24) found strong uptake and support for six reviewed SRL models, whereby he concluded that "more longitudinal research on SRL, which focuses on its development during more specific and shorter periods of time, is needed. For example, studies that focus on one specific crucial academic year (e.g., first year of university)."

As indicated previously, a range of approaches have been developed to measure SRL. In a review of SRL measurement approaches used since the 1990 ies, Panadero et al. (2016) argued that there were three waves of SRL measurement approaches. During the first wave, mostly SRL were measured from a static perspective using self-reports (Pintrich & De Groot, 1990; Vermunt, 1996). However, the trait-like manner of SRL limited opportunities to capture intervention effects on self-regulation of students.

In the second wave of SRL measurement approaches during the 2000s, SRL measurements moved more to a process-based, dynamic, and interactive approach, whereby "on-the-fly" and online measures were used to capture students' activities during learning tasks (Panadero et al., 2016). Using a combination of continued self-surveys and think-aloud protocols in controlled lab environments and classroom settings, detailed, and fine-grained computerised and/or human coded data and perspectives were obtained to understand the more complex, dynamic, and interlinked SRL approaches (e.g., Greene & Azevedo, 2009; Järvenoja & Järvelä, 2005). Of course an obvious limitation of these kinds of approaches is that students are potentially prompted on their self-regulation during their learning processes, and the scalability beyond the lab-environment of these process-based studies might be limited.

In the third wave, Panadero et al. (2016) argued for a range of methods and instruments to combine the measurement and intervention effect. One example provided by Panadero et al. (2016) is learning diaries as discussed by Schmitz and Perels (2011), whereby students actively reflected and documented their learning processes and also completed pre-post measurements of SRL. In addition, in a study of 788 MOOC learners Littlejohn, Hood, Milligan, and Mustain (2016) found that learners' motivations and goals substantially influenced learners' conceptualisation of the learning environment, and how they engaged with the learning processes. This third wave is closely linked to the increased presence of technology in and outside the classroom, and the emergence of learning analytics, which is described in the next section.

2.2. SRL in computer-supported settings: a learning analytics perspective

Within the learning analytics field, there is an emergence of literature that uses factors of SRL to understand how students are setting goals and solve computer-based tasks (Azevedo et al., 2013; Buckingham Shum & Deakin Crick, 2012; Winne, 2017). For example, using the software tool nStudy Winne (2017) recently showed that trace data from students in forms of notes, bookmarks, or quotes can be used to understand the cycles of self-regulation. In a study of 285 students learning Business French, using log-file data Gelan et al. (2018) found that engaged and self-regulated students outperformed students who were "behind" in their study. In a recent review on the use of learning analytics dashboards, Bodily et al. (2018) conclude that many dashboards use principles and conceptualisations of self-regulation, which could be used by teachers and students alike to support SRL, assuming these teachers and students have the capability to use these tools.

At this point, it would be useful to make a distinction between variable-centred and person-centred modelling approaches. In empirical educational research, a majority of studies is based on *variable-centred modelling approaches*, such as regression, factor analysis, or structural equation modelling. Such choice of statistical techniques is in line with the goal of most studies: to provide evidence, or the opposite case, to falsify, educational theories. Theories that are formulated as the existence of certain relationships between variables. Beyond the testing of these hypothesised relationships, also the case of predicting outcomes or studying how antecedents influence their consequences, require variable-centred modelling approaches and statistical dependence techniques that correspond to these approaches (Howard & Hoffman, 2018; Laursen & Hoff, 2006; Malcom-Piqueux, 2015; Masyn, 2013; Morin, Bujacz, & Gagné, 2018; Marsh, Lüdtke, Trautwein, & Morin, 2009).

In contrast, *person-centred modelling approaches* (Howard & Hoffman, 2018; Malcom-Piqueux, 2015; Masyn, 2013; Morin et al., 2018) have the goal to group individuals, such that people within each category are similar to each other and different from individuals in other categories. A major reason to apply person-centred modelling lies in characteristics of the data, in particular when using large data sets from contexts with "diverse" heterogenous students. Variable-centred approaches are based on the strict assumption "that all individuals from a sample are drawn from a single population for which a single set of "averaged" parameters can be estimated" (Morin et al., 2018). In contrast, person-centred approaches "relax this assumption and consider the possibility that the sample might include multiple subpopulations characterized by different sets of parameters.

Person-centred approaches thus provide a rich complement to traditional variable-centred methods, allowing researchers to model complex processes in a more heuristic way" (Morin et al., 2018). Since research questions are often formulated at the variable level, with the aim to corroborate or falsify educational theories, contemporary empirical studies often adopt a two-step approach: start with a person-centred approach to decompose a heterogeneous sample into homogeneous clusters of classes, and continue with a variable-centred approach based on the homogeneous sub-samples (Marsh et al., 2009; Morin et al., 2018).

Learning analytic studies (Nguyen, Rienties, Toetenel, Ferguson, & Whitelock, 2017; Fincham, Gasevic, Jovanovic, & Pardo, 2018; Jovanović et al., 2017; Kovanović et al., 2018) often apply such two-step approaches combining person-centred methods with variable-centred methods, when the aim of such studies is to design learning feedback based on early indicators of the learning process, or to signal students at risk of dropout. Using statistical techniques such as cluster analysis or latent class analysis, so-called interdependence techniques, these type of studies intend to find clusters or classes of students who first of all satisfy the requirement of homogeneity, and nest represent groups of students demonstrating similar learning behaviours, who may profit from "personalised" learning feedback.

For example, using cluster analysis techniques Jovanović et al. (2017) unpacked the user engagement patterns (e.g., engagement with videos, documents, problem sequences) of 290 engineering students during 13 weeks, and found five distinct clusters of student behaviour: intensive, strategic, highly strategic, selective, and highly selective. In follow-up research in the same research context by Fincham et al. (2018) with 1138 students, eight learning strategies were initially identified from log-file data using cluster analysis. Follow-up interventions half-way through the course showed that feedback can actively encourage learners to adjust their learning strategy (Fincham et al., 2018).

These differences in modelling goals are linked with different epistemologies, and data requirements. Variable-centred approaches require homogeneous populations: the same associations between antecedent and consequence variables govern learning behaviour of all subjects. If variable-centred approaches are applied to samples that are heterogeneous in nature, such as in our context (see section 3.1-3.2), the estimated relationships will be an average of different relationships existing in the different groups, and will generally lead to incorrect conclusions and incorrect learning feedback. In contrast, person-centred approaches build on the assumption of a heterogeneous population that is grouped into homogeneous clusters or classes with regard to learning behaviours (Laursen & Hoff, 2006).

The methodological setup of our study fits within the typical learning analytics framework: we intend to identify groups of students that share a similar learning profile in Sowiso, with the aim to identify relatively similar groups for whom we can provide effective automated learning feedback in the near future. We intend to do so as early as possible in the course, to allow for timely feedback. Indeed, recent research has shown that learning analytics approaches can help teachers and students to successfully intervene in processing of a task (Fincham et al., 2018; Mejia et al., 2017). For example, in a lab-based study Mejia et al. (2017) tested the role of SRL as a mediator for reading comprehension, through which, by providing visualisations of reading difficulties to learners helped them to reflect, the students self-regulated and improved their learning outcomes.

