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Tracking Patterns in Self-Regulated Learning Using Students' Self-Reports and Online Trace Data

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Abstract

For decades, self-report instruments – which rely heavily on students' perceptions and beliefs – have been the dominant way of measuring motivation and strategy use. Event-based measures based on online trace data arguably has the potential to remove analytical restrictions of self-report measures. The purpose of this study is therefore to triangulate constructs suggested in theory and measured using self-reported data with revealed online traces of learning behaviour. The results show that online trace data of learning behaviour are complementary to self-reports, as they explained a unique proportion of variance in student academic performance. The results also reveal that self-reports explain more variance in online learning behaviour of prior weeks than variance in learning behaviour in succeeding weeks. Student motivation is, however, to a lesser extent captured with online trace data, likely because of its covert nature. In that respect, it is of importance to recognize the crucial role of self-reports in capturing student learning holistically. This manuscript is 'frontline' in the sense that event-based measurement methodologies with online trace data are relatively unexplored. The comparison with self-report data made in this manuscript sheds new light on the added values of innovative and traditional methods of measuring motivation and strategy use.

Keywords: Self-Regulated Learning; Self-Report Measures; Event-Based Measures; Online Trace Data

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1. Introduction

Motivation and strategy use are core concepts in the literature on learning and instruction. Widely known and prominent in contemporary educational psychology is the theory of Self-Regulated Learning (SRL), which integrates these constructs in explaining student success. SRL can be defined as "an active, constructive process of goal setting and attempting to monitor, regulate, and control cognition, motivation, and behaviour, guided and constrained by goals and the contextual features in the environment" (Dinsmore, et al., 2008; Jupp, 2006; Panadero, et al., 2016; Panadero, 2017; Pintrich, 2000, p. 453). SRL is an internal process that we cannot directly access, such that proxies are necessary to assess this SRL process (Boekaerts & Corno, 2005).

For decades, it has been argued that aptitude-based self-report instruments – which rely heavily on students' perceptions and beliefs – do not fully capture SRL. Theories of SRL emphasize that each instance of self-regulation is a function of the individual's dynamic interaction with the learning environment, but few instruments satisfactorily capture such data (Boekaerts, et al., 2000; Efklides, 2011; Veenman, 2011; Winne & Perry 2000). Yet, self-reports have remained the dominant way of measuring SRL (Boekaerts & Corno 2005; Winne and Perry 2000), as the implementation of more time-intensive data collection methods, such as thinking-aloud protocols, event-based self-reports, or observations, are often times not feasible in educational settings. The recent introduction of tracing methods in online learning environments mainly through learning analytics (Greller & Drachsler, 2012) sparked the development of an alternative event-based measurement method of SRL, enabling a form of online observation methods, while influencing the learning process as little as possible (Panadero et al., 2016). These measurement methods are spurred by active efforts in the learning analytics community to bridge the gap between learning sciences and data analytics. However, so far learning theories such as SRL are seldom used as theoretical basis for the design and evaluation of tracing methods (Jivet, et al., 2017; Jivet, et al., 2018). Furthermore, there is a dearth of empirical work into the potential of online observation methods to complement self-reports on SRL. The purpose of this study is therefore to triangulate constructs suggested in SRL theory and measured using aptitude-based self-reported data with revealed online traces of learning behaviour.

This study takes place in the context of the implementation of a Learning Analytics application, called 'the Learning Analytics Experiment' in Dutch higher education. The main aim of the project was to create an opportunity for institutions, teachers, and students to gain experience with different facets of learning analytics (e.g. privacy, feedback provision, insight in the use of learning materials, etc.). The online traces of students' learning behaviour were recorded using xAPI (or Tin Can) trackers, which have the potential to track learning experiences and store records of learners' (e.g. '*access video*' or '*receive grade*'). The trackers used in this study captured information specifically on the use of learning materials, such that the use of the online learning environment can be compared between students over time in light of different components of SRL. This study describes an implementation of the xAPI trackers in a mandatory first-year statistics course at a Dutch university, during two consecutive academic years. During the implementation, self-reports on motivation and strategy use were collected to triangulate the trace data. This offered a rich case to unpack the aggregated data collected with self-reports and to, vice versa, colour the trace data with self-reports on motivation and strategy use. Accordingly, this study aims to shed light on two of the central questions addressed in this special issue: *In what ways do self-report instruments reflect the conceptualizations of the constructs suggested in theory related to motivation or strategy use?* And: *How does the use of self-report constrain the analytical choices made with that self-report data?*

2. Theoretical framework

2.1 Complementarities of self-reported SRL measures and online trace data

Online learning environments are central in today's higher education, as they not only form a learning portal for a variety of purposefully selected learning resources, but also help to navigate through the course, enable students to be in contact with the instructor and peers, and to engage in various learning activities in a student-led fashion (Lust et al., 2012; Molenda, 2008). Students leave traces when interacting with these online learning environments. Trace data can be defined as “observable evidence of particular cognitions that are obtained at points where a cognitive process is applied while completing a task” (Howard-Rose & Winne, 1993, p. 594). A growing body of literature confirms the importance for online learning environments for learning outcomes. Gašević, et al., (2014), for example, showed that the number of logins, number of operations performed on discussion forums and resources accounted for approximately 21% of the variance in academic performance. This finding is in line with earlier research on the relation between the frequency of visits to an online learning environments and students’ academic performance (Coogan et al., 2005; DeNeui & Dodge, 2006; Wang & Newlin, 2000). Models on SRL provide a holistic theoretical foundation for the relation between observed student behaviour in online learning environments and academic performance, based on the cognitive, metacognitive, behavioural, motivational, and affective aspects of learning (Panadero, 2017). One of the latest meta-analyses on the effect of SRL (Sitzmann and Ely, 2011) shows that the four biggest predictors of learning gains — goal level, persistence, effort, and self-efficacy — have a significant motivational value. Longitudinal investigation of the interaction between motivation, strategy use, and the learning environment is, however, scarce (Panadero, 2017).

There are several reasons to believe that online trace data hold potential for tapping into the process of SRL. Students (especially in higher education) are the agents in online environment usage: they determine which resources are used and how these resources are used. The effects of the instructional design of a learner’s environment are therefore never deterministic, since the use of the environment depends on the personal goals, motivation, and volition of the student (Winne & Baker, 2013). Usage of online environment can be considered a skill in itself, as it requires a repertoire of learning strategies, confidence, and competences. As Lust and colleagues (2012) put it, online environments are only beneficial when learners recognize the learning resources as a learning opportunity for which they are motivated to spent effort and time on. In other words, effective use of online learning environments can be conceptualized as a manifestation of SRL. The extent to which an individual student is motivated and able to self-regulate their learning process is thus a prerequisite for effective tool-use (Winne & Baker, 2013; Lust, et al., 2012). In addition, and elaborately described by Fryer (2017), the relation between motivation, strategy use, and the use of learning environments can be conceptualized as reciprocal. Namely, learning activities undertaken in the process phase of learning, as well as the resulting product of learning, feed back to students’ beliefs, attitudes, and ideas around motivation, strategy use, and self-regulation that play a role in the presage stage of learning. Online trace data, thus, reflects the dynamic relation between students and their learning experiences over time.