It is for this reason that clustering techniques are often applied in learning analytics studies (Nguyen et al., 2017; Fincham et al., 2018; Jovanović et al., 2017), which are based on trace variables of learning behaviour, as these indicators get "shaped" from the beginning of the course onwards. In this learning setting, the student population is heterogeneous in terms of prior knowledge and prior education, and this heterogeneity is expected to impact learning behaviours (e.g., a need to actively engage in Sowiso because of a lack of Mathematics prior knowledge). Therefore, conditions for variable-centred approaches to modelling are not likely to satisfy (Howard & Hoffman, 2018) and two-step approaches starting with person-centred methods (Fincham et al., 2018; Malcom-Piqueux, 2015; Masyn, 2013) seem more appropriate in our context, with the aim to identify characteristics profiles of learning.

Building on the early conceptual work of dispositional learning analytics by Buckingham Shum and Deakin Crick (2012), in this context of learning mathematics we extensively explored how common educational theories like SRL work in practice when linking dispositional data, such as motivation and self-regulation, with detailed learning processes and outcome data in naturalistic settings. Our longitudinal work over a decade with ten thousand + business students linking their learning dispositions data with how they engage in a blended mathematics course indicate a much more complex, dynamic, and intertemporal interplay of affect, behaviour, and cognition (Tempelaar et al., 2015, 2017, 2018). For example, using K-means clustering of quiz scores, traces in Sowiso, and learning disposition data, including learning processes and self-regulation by Vermunt (1996) and Control-Value Theory of achievement emotions by Pekrun (2000), Tempelaar et al., 2018 found six clusters of students, who substantially differed in academic performance, how they made use of Sowiso, which in turn was related to their learning dispositions. In particular, six relatively unique clusters of students were identified, who significantly differed in their self-regulation, how they worked with the mathematics tasks in Sowiso, and their academic performance (Tempelaar et al., 2018). However, these analyses were conducted on an aggregate course level, which may ignore the complex notions of how and when students self-regulate their learning over time.

2.3. SRL and temporal analytcics

In order to advance our insights into SRL and the complex learning processes, we propose to combine insights from SRL with recent temporal analytics research. Of course the notion of time in learning can take many forms, from longitudinal studies contrasting data of learners across modules and qualifications over years, months, or weeks, to lessons within a course, activities within a task, and how learners navigate within a respective activity. Time management, which is closely related with temporal analyses, has been well-documented and empirically tested as one of the key predictors in academic performance (Broadbent & Poon, 2015; Claessens, van Eerde, Rutte, & Roe, 2007; Kim & Seo, 2015). Time management refers to learners' efforts to effectively achieve certain educational goals within a given period of time. There are strong conceptual links with SRL, since time is related to how students' plan learning as well as to goal setting process (Hadwin et al., 2011; Winne, 1995; Zimmerman, 2000).

Numerous studies have confirmed that students who manage their time ineffectively (e.g. procrastinating, cramming for exam) performed poorly on academic tasks (Nguyen, Huptych, & Rienties, 2018; Cerezo, Esteban, Sánchez-Santillán, & Núñez, 2017; Jovanović et al., 2017; Kim & Seo, 2015). For example, in a self-report study amongst 446 US students Wolters, Won, and Hussain (2017) found that time management was a key aspect of SRL, and procrastinating in particular. Nonetheless, the majority of time management studies mainly rely on self-reported measures (Claessens et al., 2007; Wolters et al., 2017). As a result, some key aspects of time management (what, when, and for how long students engage) have not been fully understood.

As a field of research learning analytics has rapidly progressed from "static" to temporal analytics (Nguyen et al., 2018; Chen, Knight, & Wise, 2018; Jovanović et al., 2017; Knight, Friend Wise, & Chen, 2017). For example, Tempelaar et al., 2018 compared the official course schedule with actual timing decisions of 200 + students during an online course of 32 weeks. The main conclusion was that large differences existed in the extent to which students kept track of the official course schedule, and that individual differences in time management went hand in hand with individual differences in course performance. However, the Nguyen et al., 2018 study was only based on process data relating learning time decision and product data relating course performance.

There remain debates of how learning constructs are conceptualized over time, how they are represented in data (Chen et al., 2018; Knight et al., 2017), and how they are related to SRL. In our current study, we aim to link similar behavioural temporal data as used in Nguyen et al. (2018), the timing decisions made in the learning process (Kovanovic et al., 2015; Winne, 2017), with the types of activities students choose to engage with, and SRL learning disposition data measured through surveys (Pekrun et al., 2011; Pekrun & Meier, 2011; Vermunt, 1996), to be able to compose alternative SRL characterizations of students who prepare in time, and students who tend to postpone.

2.4. Research questions

Even though an emerging body of SRL literature has focussed on how self-regulation influenced learning processes and students' behaviour in face-2-face learning settings, limited research has explored specifically how SRL works in naturalistic online and blended learning settings in higher education (Panadero, 2017; Winne, 2017). Building on our previous research in a data-rich context in a blended mathematics course (Tempelaar et al., 2017, 2018), we aim to critically examine the intertemporal impact of how 1035 students chose to engage with a suite of different learning activities in a Sowiso platform over a period of seven weeks, and in particular when and how, and whether this is related to their self-regulation strategies.

In line with person-centred approaches, we particularly are interested to identify common engagement patterns when and how students engage with Sowiso. In particular whether fine-grained learning analytics trace data of how (e.g., attempting to solve a task, asking a worked-out example, using hint to solve a task) students aim to solve mathematics exercises and when (e.g., before the tutorial group, before the formative assessment, and/or before the exam) has received limited empirical attention in previous research. (Research Question 1).

RQ1 What are common engagement patterns in Sowiso how (e.g., asking a worked-out example) and when (e.g., before the tutorial group) students choose to engage with 429 mathematics exercises?

While previous research using cluster analyses have identified that some groups of students substantially differ in how they engage with tasks over time (Fincham et al., 2018; Gelan et al., 2018), whether this has an impact on academic performance still remains unclear. In Research Question 2 we aim to explore whether (or not) these different engagement patterns in Sowiso actually matter in terms of academic performance.

RQ2 How are the temporal engagement patterns in Sowiso (i.e., the cluster profiles) related to academic performance?

Finally, in line with recommendations by Buckingham Shum and Deakin Crick (2012) we have collected a range of dispositional learning data from these students, including learning processing and regulation strategies by Vermunt (1996) and Epistemic Emotion (Pekrun & Meier, 2011) at the beginning of the course, and Control-Value Theory of Achievement Emotions (Pekrun, 2000) mid-way in the course. Given our temporal focus in this study, we appreciate that, ideally, we would have also collected rich fine-grained SRL data from students throughout the course to link the temporal learning analytics with how students chose to engage with Sowiso at the various points in time. However, in this explorative study we aim to explore whether more static, learning dispositions data on self-regulation and emotion as measured in Week 0 and Week 4, can provide some meaningful insight into how students engage with Sowiso.

In a way, we aim to connect the three waves of SRL measurements identified by Panadero et al. (2016) to provide one potential temporal perspective of SRL on a large, naturalistic environment where students have a range of learning choices to achieve their own learning objectives. If these learning dispositions might explain some of the engagement patterns in Sowiso in the weeks directly following the respective measurements, this might provide some potential insights and future "automated" feedback options to both students and teachers. Perhaps more importantly, by linking learning dispositions with engagement of time we might be able to provide some theoretical advancements of the cyclical nature of SRL (Järvelä & Hadwin, 2013; Winne, 1995). Our study builds on the presumption that learning feedback is actionable when it addresses dispositions, in specific a potential lack of adaptive dispositions or high levels of maladaptive dispositions. Rather than providing students with a generic advice as 'you better become more active, you are lacking behind your peers', our study seeks to identify what dispositions are linked with our measures of learning behaviour, so that we may differentiate in learning feedback between a student lagging behind because of bad time management and a student lagging behind because of lack of self-regulation, or "negative" learning emotions.