2.2 Removing analytical restrictions of inventories on motivation and strategy use with online trace data

An event-based measure of SRL with online trace data arguably has the potential to remove analytical restrictions of aptitude measures. Firstly, and according to the overconfidence effect, unrealistically favourable attitudes that people have towards themselves (Taylor & Brown, 1988) can impose an upward bias in self-reports of motivation and strategy use. In other words, students might apply less and less effective study strategies than self-reported. Zhou and Winne (2012) confirm this theory empirically by showing that “trace data”-based measures of student achievement goal orientation were much stronger associated with learning outcomes than with self-reported ones. This is particularly pressing since existing research suggests that learners tend to use ineffective learning strategies (Jamieson-Noel & Winne, 2003), and do not make effective use of available resources to optimize their learning, even in those environments that build on effective learning designs (Ellis, et al., 2005; Lust, et al., 2013). As discussed in this special issue, potential reasons are students’ cognitive processing capacity (Chauliac, et al., 2020), exerted effort (Iaconelli & Wolters, 2020), and student characteristics (Vriesema & McCaslin, 2020). Comparing self-reported data with online traces of learning behaviour taps right into a potential upward bias in self-reports on motivation and strategy use. Since online traces of learning behaviour do not suffer from socially desirable responding bias, it is possible that they provide a better approximation of motivation and strategy use. Secondly, inventories are restricted as they often predetermine the level of aggregation in the analysis of data on motivation and strategy use (e.g. fixed at student-level), which, as a result, generates student-focussed or aptitude-based measures. This jeopardizes the potential of adapting effectively to individual needs and preferences during a study episode or educational program. Alongside self-report instruments that operationalized motivation and self-regulation as event-bound (Winne, 2010), event-based trace data of learning behaviour can provide a dynamic insight in how motivation and strategy use does not only vary between students, but also within students over time. This is particularly relevant since previous research show that self-motivational beliefs and strategy use can vary considerably over the course of a study episode, or throughout the educational program (Boekaerts et al., 2000; Efklides, 2011; Veenman, 2011; Winne & Perry 2000). One example is presented in this special issue by Moeller, et al., (2020) in their study on this intra-individual variation in self-motivational beliefs.

2.3 Status of research on SRL combining self-reports and online trace data

Up until now, empirical studies on SRL that use online trace data often aim at identifying different patterns of usage behaviour. This has led to a wide variety of student typologies aiming at a better understanding of the type of learning strategies used by students, looking at the use of information-tools (such as forums, instruction video's, and interactive mind maps) over the duration of a course (Heffner & Cohen, 2005; Hoskins & van Hooff, 2005; Huon, et al., 2007). Examples of typologies are the active and passive users of forums (Hoskins & van Hooff, 2005); the early-, constant-, and late users (Knight, 2010; Lust, et al., 2012); the low-, average-, and high frequency users (Bera & Liu, 2006; Jiang, et al., 2009). Research methods in identifying learning strategies inferred from online trace data evolve rapidly. A recent strand of research on trace data adopts data mining techniques in detecting striking, previously unknown, patterns in study tactics and strategy use (Han, et al., 2011). In general, it remains a challenge to qualify these patterns, typologies, and clusters of study tactics, and to make these insights actionable for instructional design accordingly. So far, studies repeatedly find that usage patterns do explain variance in academic performance (e.g. Cho & Yoo, 2017; Cornelisz & van Klaveren, 2018; Gašević et al., 2014; Han et al., 2011; Schmitz et al., 2018), but what type of self-regulation it represents and the quality thereof remains a black box. Only a handful of studies focussed on triangulation of self-reports specifically on SRL using online trace data of student learning. The few studies that describe a quantitative comparison of self-reports on SRL and online trace data show that the relation between these two sources of data is not straightforward. Hadwin, et al. (2007) used ten relevant items from the motivated Strategies for Learning Questionnaire (MSLQ) on strategy use to explain students' learning in gStudy, a web-based learning environment in which students read texts, summarize, and use concept maps in an introductory educational psychology course (N = 188). They clustered students into four groups based on self-reported SRL data and found their actual learning patterns in gStudy differed substantially, even among students from the same cluster. Kim, et al. (2018) made a similar comparison among undergraduates in Korea. They analysed online trace data from 284 undergraduate students enrolled in an asynchronous online statistics course. Based on self-reports collected with the MSLQ, students were classified as fully, partially, or not self-regulating. Surprisingly, this distinction did not reveal different patterns in online traces of learning. The main difference between the groups was timing in study behaviour, students classified as not self-regulating studied mainly shortly before the examination, which was negatively related to academic performance. A study of Guerra, et al. (2016) used the achievement-goal questionnaire and online trace data (N = 89). Their study shows that students who report a high mastery-approach show a higher level of activity in the online learning environment. There results also suggest that highly motivated students are more sequential in their patterns of navigation, which means students are less likely to follow the suggested order of topics to study. Cho & Yoo (2017) adopted a different approach and compared precision in prediction of students' academic performance based on patterns in self-reports based on MSLQ and patterns in online trace data established with data mining techniques (N = 60). The model based on online trace data provided a more precise prediction. The authors note that this might be partially due to the fact that the trace data provided more variables and was based on a bigger data set. Also, the study did not address whether or not it is likely that the self-reports and online trace data actually measured the same constructs. Like in the studies described earlier, the inventory is aptitude-based (Muis, et al. 2007; Zimmerman, 2008), whereas the online trace data is event-based. In this special issue, Rogiers et al. (2020) present one of the first studies in this space that compares event-based self-report data with trace data. Overall, the interpretation of online trace data in light of self-reports is not clear-cut, there are many questions left unanswered about the relationships between the constructs measured with an instrument such as the MSLQ and online trace data collected in different education settings.

3. Research questions and hypotheses

The aim of this study is to further explore the relationship between measures of SRL through self-reports and online trace data, by scrutinizing variance in self-reports and online trace data between and within students. Because the online traces of learning behaviour are event-based, our study provides a dynamic insight in how motivation and strategy use vary between *and within* students over time. The findings are instrumental in guiding innovations in education towards effective personalized learning. Accordingly, the following research questions are formulated for this study:

1. To what extent do self-reports explain variance in online trace data of learning behaviour?
2. How stable is the relation between self-reports and online trace data throughout the various weeks of the course?
3. How well do self-reports explain student performance in comparison to online trace data?

Following Fryer (2017), we expect that self-reports on motivation, strategy use, and self-regulation gauge between-student differences in the presage stage and that online trace data gauges the process phase of learning. With respect to the first research question, it can, therefore, be expected that self-reports explain substantial variance in learning behaviour observed through online trace data. Furthermore, student differences in the presage stage will likely be affected over time by the feedback loop between the presage, process, and product phase. Therefore, it can be expected that the self-reports predict online learning behaviour most precisely at the time the self-reports are administered. With respect to research question two, thus, we expect that the relationship between self-reports and online trace data varies over time. Finally, in light of the third research question, we expect online trace data to explain an equal amount or more variation in student performance than self-reports, in line with the findings of Cho and Yoo (2017).