RQ3: How do different temporal engagement patterns relate to Self-Regulated Learning strategies?

3. Method

3.1. Context and setting

This study took place in a large-scale introductory mathematics and statistics course for first-year undergraduate students in a business and economics programme in the Netherlands, with a study load of 20 h per week, for a period of seven weeks. This module was a compulsory, first module for all first year students, and often a stumbling block for students with limited mathematics affinity. The educational system is best described as 'blended' or 'hybrid'. The main component was face-to-face: Problem-Based Learning (PBL), in small groups (14 students), coached by a content expert tutor. Participation in tutorial groups was required, and constituted around 2 × 2 h per week. Furthermore, once a week there was a 2 h lecture to introduce the key concepts in that week. The remaining

14 h were self-study, which were supported by printed materials (i.e., textbooks) and two interactive e-tutorials: Sowiso (https://sowiso.nl/) and MyStatLab (MSL) (Tempelaar et al., 2015, 2018). This design was based on the philosophy of student-centred education, placing the responsibility for making educational choices primarily on the student (Fincham et al., 2018; Jovanović et al., 2017). In line with the principles of PBL, feedback derived from our LA-applications was shared with students and tutors. The tutors, in their bilateral contact with the students of their tutorial groups, also took care of the 'prompting' when needed: they discussed the consequences of the feedback, and potential options to improve. Since this prompting took place in class or on the periphery of the tutorial sessions, it remains unobserved.

In terms of the timing of learning, this study distinguished three relatively distinct learning phases. Phase 1 prepared students for the next tutorial session. Since most of the learning took place during self-study outside class in Phase 1, face-to-face time was used to discuss solving "advanced" maths problems. Phase 1 was not formally assessed, other than that such preparation allowed students to actively participate the discussion of the problem tasks in the tutorial session. For a detailed overview of the respective timings of the various phases and measurements, we refer to Appendix Fig. 1.

Phase 2 was the preparation of the quiz session, one or two weeks after the respective tutorial. Using and achieving good scores in Sowiso and Statlab in Phase 1 was "incentivised" by providing bonus points for good performance in quizzes in Phase 2, which were taken every two weeks in "controlled" computer labs, and consisted of test items that were drawn from the same item pools applied in the practicing mode. This approach was chosen to encourage students with limited prior knowledge to make intensive use of the e-tutorials.

Phase 3 consisted of the preparation of the final exam, at the end of the course. Phase 3 included formal, graded assessments. The written exam was a multiple-choice test of 20 questions on mathematics, as well as 20 questions on statistics. These questions could be practiced using the text book materials and the e-tutorial modes. Students' timing decisions therefore related to the amount of preparation in each of the three consecutive phases.

3.2. Participants

We included 1035 first-year students in this study who had been active in at least one digital platform. Of these students, 42% were female, 58% male, 21% had a Dutch high school diploma, and 79% were international students. Amongst the international students, neighbouring countries of Germany (34.2%) and Belgium (19.8%) were well presented, as well as other European countries. 5.0% of students were from outside Europe. High school systems in Europe differ strongly, most particularly 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, preparing for social sciences, or preparing for humanities. To enter this international business programme, prior mathematics education preparing social sciences is required, while 31.5% of the students followed the highest 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 students' learning strategies and tasks.

A particularly innovative feature of our student-centred design was that students' learning dispositions data (see section 3.4) were provided back to students with "semi-automated" feedback. Furthermore, during the first couple of weeks aggregated data from these learning dispositions were used as data for an individual student project, where students learned to apply basic statistical computations whilst comparing their learning dispositions to average levels with other students. Therefore, students received substantial opportunities to learn about their initial SRL, and those of others, and were given guidance and skills sessions how to potentially change their study strategies.

3.3. E-tutorial trace data

Trace data were collected from both e-tutorial systems (Sowiso, mathematics, and MSL, statistics), as well as Blackboard, which was used as the university-wide generic learning management system to provide general information and links to Sowiso and MSL. Sowiso data were fine grained in that it recorded every single student activity, including time stamp, type of activity, and learning outcome. Unfortunately, MSL and Blackboard data were less fine-grained, aggregating activities into daily periods, and excluding information on activity type. Therefore, our study focused only on trace data of the Sowiso e-tutorial of both product and process type (Azevedo et al., 2013). The product variable was mastery: the percentage of the in total 429 mathematics exercises offered by Sowiso successfully solved by

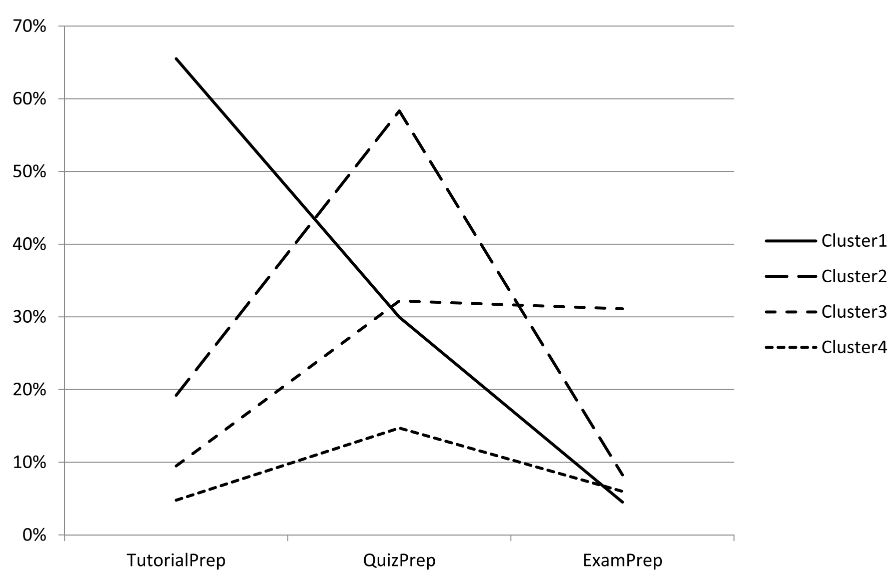


Fig. 1. Mastery levels representing timing decisions by students in the four clusters.

each student, as part of the preparation in the three different learning phases. To investigate these timing decisions, we distinguished mastery achieved in each of the three phases:

- *TutorialPrep*: mastery acquired in Phase 1, measured at the start of the weekly tutorial sessions;
- *QuizPrep*: mastery acquired in Phase 2, measured at the start of the biweekly quiz sessions;
- *ExamPrep*: mastery acquired in Phase 3, measured at the moment students wrote the exam.

In addition to tracking in which learning phase students were engaging, the Sowiso platform offered process-type data about how students solved the 429 exercise. When a student started a new exercise, four support options were available: check (i.e., check the answer before submitting); worked-example (i.e., provide worked-example illustrating the various steps and afterwards receiving a similar but new exercise); hint; and theoretical (i.e., view the theory page explaining the mathematical principle. The merits of the worked examples principle in the initial acquisition of cognitive skills are well documented (Tempelaar et al., 2018; Renkl, 2014). In particular, the use of worked examples in mathematics e-tutorials is linked to gaining deep understanding. Compared to the use of erroneous examples, tutored problem-solving (providing hints), and untutored problem-solving in computer-based environments, the use of worked examples may be more efficient as it reaches similar learning outcomes in less time and with less learning efforts. Therefore, to investigate individual differences in the use of learning resources, we distinguished the total number of student attempts of any type, together with the breakdown of these attempts into the use of different types of learning resources:

- *Attempts*: the total number of attempts solving the exercises;
- *Solutions*: the fraction of Attempts where students called for a complete solutions, or worked-out example;
- *Hints*: the number of hints called for by students whilst solving Sowiso exercises.

Combining these three process variables with the three different learning phases generated in total nine trace-based process variables: Attempts, Solutions and Hints to prepare the tutorial sessions (Phase 1), to prepare the quiz sessions (Phase 2), and to prepare the final exam (Phase 3). Since all of these variables had right skewness, the log-transform was applied to improve normality of the constructs. Since the number of exercises varied across the several weeks, the use of solutions and hints was expressed as a percentage of the number of exercises one can call a solution of hint for.

3.4. Survey data

3.4.1. Learning process and regulation strategies

Learning processing and regulation strategies, shaping self-regulated learning, were based on Vermunt's student's learning pattern (ILS) instrument. In addition to self-regulation dimension, the learning pattern model presents a broader conceptualisation of regulation of learning by incorporating external regulation, and lack of regulation. In our context, students' regulation strategies were also influenced by external resources (e.g. Sowiso e-learning platforms). Therefore, their behavioural traces are proxies of their external regulation processes. Secondly, as part of the regulation process, students seek to evaluate their learning progress through external means (e.g. discussion with their teacher and fellow students during the tutorials, participate in quizzes, and finally in exams). The timing of their engagement can demonstrate how students' regulation activities are driven by different types of self-regulation. For a detailed discussion on the interplay of ILS, self-regulation, and external regulation, we refer to a recent review by Vermunt and Donche (2017). Our study focused on the two domains of cognitive processing strategies, and metacognitive regulation strategies. Both components were composed of five scales. The five processing strategies were ordered from deep approaches to learning at the one pole, to stepwise or surface approaches to learning at the opposite pole:

- Critical processing: students form own opinions when learning,
- Relating and structuring: students look for connections, make diagrams,
- Concrete processing: students focus on making new knowledge concrete, applying it
- Analysing: students investigate step by step,
- Memorizing: students learn by heart.

The first two scales, critical processing and relating and structuring, together shape the *Deep learning* processing strategy. The last two scales, analysing and memorizing, shape the *Step-wise* or surface learning processing strategy. *Concrete* or strategic processing represent an application oriented learning strategy. For exemplary items of these scales and other scales mentioned below, as well as Cronbach alphas, see Appendix Table 1.

Likewise, the five metacognitive regulation strategies describe how students regulated their learning processes, and allow positioning students in the spectrum from self-regulation as the main mechanism, to external regulation. The scales are:

- Self-regulation of learning processes,
- Self-regulation of learning content,
- External regulation of learning processes
- External regulation of learning results,
- Lack of regulation.

The two main regulation strategies are *Self-regulation* and *External regulation* of learning, beyond the absence of any type of regulation: *Lack of regulation*. These ten scales were distributed in the first week of the course.

3.4.2. SRL and emotions

As highlighted by a range of SRL theorists and described elsewhere in this special issue (Verstege et al., 2019), there is a strong conceptual link with SRL and emotions when learners work their ways into a range of tasks (Hadwin et al., 2011; Järvelä & Hadwin, 2013; Panadero, 2017; Winne, 2017). While achievement emotions, described in the next section, arise from doing learning activities, like doing homework, epistemic emotions are related to cognitive aspects of the task itself. Prototypical epistemic emotions are curiosity and confusion. In this study, epistemic emotions were measured with the Epistemic Emotion Scales (EES: Pekrun & Meier, 2011), which like the ILS were distributed at the start of the course. That instrument included the scales:

- *Surprise*: neutral epistemic emotion,
- *Curiosity*: positive, activating epistemic emotion,
- *Confusion*: negative, deactivating epistemic emotion,
- *Anxiety*: negative, activating epistemic emotion,
- *Frustration*: negative, deactivating epistemic emotion,
- *Enjoyment*: positive, activating epistemic emotion,
- *Boredom*: negative, deactivating epistemic emotion.

In order to provide sufficient incubation of the learning design and task environment, after four weeks we distributed one addition learning disposition survey instrument, namely the Control-Value Theory of Achievement Emotions (CVTAE: Pekrun, 2000; Pekrun et al., 2011). CVTAE postulates that emotions that arise in learning activities differ in valence, focus, and activation. Emotional valence can be positive (enjoyment) or negative (anxiety, hopelessness, boredom). CVTAE describes the emotions experienced in relation to an achievement activity (e.g., boredom experienced whilst preparing homework) or outcome (e.g., anxiety towards performing at an exam). The activation component describes emotions as activating (i.e., anxiety leading to action) versus deactivating (i.e. hopelessness leading to disengagement). For this study, based upon our previous research (Tempelaar et al., 2015) we made a selection of four scales measuring learning emotions using the Achievement Emotions Questionnaire (AEQ: Pekrun et al., 2011), which were found to be most strongly related to course performance:

- *Enjoyment*: positive, activating learning emotion,
- *Anxiety*: negative, activating learning emotion,
- *Boredom*: neutral, deactivating learning emotion,
- *Hopelessness*: negative, deactivating learning emotion,
- *Academic Control*: antecedent of all learning emotions.

3.5. Statistical analyses

Building on person-centred approaches (Malcom-Piqueux, 2015) using cluster analysis techniques to distinguish "unique" and common clusters of learners based upon actual learners' engagement and behaviour (Tempelaar et al., 2017; Fincham et al., 2018; Jovanović et al., 2017) that satisfy requirements of homogeneity (Howard & Hoffman, 2018), the analysis was carried out using k-means cluster analysis based on nine Sowiso trace-based process variables: Attempts, Solutions, and Hints to prepare the tutorial sessions, to prepare the quiz sessions, and to prepare the final exam. One obvious strength which is at the same time a limitation of cluster analysis techniques is that participants with similar characteristics and behaviours will be clustered together, even though there might be subtle or substantial differences within a respective cluster. For example, our previous research included more broader data of learning dispositions data, Sowiso, and academic performance in our clustering procedure (Tempelaar et al., 2018) from an aggregate, static perspective, which might force particular students into a cluster based upon some shared (but not all) patterns across these variables. Therefore, in this study we excluded the use of disposition data in the person-centred modelling approach, and we clustered students solely on the Sowiso trace data from a temporal perspective.

In other words, we specifically chose to focus our cluster analyses on what common groups of students did and when in Sowiso, which we afterwards linked with their learning dispositions and academic performance. The number of clusters was chosen to have maximum variability in profiles, without going into very small clusters (the smallest cluster contains at least 10% of the number of students, i.e., n = 133). We opted for a four-cluster solution, as solutions with higher dimensions did not strongly change the characteristics of the clusters, but tended to split the smaller clusters into even smaller ones. As a next step in the analysis, shaping the variable-centred analysis step, differences between profiles were investigated with ANOVA. All analyses were done using IBM SPSS statistical package. Ethics approval was obtained by the Ethical Review Committee Inner City faculties of Maastricht University (ERCIC_044_14_07_2017).

4. Results

4.1. RQ1 student engagement profiles by clustering sowiso trace data

At the end of the course, students mastered on average 67.1% of all 429 exercises in Sowiso. However, as is visually illustrated in Fig. 1, the build-up of this mastery was unequally spaced in time. Some students did most of their learning to prepare the tutorial sessions in Phase 1, leaving limited materials left for later learning phases, while the majority of students postponed learning to Phase 2, as a preparation for the quiz sessions.

In terms of Research Question 1, we identified four relatively distinct unique engagement profiles in Sowiso. Cluster 1 represents the profile of the "active", self-regulated student. Based upon the log-data of Sowiso, the mastery of these 215 students at the start of the face-to-face tutorial session (i.e., Phase 1) is on average just below 70%, leaving very little of the materials to be mastered in the following two learning phases. In contrast, the other profiles of students achieved average mastery levels not exceeding 20% at Phase 1. Furthermore, at Phase 2 the Cluster 1 students mastered more than 95% of all topics at the Quiz.