This study adds to the existing literature as follows. Firstly, there are only a few studies so far that tapped into the relationship between self-reports and online trace data. Given the sensitivity of the usage patterns to the instructional design of an online learning environment (Gašević, et al., 2016), it is of great importance that a broad range of educational settings are explored with online trace data. The course, instructional design, and educational setting investigated in this study is considered particularly relevant because it is highly representative for other courses in mainstream Dutch higher education and since this particular course plays a crucial role in all social science programs in the Netherlands. In addition, this study compares multiple cohorts, which yields insight in continuity and change of strategy use with the constant evolvement of course design. Secondly, the few studies that have been comparing self-reports and online trace data so far dealt with relatively small sample sizes (Cho & Yoo, 2017; Guerra et al., 2016; Hadwin et al., 2007; Kim et al., 2018) or did not measure the full range of self-motivational beliefs and strategies with self-reports (Hadwin et al., 2007; Cho & Yoo, 2017). As a result, there is no clarity, yet, on the relevance and actionability of online trace data in comparison to inventories on motivation, strategy use, and self-regulation.

4. Methodology

4.1 Participants

The data used consist of self-reports and detailed log-data on SRL, collected among two cohorts of first year students at the Faculty of Behavioural and Movement Sciences during a mandatory statistics course that took place between October and December 2016 (N = 435; 94.44% female, M_{age} = 20.60 years, SD = 5.18) and 2017 (N = 489; 78.90% female, M_{age} = 20.88 years, SD = 3.48). The 2017 cohort included international students, as this was the first year that this course was also taught in English. The Faculty of Behavioural and Movement Sciences offers the following educational programs: movement sciences, education sciences and behavioural, developmental and clinical psychology.

4.2 Course design

4.2.1 Online learning environment

The online learning environment was available to all students throughout the course and its usage was not mandatory in any sense. In 2016, the online learning environment consisted of a learning management system (Blackboard) and a separate online learning tool, called I Hate Statistics[1]. Blackboard is one of the leading commercial LMS software packages used by North American and European universities (Itmazi & Megias, 2005; Munoz & Duzer, 2005). From the start of the academic year 2017-2018, the institution switched to a new learning management system, called Canvas. Together with the standard features of LMSs, Canvas provides advanced options like learning outcomes, peer review, migration tools, e-portfolios, screen sharing and video chat etc. Canvas is gaining popularity, hundreds of colleges, universities, and school districts currently use this package (www.instructure.com).

Across cohorts, the learning management system was structured in a similar fashion. Both Blackboard and Canvas provided students with three types of tools: 1) an information tool (lecture slides, instruction video's, and general course information), which provided the course content in a structured way; 2) a cognitive tool for self-assessments that enabled students to interact with the subject matter, to assess and to reflect on the learning content; and 3) a communication tool (forums) that enabled students to communicate with peers and instructors (Lust, et al., 2012). The tools were structured based on the week-topics of the course and were available at all times throughout the course.

The learning management system referred students to 'I Hate Statistics', which provided students with an online environment for practicing and studying, where students could engage in lessons, challenges, and self-assessments that were related to the week topics, or to other topics that were available in this environment. Each challenge consisted of on average maximal ten questions; yet, the challenge was automatically finished when students correctly answered five questions within the challenge. A unique feature of the environment was that it is built around the statistics course and offered content in a particular week that was similar to the content offered in the lectures and seminars.

The xAPI tracking method is applicable for all online learning environments (see for example https://xapi.com/). In the context of this study, it was used to gain insight into the use of learning materials in the learning management systems. The teacher created so-called 'recipes' and placed them in Blackboard, where the use of information resources and participation in online activities were tracked. These recipes ensured that the desired statistics were generated, as well as information on the type of tool that was used (e.g. slides, challenges, lessons) an action verb (e.g. accessed, received), and a label (e.g. lessons on the chi-square test, lecture slides of week 1). A comparable tracking method was used in I Hate Statistics, which generated similar data about the use of the learning materials.

4.2.2 Instructional design

During the eight-week introductory statistics course, students had to attend two lectures each week in which theoretical concepts were addressed. Additionally, they had to attend one seminar each week with mandatory attendance in which the assignments and the subject matter were discussed and opportunities for peer- and teacher feedback were organized. Offline and in the course manual, students were referred to the textbook that the teacher selected as a starting point for the course. Use of this textbook is not traced within the online learning environment. The online learning environment provided opportunities for self-assessments. The self-assessments in the learning management systems and *I Hate Statistics* were similar in nature and contained multiple-choice questions in which knowledge and comprehension were assessed. The learning management system contained four self-assessments; *I Hate Statistics* contained eight self-assessments on the course topics. In the second year of this study, it also gave access to a practice exam, with questions that were representative for the final exam. At the end of the course (week 8) each student was graded based on a final multiple-choice exam and on a research report.

4.3 Instruments

4.3.1 Self-reports

The motivated Strategies for Learning Questionnaire (MSLQ), a measure developed by Pintrich and colleagues (McKeachie, et al., 1985; Pintrich, 1991; Pintrich, et al., 1987; see also Duncan and McKeachie, 2005, for a more in-depth discussion), was used to assess self-reports on SRL. The MSLQ was derived from an extensive body of literature and was one of the first inventory on the quality of student learning that not only included attitudes, motivation, and strategy use, but also self-regulatory strategies (Entwistle & McCune, 2004). The MSLQ was progressive at the time by including the dimension of students' consciousness about the teaching-learning environment, leading to adaptation of ways to tackle academic work (Entwistle & McCune, 2004). Several studies argue that there is piecemeal evidence for the scale structure of the MSLQ (Hilpert, et al., 2013; Tock & Moxley, 2017), yet, to this date, this inventory for students in higher education is still considered relevant in light of the wide range of motivation, affect, strategy use, and self-regulation it covers. Appendix A provides a description of the scales, along with a couple of sample items per scale.

The MSLQ was administered once in the seminar of week four, along with several general questions about background variables, such as age and gender. The MSLQ contained 81 questions of which 31 items determined students' motivational orientation towards the course and 50 items assessed metacognition. The questions assess the propensity of students to engage in self-regulated learning within the specific context of this course, but, overall, the MSLQ has been classified as an aptitude measure of self-regulated learning (Muis et al., 2007; Zimmerman, 2008). Students answered with a 7-points Likert scale, ranging from 'not at all true for me' to 'very true for me'. The motivational orientation is divided into six subscales: Intrinsic goal orientation, extrinsic goal orientation, task value, self-efficacy, control beliefs and test anxiety. Metacognition was scored on nine subscales: rehearsal, elaboration, organization, critical thinking, metacognitive self-regulation, time and study environment, effort regulation, peer learning and help seeking. A definition per subscale is provided in Appendix A. For a complete description of the MSLQ and each of its subscales we refer to the manual of the MSQL (Pintrich, 1991).

Reliability coefficients were determined with the Cronbach's Alpha (see Appendix A). It is important to note that the reliability of the goal orientation sub-scales is poor. Scrutinizing the data per item did not point out particular weak items that could be removed from the scale to improve reliability.

4.3.2 Online trace data

Online trace data was obtained as part of the project 'the Learning Analytics Experiment'. The teacher of the course was actively involved in defining what type of data was collected. The teacher was facilitated to track any learning activity in the learning management system with trackers designed by SURFnet and the Amsterdam Center for Learning Analytics (ACLA). The trackers were based on xAPI recipes (a set of rules). The teacher defined the set of rules, based on activities, verbs, and labels. For example, 'formative exam' (activity) - 'accessed' (verb) - 'week 3' (label). After defining a recipe, a HTML-code was provided that accordingly was embedded in the online learning environment, often in the form of an empty object in the environment.

In addition, the designers of the application I Hate Statistics provided access to the data they collected on each learning activity a student engaged in, as well as the timestamp, the length of the learning activity, the number of questions that a student answered within a lesson or a challenge, and the success rate within a lesson or challenge was logged for each student.

After processing the data, variables were selected to be included in the current study, following the work of Guerra and colleagues (2016), Kim and colleagues (2018), and Theobold and colleagues (2018), These variables are described in Table 1. The count- and time- based variables were aggregated to the week level based on the week-based structure of the course; Each week was structured around a particular topic. The variables Sequential Navigation and Distributed Learning provide a metric (respectively a ratio and a count measure) on student level, in order to deduce an overall measure of students' patterns in use of the online learning environment throughout the eight weeks of the course.

Table 1

Interpretation of Online Trace Data in Week- and Student Level Variables

Variable	**Operationalization**
Total Time Investment in Practicing	Week level count of minutes of practicing time in I Hate Statistics. I Hate Statistics provided the only online opportunities to practice the subject matter, time spent practicing was captured by the application. The xAPI trackers on the other resources available online did not capture the time students spend interacting with it, which means this is excluded from this variable.
Total Participation in Learning Activities	Week-level count of the number lessons, challenges, videos, lecture slides, course information, and blog posts students accessed during the eight-week course. Self-tests and forum visits are excluded from this variable.
Seeking and Providing Help	Week-level count of the number of forums threads accessed by the students during the eight-week course.
Self-Assessment	Week-level count of self-tests students took. In the first four weeks of the course, two self-tests were available to the students. In the sixth week, a practice exam was available to the students online. Self- tests contained several multiple-choice questions or open questions that covered different topics of the lecture. At the end of each self-test, students received feedback and an explanation if an answer was wrong. Each student had permission to run every self-test as many times as desired.
Sequential Navigation	Week-level count of within-topic or next-topic accessed resources. Every act of accessing a learning resources (as defined under total participation in learning activities) was classified into four different groups: (1) *within-topic*, which indicates accessing a learning activity related to the week topic; (2) *next-topic*, which indicates accessing a learning activity related to next week's topic (according to the sequence of topics in the course), (3) *jump- forward*, which indicates accessing a learning activity related to a topic of two or more weeks away from the current topic, and (4) *jump- backward*, which indicates accessing a learning activity related to a previous week topic. A *within-topic* or *next-topic* move represents a sequential navigation, while a *jump-forward* or *jump-backward* move represents a non-sequential navigation pattern. We then computed the ratio of sequential navigation versus non-sequential accessing acts per student per week up until week 6. In each of the first 6 weeks a new topic was introduced, week 7 covered all topics and week 8 was dedicated to the final exam.
Distributed Learning	Student level count of the number of weeks in which each student had accessed learning resources in the online learning environments irrespective of the actual amount of time students spent online. Higher values on this variable suggest a more distributed, continual engagement with the course content. Values on this variable could possibly range from zero to eight, as the course duration was eight weeks.

4.3.3 Academic performance

Students' academic performance is measured with the summative course evaluation. At the end of the course students' final grade was determined based on the results of a multiple-choice exam and the grading of the research report. The exam included 30 four-answer choice questions; ten questions targeted knowledge, ten targeted insight, and the other ten targeted calculations. Appendix B provides sample questions of each category. The exam was designed by the course coordinator. In general, all course coordinators are equipped with a training that covers basic knowledge and skills on constructing multiple choice tests. The course coordinator had, furthermore, access to a data base with high-quality questions used in previous years, which – albeit slightly modified – could be used to put together the exam. The exam underwent peer review and psychometric tests, the latter was used in the grading process. Final grades were scored on a scale from 1 to 10 with 10 being the highest and with 5.5 as passing threshold.

4.4 Procedure

Students were provided with an informed consent form for both the self-report data and the online trace data. In the 2016 cohort, informed consent for the online trace data was obtained at the beginning of the course, whereas informed consent for the self-report data was obtained during the student survey in week 4 of the course. In the 2017 cohort, students were provided with one informed consent form including permission to use both sources of data at the beginning of the course.

4.5 Analysis strategy

Data preparation procedures were applied prior to the analysis. Homogeneity of the data across cohorts was established for motivation and strategy use reported by students, for the variables based on the online trace data, and for academic performance, using Levene's test for homogeneity of variance and independent-sample t-tests. Multiple imputation methods were applied to deal with missing data on items of the MSLQ scales in the following analyses, using the Markov chain Monte Carlo method with a number of 10 iterations, with IBM SPSS Statistics 25.

To answer the first research question, the extent to which student self-reports tap motivation and strategy use as reflected in the online trace data online learning behaviour was examined. To that end, explained variance in online trace data of learning behaviour by student self-reports was investigated with ordinary least square regression analyses. Total participation in learning activities was used as dependent variable, because it identified between-student and between-week variance and comprised student engagement in both the learning management system and the online practicing environment. After looking at the data on the course level, models were tested on a week level, in order to gauge variability in the relation between online trace data and self-reported data based on the MSLQ and answer the second research question.

To answer the third research question, the relation between self-reports and online trace data was gauged with a third proxy of student motivation and strategy use: student academic performance based on students' grade on the multiple-choice exam at the end of the course. The proportion explained variance in academic performance by online trace data and self-reports was identified with ordinary least square analyses, separately and combined. In all analyses, students' gender and age were included as control variables.

5. Results

5.1. Descriptive statistics

In total, 605 students gave active consent to include their data collected during the course for these students could be used in the analyses. The results of the homogeneity tests and descriptive statistics are shown in Table 2. Both the self-reports and the online trace data differ significantly between the cohorts, likely related to the introduction of the practice exam for the 2017 cohort and the demographical shift based on the inclusion of international students in 2017. For example, the level of extrinsic motivation is significantly higher in the second cohort, as well as the average number of self-assessments per student per week. Even though students in the 2017 cohort engaged significantly more in self-assessments, their participation in online learning activities was on average significantly lower and they engaged in online learning activities in six out of eight weeks versus seven in 2016.