Cluster 2 students, with 413 students by far the largest cluster, concentrated on the preparation of the quiz sessions by studying quite hard in Phase 2, and achieving nearly full mastery towards the end of Phase 3. The remaining students in Cluster 3 and Cluster 4 did not achieve those levels of mastery. For example, the small Cluster 3, containing 133 students, distributed their learning over the second and third learning phase. Cluster 4 students, 215 in total, essentially learned without using Sowiso, and achieved relatively low levels of mastery during the three Phases.

It is important to be careful in labelling students into one overarching category, particularly given the strong diversity of the students in this context. However, given the focus of this study, it might be useful to provide some broad categorizations of these four user profiles. We label cluster 1 students as *Early Mastery B-learners*, where B stands for blended. Given that cluster 2 students primarily started to become active learners during Phase 2 before the quiz, when bonus points were on the table, we label them as *Strategic B-learners*. Cluster 3 learners primarily became active just before the exam period, therefore we label them as *Exam-driven B-learners*. Finally, Cluster 4 learners were relatively inactive in Sowiso throughout the seven weeks, therefore we label them as *Inactive B-learners*. Of course these learners could be very active learners using the offline learning materials, engaged extensively in self-study or peer-study, and/or used a self-regulation strategy that focussed on different outcomes.

By looking beyond the timing of engagement in Sowiso towards how learners were trying to solve the 429 exercises, we identified limited changes in the patterns of these profiles. The use of hints appeared to be a relatively infrequent learning strategy, in fact on average no more than 3.9% of the exercises students used this option. In contrast, the use of worked-examples solutions was far more wide-spread: on average, students called for a worked example for 43% of the exercises. However, there were no marked differences in the patterns of calling for worked examples between the four student profiles, as illustrated in Fig. 2.

Comparing Figs. 1 and 2 signals that learning in later phases came with a higher use of worked examples. For instance, Cluster 2 Strategic B-learners called on average 0.33 solutions per attempt in Phase 1, 0.35 in Phase 2 and 6.5 solutions per attempt in the last learning phase. Similar patterns emerged for the other clusters, whereby in particular at later Phases the use of worked-examples became more frequent. In other words, students dynamically changed their SRL strategies and their user behaviour over time during the three Phases.

4.2. RQ2 relevance of clustering based profiles for course performance

In terms of addressing Research Question 2, to what extent is the profiling of students using Sowiso engagement predictive for their course performance, Fig. 3 provides a straightforward answer to this question. There were clear average performance differences between the four clusters in terms of their quiz scores for mathematics (eta squared effect size equal to 36.9%), exam score for mathematics (eta squared effect size equal to 13.8%), and total course score, including both mathematics and statistics performance (eta squared effect size equal to 25.3%). All course performance measures are expressed as a proportional score, where the typical grading rule applied in Dutch education is that scores above 0.55 indicate a pass. In other words, many Exam-driven and Inactive B-learners seemed to underperform over time, and might be potential candidates for additional support and intervention strategies.

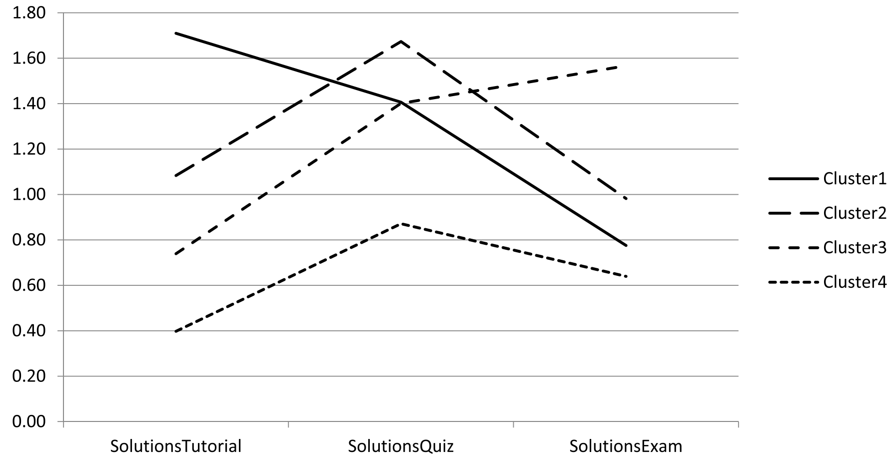


Fig. 2. Use of worked examples by students in the four clusters in different learning phases (expressed as logged value of cluster average per 100 exercises).

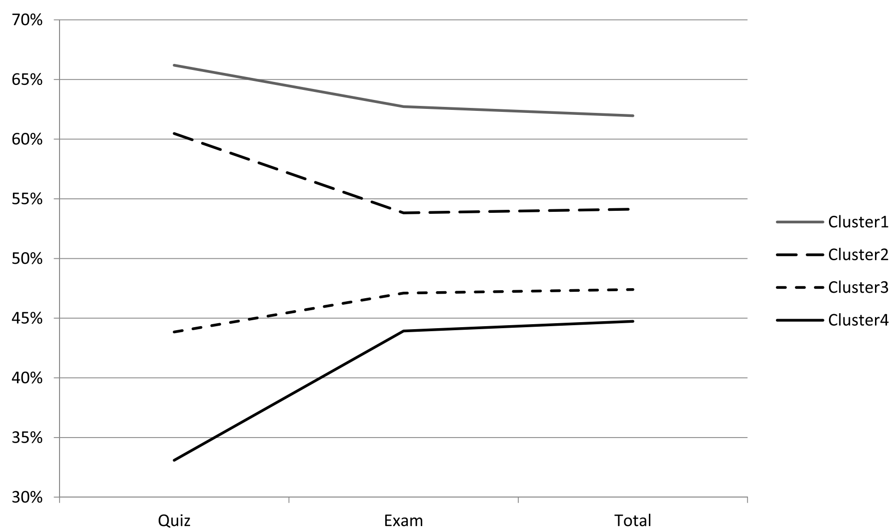


Fig. 3. Average course performance by student profile (percentage of maximum score).

4.3. RQ3 profiles, cognitive processes and metacognitive regulation strategies

Finally, in terms of Research Question 3 we were interested in how the four cluster profiles related to our "static" measurements of students' SRL approaches to learning, expressed as cognitive processing strategies and metacognitive regulation strategies, and emotions. ANOVA tests pointed towards four approaches to learning scales, demonstrating differences significant beyond the 0.01 level: *Step-wise learning*, *Concrete learning*, *External regulation* and *Lack of regulation*.

As illustrated in Fig. 4, within the cognitive processing scales of Deep, Step-wise and Concrete learning, Early-Mastery B-learners (cluster 1) students demonstrated the most flat profile: scores of all three processing scales were about the same level. Clusters 2 and 3 did not differentiate, but the Inactive B-learners (cluster 4) did illustrative substantial differences, with relative low levels of Step-wise learning, and high levels of Concrete learning.

Cluster differences were larger for the learning regulation strategies, and did exhibit more variability. All our students, irrespective of their profile, demonstrated relative high levels of External regulation of learning, and lower levels of *Self-regulation*. Our Early Mastery Cluster 1 students stood out by the highest levels of External regulation, while cluster 4 students had the lowest. An opposite pattern was visible in the scale *Lack of regulation*.