Table 2

Tests of Homogeneity

	Cohort 2016		Cohort 2017		Levene's test for equality of variances	T-test for equality of means
	N	*M* (*SD*)	*N*	*M* (*SD*)		
Age	121	20.57 (5.18)	393	20.84 (3.43)	*	
Grade Multiple Choice Exam	116	6.80 (1.86)	429	6.57 (2.31)	***	
Grade Research Report	111	6.48 (1.58)	337	6.81 (1.67)		
Intrinsic Goal Orientation	120	4.89 (0.87)	396	4.74 (0.87)		
Extrinsic Goal Orientation	120	4.09 (1.32)	396	4.49 (1.10)	**	**
Task Value	120	4.81 (0.90)	396	4.95 (0.85)		
Self-Efficacy	120	4.54 (0.91)	396	4.28 (1.05)		*
Test Anxiety	120	4.17 (1.20)	396	4.24 (1.31)		
Control of Learning Beliefs	120	5.47 (0.87)	396	5.43 (0.92)		
Metacognitive Self-Regulation	120	4.16 (0.70)	395	4.37 (0.76)		**
Rehearsal	119	4.51 (1.03)	395	4.28 (1.19)		*
Elaboration	119	4.83 (0.82)	324	5.05 (0.85)		*
Organization	119	4.50 (0.98)	395	4.64 (1.11)	*	
Critical Thinking	119	3.20 (0.87)	395	3.72 (1.14)	***	***
Time and Study Environment	119	4.58 (1.12)	395	4.76 (0.96)	*	
Effort Regulation	119	4.87 (1.14)	394	4.58 (1.24)		*
Peer Learning	119	3.60 (1.16)	395	3.70 (1.27)		
Help Seeking	119	4.52 (1.12)	395	4.06 (1.23)		**
Total Time Investment (min)	120	36.81 (76.94)	429	29.20 (98.04)		
Total Participation	121	20.51 (7.18)	479	12.48 (7.02)		***
Seeking and providing help	121	0.92 (3.00)	479	1.12 (2.26)		
Self-Assessment	121	1.25 (0.71)	479	8.18 (10.54)	***	***
Sequential Navigation	121	0.35 (0.15)	470	0.34 (0.20)	*	
Distributed Learning	121	7.19 (1.00)	479	6.20 (1.94)	***	***
						Chi-square test, χ
Gender (1 = female)	121	0.87 (0.34)	395	0.81 (0.39)		7.64, p = .17

* α =.05; ** α =.01; *** α =.001

5.3 The relationship between self-reports and online traces of motivation and strategy use over time

The variables obtained through self-reports were regressed on online trace-data, both on student- and week-level, using standardized values, revealing how stable relationship between self-reports and online trace data is over time. Student controls (age, gender, and cohort) were included in each of the models. The results are presented in Table 3. A comparison of the adjusted R^2 of the baseline model and the model of the sum of participation over the whole course reveals that students' self-reports on motivation and strategy use explain about 9% of variance in the resources accessed in the online learning environment.

The adjusted R^2 of the models across weeks indicate that students' self-reports seem to explain more variance in participation in the weeks prior to the collection of the self-reports (week 4) than participation in the weeks afterwards. The self-reports on time and study environment management explain a substantial proportion in variance in participation up and including week 4, but this changes in the weeks after the self-reports were collected. Self-reports on rehearsal and elaboration strategies emerge as significant predictors of participation in week 3-6 and week 8.

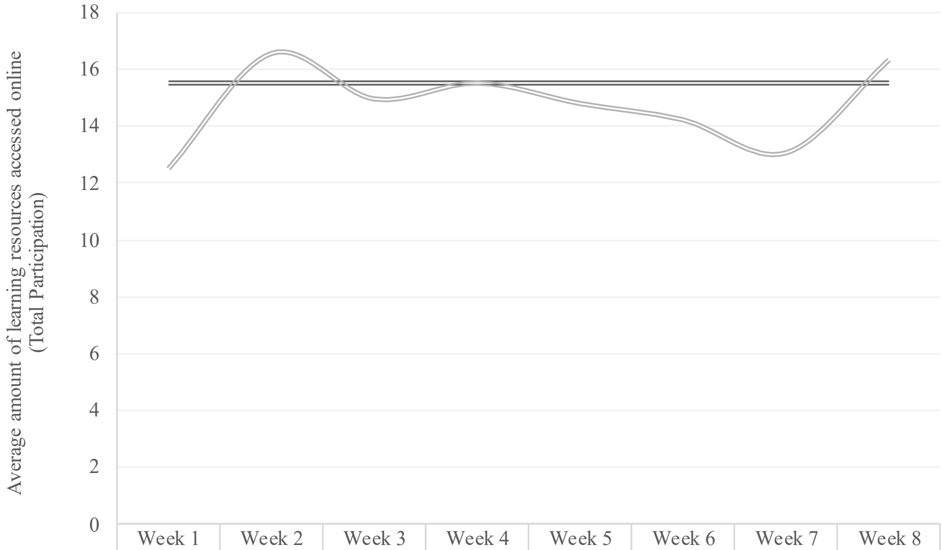
Figure 1 shows the extent to which predictions of participation based on the online trace data of week 4 and the self-reports are representative for participation in other weeks. Actual participation levels reveal that student participation fluctuates over time, with on average a peak in week 2 and week 8.