Effect sizes of the cluster differences were, however, quite limited. The largest clusters were in the regulation scales, 2.6% and 2.1%, with 1.2% and 0.7% eta squared values for the two processing scales demonstrating significant level differences.[1] In other words, although substantial differences were found in Sowiso behaviour of these four profiles over time, relatively limited explained variation could be retrospectively derived from the SRL learning dispositions that were measured at the beginning of the course.

As indicated in Fig. 5, Epistemic learning emotions demonstrated significant differences between the four profiles on all scales (beyond the 0.001 level), with the notable exception of *Surprise*. Effect sizes were again very modest, ranging from approximately 2.0% for *Curiosity*, *Confusion*, *Anxiety*, *Frustration*, and *Enjoyment*, to 3.3% for *Boredom*.

The patterns visible in Fig. 5 with regards to the valence of epistemic emotions were clear, as only Surprise had a neutral or undetermined valence, while all other emotions all have a positive or negative valence. The Early Mastery B-Cluster 1 students demonstrated highest levels of positive epistemic emotions Curiosity and Enjoyment, and lowest levels of negative epistemic emotions: Confusion, Anxiety, and Frustration. In contrast, the

[1] See online Appendix for detailed breakdown of these results.

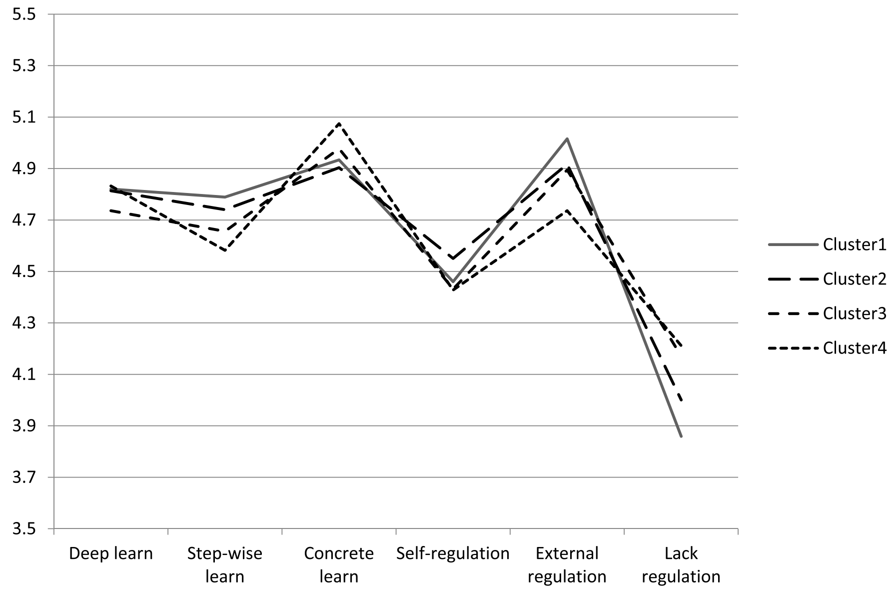


Fig. 4. Average levels of approach to learning scales by student profile (Likert 1 … 7 scale).

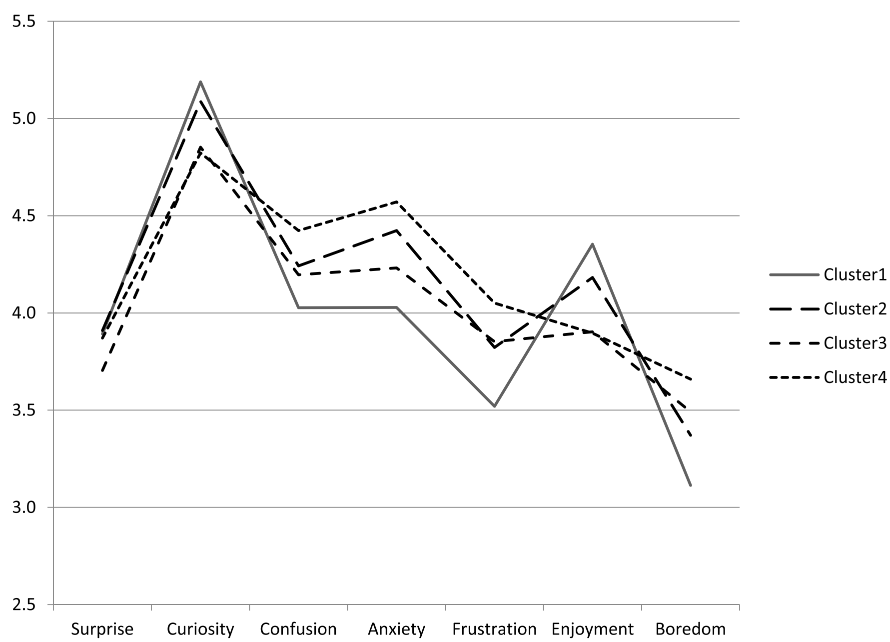


Fig. 5. Average levels of epistemic learning emotion scales by student profile (Likert 1 … 7 scale).

Inactive B-Cluster 4 students took the opposite positions: on average high on negative emotions, low on positive emotions, with Cluster 2 and 3 students taking intermediate positions.

Exactly the same patterns, but with enlarged effect sizes, were visible from the activity type of learning emotions, which were measured after four weeks into the course: see Fig. 6. All cluster differences were statistically significant below the 0.001 level. *Academic control*, the direct antecedent of activity emotions according to the control-value theory, demonstrated cluster differences with the same patterns as observed before, cluster 1 students scoring high, cluster 4 students scoring low, but the effect size was still quite limited: 2.1%.

The single positive activity emotion, *Enjoyment*, had the same pattern but with somewhat larger effect size, 3.3%. The largest effect sizes were amongst the activity emotions with a negative valence: *Anxiety*, 4.3%; *Boredom*, 8.9%; and *Hopelessness*, 4.5%. Different from the cluster differences analysed above, we now saw that all clusters differentiate, with the order of the clusters determined by the amount of timely preparation in Sowiso.

5. Discussion and conclusions

In this empirical analysis, we investigated the relations between 1035 students' timing decisions what, how, and when to study in the blended mathematics environment Sowiso and their self-regulated learning (SRL) dispositions. In line with our previous work conducted in a fully online environment (Nguyen et al., 2018), in terms of Research Question 1 our first important finding in our blended learning context was that the timing decision how students chose to engage with the mathematical e-tutorial Sowiso seemed to be dominant, and the main predictor of the outcome of our cluster analysis.

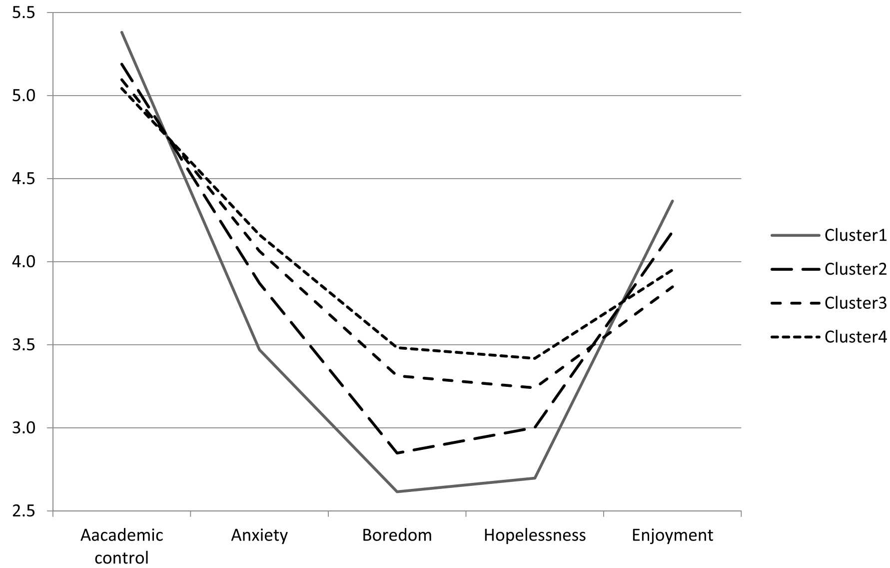


Fig. 6. Average levels of activity learning emotion scales by student profile (Likert 1 … 7 scale).

In line with previous research (Azevedo et al., 2013; Fincham et al., 2018; Malmberg et al., 2017; Winne, 2017), we found four distinct Sowiso engagement profiles of our 1035 learners. While others identified 4–8 meaningful clusters when looking at engagement data (Fincham et al., 2018; Jovanović et al., 2017), our data seemed to suggest four unique profiles: Early Mastery B-learners, Strategic B-learners, Exam-driven B-learners, and Inactive B-learners. These four profiles of learners not only differed in terms of aggregate engagement, but in particular also in their respective timings of when learners engaged with the 429 Sowiso exercises, and how they made use of specific learning resources (e.g., worked examples, hints) in Sowiso. While Early Mastery B-learners primarily engaged with Sowiso before the next tutorial group meeting (Phase 1), Strategic and Exam-driven B-learners waited to engage with Sowiso just before the "assessment moments" in the course (Phase 2 and 3).

In addition, while Early Mastery B-learners primarily used worked examples of Sowiso at Phase 1, Strategic B-learners primarily used these worked examples in Phase 2, while Exam-driven B-learners used these learning resources just before the exam in Phase 3. In other words, beyond differences in overall engagement patterns in Sowiso in terms of number of attempts, mastery, and time spent in Sowiso, our temporal analyses showed substantial differences in when students self-regulated their engagement in Sowiso. Furthermore, as argued by Renkl (2014) the four profiles differed substantially in how learners made use of respective learning resources. This is an important finding, as providing automated feedback in the future to students (e.g., "Please engage with worked out-examples 48 and 52 before you go to the next tutorial this Thursday") might be particularly relevant for some clusters of students, while not for others like Early Mastery B-learners.

In terms of Research Question 2, we found strong support that these different temporal engagement patterns of students over the three phases of the course (i.e., before the tutorial, before the quiz, before the exam) were significantly associated with academic performance. In line with expectations from SRL (Boekaerts, 1997; Järvelä & Hadwin, 2013; Vermunt, 1996; Winne, 1995), on average Early Mastery and Strategic B-learners performed well academically throughout and at the end of the course, while Exam-driven and Inactive B-learners seemed to struggle during the course, and several failed to bridge the gap before the exam. Obviously, models developed in this study are all of correlational type, and do not allow for straightforward causal interpretations. However, the different timing of the several measurements implies that learning dispositions act as antecedents of learning behaviour and learning emotions, with learning performance as a consequence.

Finally, in terms of Research Question 3 the combination of data about user engagement, temporal data, and the SRL learning dispositions (Pekrun et al., 2011; Pekrun & Meier, 2011; Vermunt, 1996) provided more nuanced understanding how students decided to work through the various learning options. In particular, our linked SRL data seems to suggest that timely preparation was related to their approaches of learning, epistemic learning emotions, and in particular activity learning emotions. In the interpretation of these relationships, the timing of the administration of the surveys is again of importance. Although the learning disposition surveys were of a cross-sectional nature, in contrast to the longitudinal trace data of Sowiso, they were measured at different moments. The approaches of learning (ILS) and the epistemic learning emotions (EES) were measured at the start of the course, and are thus best characterized as antecedents of learning behaviour measured through the trace variables. That is: the timing decisions students took with regards to the use of Sowiso were anteceded by differences in their approaches to learning, and differences in epistemic learning emotions.

In contrast, the activity emotions (AEQ) were collected exactly halfway in the course, and were thus timed in the middle of the seven week time window of Sowiso trace observations. Here, there was no unidirectional antecedent or consequence relationship: activity emotions will influence the intensity of using Sowiso, and vice versa, learning activities in Sowiso will influence activity emotions. We found largest effect sizes in the learning emotion Boredom, which we previously found using static analyses in one of the earlier cohorts of this mathematics course (Tempelaar et al., 2015). At the start of the course, levels of epistemic boredom already predicted the timing of student learning, be it with small effect size. Half way in the course, we found the same pattern of cluster differences, but of enlarged size in activity type of learning boredom. This suggests that in addressing the learning tasks, students were confirmed in their affects related to learning mathematics, and these affects in turn may have influenced their timing and intensity decisions in the learning process.

While previous research found that learners have different learning strategies, we are one of the first to specifically link students' SRL with when, what and how they study in a large, naturalistic environment where students were working on complex mathematics problems over a period of seven weeks. All learning in our mathematics context is of self-regulated learning type, in the sense that students are taking a course based on student-centred learning principles. Knowing the learning goals of the course, students decide for themselves about which learning resources to use, what timing to apply, and with what intensity. In line with other studies in blended environments (Fincham et al., 2018; Jovanović et al., 2017), the first decision students take is to divide their learning efforts over the face-to-face and online modes. These modes differ in accessibility: the problem-based learning mode of our face-to-face component of the blend is characterized by relative open, unstructured problems, lacking the many scaffolds that are available in the online component of the blend.

It is exactly the External regulation scale of the learning approaches instruments that assesses students' needs for those scaffolds. The scaffolds in Sowiso allow students to break down the learning process into subsequent steps, and they are continuously provided with interactive feedback, and opportunities to choose the types of learning resources that may best fit with their preferred learning strategy. Next, it is the scale of Step-wise processing that measures students' tendency to learn in a step-wise manner and indeed, we find cluster differences in this scale, be it again of small size. In a sense, these outcomes seem paradoxical: in a student-centred learning environment, we find that the less adaptive students, those depending on External regulation and Step-wise learning, are the more intensive and timely users of Sowiso. However, the more adaptive learners in our SRL context, the learners with a tendency to Deep learning and the skills to rely on Self-regulation of learning process and learning content, are better equipped to do most of their learning in the more challenging problem-based learning mode.

Thus, the intensity and timing of their learning in Sowiso is the outcome of two opposite effects: as adaptive learners, they will tend to be more active learners, but again as adaptive learners, they are less depended upon the scaffolds and external regulation offered by Sowiso. It is only in the situation that we could measure the learning in the face-to-face component, in a similar detailed manner as for example done by Malmberg et al. (2017), that one will be able to get more insights in how students self-regulate between the online and face-2-face learning options.

5.1. Limitations and future research

One obvious limitation of our study is the specific context. All students have to follow this module as part of their first year. However, students are not "forced" to use the blended-part of the mathematics course, which might explain why the various SRL measures were only related with a small effect size to how, what, and when students were learning in Sowiso. Furthermore, there is an obvious large 'blind spot' in that the learning processes during the face-to-face component, beyond attendance, are not accurately captured and measured. This amongst others implies that we could not observe what conversations students had with their tutors regarding the LA generated learning feedback, and the eventual prompts based on that feedback. Nonetheless, in contrast to previous studies that tried to infer SRL strategies from user behaviour (Tempelaar et al., 2018; Fincham et al., 2018; Jovanović et al., 2017; Kovanović et al., 2018), we aimed to explore how three SRL learning disposition instruments connected to what, when and how students learners over time over a long period with a large sample.