Table 3

Self-Reports Regressed on Online Trace Data

Dependent variable: Total Participation	Baseline	Sum	Week 1	Week 2	Week 3	Week 4	Week 5	Week 6	Week 7	Week 8
	***B* (*SE*)**	***B* (*SE*)**	***B* (*SE*)**	***B* (*SE*)**	***B* (*SE*)**	***B* (*SE*)**	***B* (*SE*)**	***B* (*SE*)**	***B* (*SE*)**	***B* (*SE*)**
Model 1: Self-Reports	N = 604	N = 604	N = 457	N = 520	N = 542	N = 531	N = 505	N = 460	N = 421	N = 445
Intercept	-.47 (.09)***	-.39 (.10) ***	-.47 (.10)***	-.42 (.11)***	-.22 (.09)*	-.13 (.09)	-.26 (.12)*	-.14 (.12)	-.07 (.12)	-.07 (.20)
Student controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Cohort control	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Intrinsic Goal Orientation	n/a	-.10 (.05)*	-.06 (.05)	-.06 (.05)	-.04 (.05)	.02 (.05)	-.04 (.06)	-.01 (.06)	.02 (.06)	-.10 (.11)
Extrinsic Goal Orientation	n/a	-.01 (.04	.03 (.04)	-.05 (.05)	.04 (.04)	-.01 (.04)	-.06 (.05)	-.01 (.05)	-.02 (.05)	.07 (.09)
Task Value	n/a	.03 (.05)	.02 (.05)	.02 (.05)	.04 (.04)	-.04 (.05)	-.04 (.06)	-.07 (.06)	.00 (.06)	.05 (.11)
Self-Efficacy	n/a	.03 (.05)	.09 (.05)	.09 (.06)	.02 (.05)	-.04 (.05)	.12 (.06)	-.10 (.07)	-.08 (.06)	.06 (.11)
Test Anxiety	n/a	-.01 (.04)	.02 (.04)	.04 (.05)	.04 (.04)	.00 (.04)	.08 (.05)	-.01 (.05)	-.02 (.05)	.04 (.09)
Control of Learning Beliefs	n/a	.06 (.04)	.04 (.04)	-.01 (.05)	.01 (.04)	.04 (.04)	.05 (.05)	.08 (.05)	.06 (.05)	-.03 (.09)
Metacognitive Self-Regulation	n/a	-.01 (.05)	-.01 (.05)	.01 (.06)	-.07 (.05)	-.06 (.05)	-.06 (.06)	.08 (.07)	.00 (.06)	.16 (.11)
Rehearsal	n/a	-.05 (.04)	-.07 (.05)	-.07 (.05)	-.02 (.04)	-.11 (.04)**	.00 (.05)	-.11 (.05)*	.04 (.06)	.14 (.09)
Elaboration	n/a	-.12 (.05)*	-.02 (.05)	-.08 (.05)	-.10 (.04)*	.06 (.05)	.05 (.06)	.10 (.06)	-.08 (.07)	-.31 (.11)**
Organization	n/a	-.02 (.05)	-.05 (.05)	.03 (.05)	.00 (.04)	.03 (.04)	.04 (.06)	-.15 (.06)	.01 (.06)	-.02 (.10)
Critical Thinking	n/a	-.02 (.04)	-.06 (.04)	-.03 (.05)	.00 (.04)	-.01 (.04)	-.03 (.05)	-.04 (.06)	-.01 (.05)	.11 (.10)
Time and Study Environment	n/a	.30 (.05)***	.31 (.05)***	.23 (.06)***	.19 (.05)***	.24 (.05)***	.11 (.06)*	.11 (.06)	.08 (.06)	-.02 (.11)
Effort Regulation	n/a	.08 (.05)	.02 (.05)	.09 (.06)	.09 (.05)	.02 (.05)	.03 (.06)	.03 (.06)	-.08 (.06)	-.13 (.12)
Peer Learning	n/a	.05 (.04)	-.04 (.04)	-.06 (.05)	-.02 (.04)	-.01 (.04)	.04 (.05)	.01 (.05)	.04 (.05)	-.01 (.09)
Help Seeking	n/a	.02 (.04)*	.08 (.04)	.05 (.04)	.03 (.04)	-.01 (.04)	.01 (.05)	.00 (.05)	-.02 (.05)	-.04 (.09)
Adjusted R^2	.19	.28	.28	.32	.21	.09	.03	.03	-.02	.04

* α =.05; ** α =.01; *** α =.001



	Week 1	Week 2	Week 3	Week 4	Week 5	Week 6	Week 7	Week 8
Prediction based on data collected in week 4	15.53	15.53	15.53	15.53	15.53	15.53	15.53	15.53
Actual	12.52	16.57	14.97	15.53	14.81	14.24	13.08	16.35

Figure 1. Predicted participation based on the regression of students' self-reports on total participation in week 4 and the actual participation across weeks

5.3 Explained variance in academic performance by self-reports and online traces of motivation and strategy use

The variables based on self-reports and online trace data were regressed on academic performance; using standardized values and in a stepwise fashion, see Table 4. Student controls (age, gender, and cohort) were included in each of the models. The differences in explained variance between Model 1 and Model 2 need to be interpreted with caution, as there are substantially fewer variables included in Model 2. Based on the explained variance of Model 3, it can be concluded that there is a substantial unique contribution of the self-report and online trace data-based variables in predicting academic performance. In the final model, there are three scales of the MSLQ that explain a substantial proportion in academic performance; self-efficacy, elaboration strategies, and effort regulation. Four variables based on the online trace data explain substantial variation; total time invested, total participation, self-assessment and distributed learning. The total time invested in the online learning environment is negative related to academic performance, even though the total amount of resources accessed by the student (i.e. total participation) is positively related to academic performance.

Table 4

Self-Reports and Online Trace Data Regressed on Academic Performance

Dependent variable: Grade on the multiple-choice exam	Model 0: Baseline		Model 1: Self-reports	Model 2: Online trace data	Model 3: Combined
	N	*B* (*SE*)	*B* (*SE*)	*B* (*SE*)	*B* (*SE*)
Intercept	604	.22 (.10)*	-.28 (.10)**	-.12 (.10)	-.21 (10)*
Student controls		✓	✓	✓	✓
Cohort control		✓	✓	✓	✓
Self-reports					
Intrinsic Goal Orientation		n/a	-.12 (.05)*	n/a	-.08 (.05)
Extrinsic Goal Orientation		n/a	-.07 (.04)	n/a	-.06 (.04)
Task Value		n/a	.01 (.05)	n/a	-.00 (.05)
Self-Efficacy		n/a	.19 (.06)***	n/a	.17 (.05)**
Test Anxiety		n/a	-.09 (.05)*	n/a	-.08 (.04)
Control of Learning Beliefs		n/a	.10 (.05)*	n/a	.08 (.04)
Metacognitive Self-Regulation		n/a	-.04 (.05)	n/a	-.02 (.05)
Rehearsal		n/a	-.07 (.05)	n/a	-.06 (.04)
Elaboration		n/a	.06 (.06)	n/a	.10 (.05)*
Organization		n/a	.07 (.05)	n/a	.06 (.05)
Critical Thinking		n/a	-.02 (.05)	n/a	-.03 (.04)
Time and Study Environment		n/a	.10 (.06)	n/a	.03 (.05
Effort Regulation		n/a	.20 (.06)***	n/a	.16 (.05)**
Peer Learning		n/a	-.00 (.05)	n/a	-.04 (.04)
Help Seeking		n/a	.02 (.04)	n/a	.03 (.04)
Online trace data					
Total Time Investment		n/a	n/a	-.12 (.04)**	-.14 (.04)***
Total Participation		n/a	n/a	.16 (.05)**	.12 (.05)*
Seeking and providing help		n/a	n/a	.05 (.04)	.02 (.04)
Self-Assessment		n/a	n/a	.24 (.05)***	.17 (.05)***
Sequential Navigation		n/a	n/a	.08 (.04)*	.01 (.04)
Distributed Learning		n/a	n/a	.08 (.05)	.10 (.48)*
Adjusted R^2		.02	.18	.18	.27

* α =.05; ** α =.01; *** α =.001

6. Conclusion and discussion

Starting from the central questions of this special issue, this study aimed to provide insight in the ways in which self-reports reflect the conceptualizations of the constructs suggested in theory related to motivation or strategy use. To that end, this study looked into the relationship between measures of SRL through aptitude-based self-reports and event-based online trace data. Using event-based measurement methods of SRL based on online trace data complementary to self-report instruments can be a first step in capturing self-regulation as a function of the individual's dynamic interaction with the learning environment (Boekaerts et al., 2000; Efklides, 2011; Veenman, 2011; Winne & Perry 2000). Capturing the individual's dynamic interaction with the learning environment can be instrumental in guiding innovations in education towards effective personalized learning and enabling educators to adapt to individual differences in SRL during a study episode or educational program.

The results of this study show that self-reports on motivation and strategy use explain 28% of variance in online study behaviour overall versus 18% in academic performance. None of the MSLQ scales on motivation significantly predicted online learning behaviour, whereas several MSLQ scales on strategy use did; namely the scales that measured rehearsal strategies, elaboration strategies, and time and study environment management strategies. Given the prominent role of personal goals, efficacy, and interest in general models for student learning (Fryer, 2017), it is striking that the MSLQ scales on motivation did not explain variance in online trace data. At the same time, these results are in line with previous research on self-reports of motivation in higher education that does show a strong relation with achievement (e.g. Hattie, 2015) but not with study behaviour measured with online trace data (e.g. Cho & Heron, 2015; Zhou & Winne, 2012). This could suggest that the motivational aspects of self-regulatory processes are not captured with online trace data, because of their covert nature. In that respect, it is of importance to recognize the crucial role of self-reports in gaining broad insights in SRL.

At the same time, the results of this study underline the added value of online trace data of learning behaviour. Firstly, online trace data of learning behaviour explained a unique proportion of variance in student academic performance. In this study, the number of logins, number of operations performed on discussion forums and resources accounted for approximately 18% of the variance in academic performance. Although this is substantially less than the 21% found by Gašević and colleagues (2014), it is equal to the amount of variance in academic performance explained by students' self-reports on motivation and strategy use. As expected and along with the findings of the study of Cho & Yoo (2017), where online trace data produced an even more precise prediction of academic performance than students' self-reports, this study provides a strong indication of the potential of online trace data to tap self-regulatory processes, in particular strategy use. The fact that online trace data still predict a unique proportion of variance in academic performance when studied in combination with self-reports might be explained by its potential to bypass a potential upward bias in self-reports of motivation and strategy use due to the overconfidence effect (Taylor & Brown, 1988) as they do not suffer from socially desirable responding bias.

Finally, this study shows that online study behaviour and the relation between self-reports and online trace data varies vastly from week to week. Students' self-reports seem to be mainly based on prior learning experiences within the course, as the reports did explain variation in online learning behaviour prior to the collection of self-reports, but substantially less thereafter. This finding is in line with the expectations around the second research question and fits the theoretical lens provided by Fryer (2017) about the feedback loop between students and their learning experiences. In light of the second central questions of the special issue addressed in this study, we can conclude that the use of self-reports does constrain the analytical choices made with self-report data to some extent: The online trace data revealed large amount of within student variance. Online trace data are therefore an important addition to self-reports in guiding innovations in education towards effective instructional design and personalized learning as they have the potential to give teachers and students real-time insights in strategy use and self-regulation.

An avenue for future research is to combine event-based self-reports and online trace data in measuring SRL. Especially since the results of this study did not identify a relation between online trace data and self-motivational beliefs, potentially due to the weak reliability of some of the MSLQ scales. Furthermore, the identified heterogeneity of the two cohorts in this study warrants further investigation. It is possible that the consent procedure in the first cohort did not yield a representative sample of the students in the first cohort with respect to their propensity to engage in self-regulated learning within the specific context of this course.

Future research is also needed to investigate how real-time measures of SRL through online trace data and self-reports can inform teaching and learning. The LISSA project is a good example where learning analytics were used to support the adviser-student dialogue, in a way that helped motivate students, triggered conversation, and provided tools to add personalization, depth, and nuance to the advising session (Charleer, et al., 2018). Similar efforts based on online trace data or event-based self-reports are scarce, but pivotal to design and evaluate personalized interventions in online learning environments that promote effective study behaviour.

7. Key points

- Self-report measures of strategy use such as management of time and study environment predict participation in online learning activities, although this relationship is not stable across weeks.
- Student self-reports seem to explain more variance in online learning behaviour of prior weeks than variance in learning behaviour in succeeding weeks.
- Self-report measures and online trace data on self-regulated learning are complementary in predicting study success as they both explain a unique proportion of variance in student academic performance.

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10. References

Bera, S., & Liu, M. (2006). Cognitive tools, individual differences, and group processing as mediating factors in a hypermedia environment. *Computers in Human Behavior*, *22*, 295-319. http://doi.org/10.1016/j.chb.2004.05.001

Boekaerts, M., & Corno, L. (2005). Self-regulation in the classroom: A perspective on assessment and intervention. *Applied Psychology*, *54*, 199-231. http://doi.org/10.1016/j.chb.2004.05.001

Boekaerts, M., Pintrich, P. R., & Zeidner, M. (2000). Self-regulation: An introductory overview. In *Handbook of self-regulation* (pp. 1-9). Academic Press.

Charleer, S., Moere, A. V., Klerkx, J., Verbert, K., & De Laet, T. (2017). Learning analytics dashboards to support adviser-student dialogue. *IEEE Transactions on Learning Technologies*, *11*, 389-399. http://doi.org/10.1109/TLT.2017.2720670

Cho, M. H., & Heron, M. L. (2015). Self-regulated learning: the role of motivation, emotion, and use of learning strategies in students' learning experiences in a self-paced online mathematics course. *Distance Education*, *36*, 80-99. http://doi.org/10.1080/01587919.2015.1019963

Cho, M. H., & Yoo, J. S. (2017). Exploring online students' self-regulated learning with self-reported surveys and log files: a data mining approach. *Interactive Learning Environments*, *25*, 970-982. http://doi.org/10.1080/10494820.2016.1232278

Coogan, J., Dancey, C. P., & Attree, E. A. (2005). WebCT: a useful support tool for psychology undergraduates–a Q methodological study. *Psychology Learning and Teaching*, *5*, 61-66. http://doi.org/10.2304/plat.2005.5.1.61

Cornelisz, I., & Van Klaveren, C. (2018). Student engagement with computerized practising: Ability, task value, and difficulty perceptions. *Journal of Computer Assisted Learning*, *34*(6), 828-842. http://doi.org/10.1111/jcal.12292

DeNeui, D. L., & Dodge, T. L. (2006). Asynchronous learning networks and student outcomes: The utility of online learning components in hybrid courses. *Journal of Instructional Psychology*, *33*, 256-260.

Dinsmore, D. L., Alexander, P. A., & Loughlin, S. M. (2008). Focusing the conceptual lens on metacognition, self-regulation, and self-regulated learning. *Educational Psychology Review, 20*, 391-409. http://doi.org/10.1007/s10648-008-9083-6

Greller, W. & Drachsler, H. (2012). Translating Learning into Numbers: A Generic Framework for Learning Analytics. *Journal of Educational Technology & Society, 15*, 42-57. Retrieved from http://www.jstor.org/stable/jeductechsoci.15.3.42

Chauliac, M., Catrysse, L., Gijbels, D., & Donche, V. (2020). It is all in the surv-eye: Can eye tracking data shed light on the internal consistency in self-report questionnaires on cognitive processing strategies? *Frontline Learning Research, 8*(3), 26–39. http://doi.org/10.14786/flr.v8i3.489

Duncan, T. G., & McKeachie, W. J. (2005). The making of the motivated strategies for learning questionnaire. *Educational psychologist*, *40*, 117-128. http://doi.org/10.1207/s15326985ep4002_6

Efklides, A. (2011). Interactions of metacognition with motivation and affect in self-regulated learning: The MASRL model. *Educational Psychologist, 46*, 6-25. http://doi.org/10.1080/00461520.2011.538645

Ellis, R. A., Marcus, G., & Taylor, R. (2005). Learning through inquiry: student difficulties with online course-based Material. *Journal of Computer Assisted Learning, 21,* 239-252. http://doi.org/10.1111/j.1365-2729.2005.00131.x.