A second obvious limitation of our context is that we did not longitudinally measure the temporal SRL of learners, and how their learning strategies might change over time. Furthermore, other SRL disposition instruments might perhaps find different, more fine-grained predictions of how students worked through the various learning processes. As students actively engaged with their own learning dispositions data in the various statistical exercises, perhaps several students might have altered their SRL, or experimented with different strategies throughout the course. Obviously, in the present context we did not specifically measure whether (or not) students might have altered their SRL strategies over time, and how these changes might be influenced by in which order students decided to learn in Sowiso, how they made decisions in terms of repetition and spacing decisions, or whether they went from concrete to abstract, or the other way around. Furthermore, we did not measure whether participants really went through the SRL cyclical phases of goal setting, performance, appraisal, and time management strategies. As highlighted by Panadero (2017), there are obvious methodological challenges when learners receive multiple rounds of SRL feedback.

Future research should explore whether (or not) students alter their SRL over time, and how this might be effectively supported with appropriate learning analytics interventions (Azevedo et al., 2013; Fincham et al., 2018). Furthermore, in line with several fine-grained studies using wearables, eye-tracking, and multi-modal sensors (Malmberg et al., 2017; Trevors et al., 2016) it would be important to understand how students' SRL decisions are made between the face-to-face, offline and online learning resources. Nonetheless, our empirical study provides clear initial evidence that using temporal analytics of log-data in conjunction with learning disposition SRL data can actively identify which students are studying in advance, and are doing well, and which students might need some additional support and personalised SRL feedback. With the rapid advancements of learning analytics and artificial intelligence, our study does highlight that fine-grained Sowiso mastery data in conjunction with timing of study can provide important person-centred insights, before any formative or summative assessments are available. Perhaps more importantly, our study highlights the feasibility of using Sowiso data as potential automated feedback prompts to students are progressing well, and which students might need more specific SRL support.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chb.2019.07.007.

Appendix

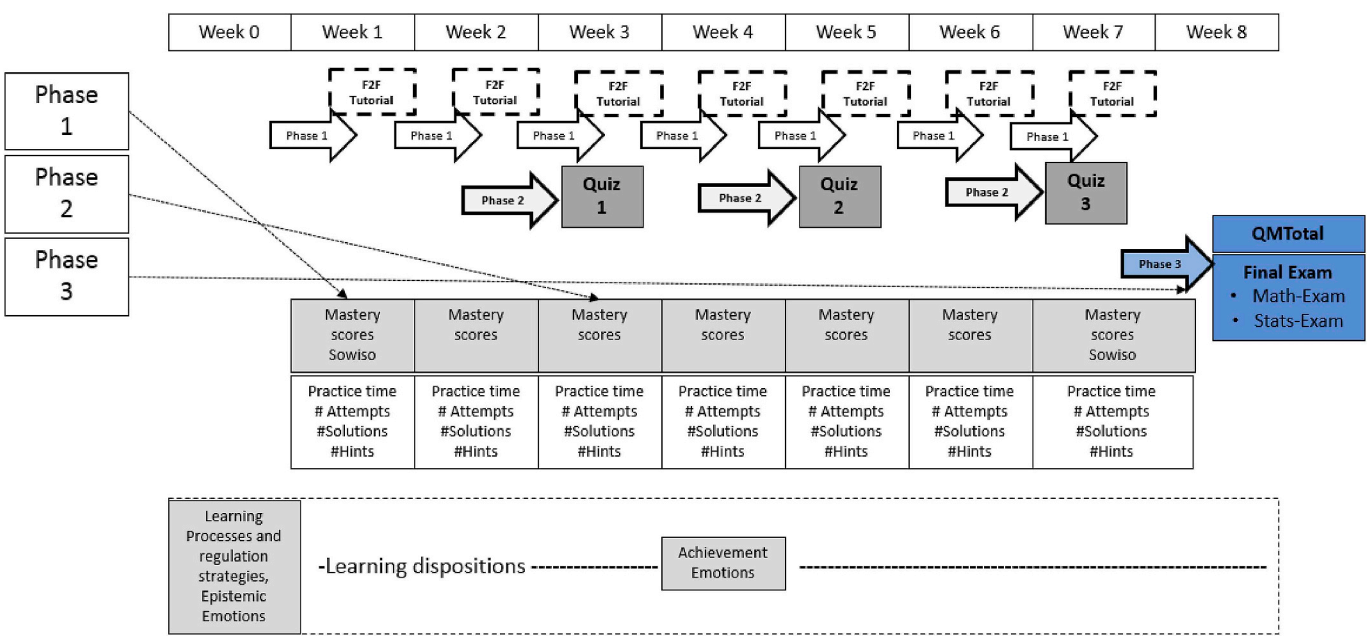
Table 1
Items from learning dispositions instruments

Scales with exemplary item	# items	Cronbach alpha	M	SD
Learning processing and regulation strategies (Vermunt, 1996)	11	0.793	4.812	1.201
Deep learning	4	0.634	4.588	1.282
–Critical processing: 'I check whether the conclusions of the authors of a textbook follow logically from the facts on which they are based.'	7	0.731	4.940	1.152
–Relating and structuring: 'I try to link up material that is new to me with knowledge that I already have of the topic being dealt with'				
-Concrete processing: 'I try to interpret events in everyday reality using the knowledge which I have gained in a course'	5	0.641	4.965	1.278

(continued on next page)

Table 1 (*continued*)

Scales with exemplary item	# items	Cronbach alpha	M	SD
Stepwise learning	11	0.745	4.698	1.323
–Analysing: 'I particularly pay attention to facts, concepts and problem-solving methods during a course'	6	0.600	4.790	1.258
–Memorizing & rehearsing: 'I repeat the most important parts of the material until I know them by heart'	5	0.691	4.588	1/397
Self-regulation of learning	11	0.750	4.485	1.448
–Self-regulation of learning processes: 'In order to test my progress in learning, I try, after studying the textbook, to formulate the main points in my own words'	7	0.680	4.692	1.454
–Self-regulation of learning content: 'If I do not understand a study text well, I try to find other literature about the subject concerned'	4	0.648	4.123	1.439
External regulation of learning: 'I study according to the instructions which are given in the teaching materials or given by the teacher'	11	0.649	4.888	1.276
Lack of regulation: 'I notice that I find it difficult to determine whether I have sufficient command of the material'	6	0.692	4.038	1.452
Epistemic Emotion Scale (Pekrun & Meier, 2011)	3	0.565	3.866	1.263
-Surprise: 'When learning math and stats, I feel surprised'				
-Curiosity: 'When learning math and stats, I feel curious'	3	0.844	5.019	1.182
-Confusion: 'When learning math and stats, I feel confused'	3	0.739	4.230	1.278
-Anxiety: 'When learning math and stats, I feel anxious'	3	0.869	4.346	1.615
-Frustration: 'When learning math and stats, I feel frustrated'	3	0.820	3.816	1.516
-Enjoyment: 'When learning math and stats, I feel excited'	3	0.876	4.112	1.362
-Boredom: 'When learning math and stats, I feel bored'	3	0.666	3.400	1.330
Achievement Emotions Questionnaire (Pekrun, 2000; Pekrun et al., 2011)	10	0.838	4.121	1.382
-Enjoyment:' I enjoy acquiring new knowledge'				
-Anxiety: 'I get tense and nervous while studying math and stats'	11	0,919	3.877	1.576
-Boredom:' The material bores me to death'	11	0.930	3.009	1.444
-Hopelessness:' I feel hopeless when I think about studying math & stats'	11	0.943	3.073	1.502
-Academic Control: '"I have a great deal of control over my academic performance in my courses'	8	0.796	5.183	1.260



Appendix Fig. 1 Design of the module and respective timings of 3 Phases

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