Entwistle, N., & McCune, V. (2004). The conceptual bases of study strategy inventories. *Educational Psychology Review*, *16*, 325-345. http://doi.org/10.1007/s10648-004-0003-0

Fryer, L. K. (2017). Building bridges: Seeking structure and direction for higher education motivated learning strategy models. *Educational Psychology Review*, *29*, 325-344. http://doi.org/10.1007/s10648-017-9405-7

Gašević, D., Dawson, S., Rogers, T., & Gašević, D. (2016). Learning analytics should not promote one size fits all: The effects of instructional conditions in predicting academic success. *The Internet and Higher Education*, *28*, 68-84. http://doi.org/10.1016/j.iheduc.2015.10.002.

Gašević, D., Kovanovic, V., Joksimovic, S., & Siemens, G. (2014). Where is research on massive open online courses headed? A data analysis of the MOOC Research Initiative. *The International Review of Research in Open and Distributed Learning*, *15*, 134-176. http://doi.org/10.19173/irrodl.v15i5.1954.

Guerra, J., Hosseini, R., Somyurek, S., & Brusilovsky, P. (2016). An intelligent interface for learning content: Combining an open learner model and social comparison to support self-regulated learning and engagement. In *Proceedings of the 21st international conference on intelligent user interfaces* (pp. 152-163). ACM.

Hadwin, A. F., Nesbit, J. C., Jamieson-Noel, D., Code, J., & Winne, P. H. (2007). Examining trace data to explore self-regulated learning. *Metacognition and Learning*, *2*(2-3), 107-124. http://doi.org/10.1007/s11409-007-9016-7

Han, J., Pei, J., & Kamber, M. (2011). *Data mining: concepts and techniques*. Elsevier.

Heffner, M., & Cohen, S. H. (2005). Evaluating student use of web-based course material. *Journal of Instructional Psychology*, *32*, 74-82.

Hilpert, J. C., Stempien, J., van der Hoeven Kraft, K. J., & Husman, J. (2013). Evidence for the latent factor structure of the MSLQ: A new conceptualization of an established questionnaire. *SAGE Open*, *3*, 2158244013510305.

Hoskins, S. L., & Van Hooff, J. C. (2005). Motivation and ability: which students use online learning and what influence does it have on their achievement? *British Journal of Educational Technology*, *36*, 177-192. http://doi.org/10.1111/j.1467-8535.2005.00451.x.

Howard-Rose, D., & Winne, P. H. (1993). Measuring component and sets of cognitive processes in self-regulated learning. *Journal of Educational Psychology*, *85*, 591. http://doi.org/10.1111/j.1464-0597.2005.00205.x

Huon, G., Spehar, B., Adam, P., & Rifkin, W. (2007). Resource use and academic performance among first year psychology students. *Higher Education*, *53*, 1-27. http://doi.org/10.1007/s10734-005-1727-6

Iaconelli, R., & Wolters, C. A. (2020). Insufficient effort responding in surveys assessing self-regulated learning: Nuisance or fatal flaw? *Frontline Learning Research, 8*(3), 105–127. http://doi.org/10.14786/flr.v8i3.521

Itmazi, J. A., & Megías, M. G. (2005). Survey: Comparison and evaluation studies of learning content management systems. *Unpublished manuscript*.

Jamieson-Noel, D., & Winne, P. H. (2003). Comparing Self-Reports to Traces of Studying Behavior as Representations of Students' Studying and Achievement. *Zeitschrift für Pädagogische Psychologie/German Journal of Educational Psychology.* http://doi.org/10.1024//1010-0652.17.34.159

Jivet, I., Scheffel, M., Drachsler, H., & Specht, M. (2017). Awareness is not enough. Pitfalls of learning analytics dashboards in the educational practice. In É. L., H. D., K. V., J. B., & M. P-S. (Eds.), *Data Driven Approaches in Digital Education: 12th European Conference on Technology Enhanced Learning, EC-TEL 2017, Tallinn, Estonia, September 12–15, 2017, Proceedings* (Lecture Notes in Computer Science (LNCS); Vol. 10474). Cham: Springer International Publishing AG. http://doi.org/10.1007/978-3-319-66610-5_7

Jivet, I., Scheffel, M., Specht, M., & Drachsler, H. (2018). License to evaluate: preparing learning analytics dashboards for educational practice. In *Proceedings of the 8th International Conference on Learning Analytics and Knowledge* (pp. 31-40). ACM. http://doi.org/10.1145/3170358.3170421

Jiang, L., Elen, J., & Clarebout, G. (2009). The relationships between learner variables, tool-usage behaviour and performance. *Computers in Human Behavior*, *25*, 501-509. http://doi.org/10.1016/j.chb.2008.12.010

Jupp, V. (2006). *The Sage dictionary of social research methods.* Sage.

Kim, D., Yoon, M., Jo, I. H., & Branch, R. M. (2018). Learning analytics to support self-regulated learning in asynchronous online courses: A case study at a women's university in South Korea. *Computers & Education*, *127*, 233-251. http://doi.org/10.1016/j.compedu.2018.08.023.

Knight, J. (2010). Distinguishing the learning approaches adopted by undergraduates in their use of online resources. *Active Learning in Higher Education, 11,* 67–76. http://doi.org/10.1177/1469787409355873

Lust, G., Collazo, N. A. J., Elen, J., & Clarebout, G. (2012). Content management systems: enriched learning opportunities for all? *Computers in Human Behavior, 28,* 795-808. http://doi.org/10.1016/j.chb.2011.12.009

Lust, G., Elen, J., & Clarebout, G. (2013). Regulation of tool-use within a blended course: Student differences and performance effects. *Computers & Education, 60,* 385-395. http://doi.org/10.1016/j.compedu.2012.09.001

McKeachie, W. J., Pintrich, P. R., & Lin, Y. G. (1985). Teaching learning strategies. *Educational Psychologist, 20,* 153-160. http://doi.org/10.1207/s15326985ep2003_5

Molenda, M. (2008). Historical foundations. In M. J. Spector, M. D. Merrill, J. van Merrienboer, & M. P. Driscoll (Eds.). *Handbook of research for educational communications and technology* (pp. 5–20). Routledge.

Moeller, J., Dietrich, J., Viljaranta, J., & Kracke, B. (2020). Disentangling objective characteristics of learning situations from subjective perceptions thereof, using an experience sampling method design. *Frontline Learning Research, 8*(3), 63–85. http://doi.org/10.14786/flr.v8i3.529

Muis, K. R., Winne, P. H., & Jamieson-Noel, D. (2007). Using a multitrait-multimethod analysis to examine conceptual similarities of three self-regulated learning inventories. *British Journal of Educational Psychology, 77,* 177–195. http://doi.org/10.1348/000709905X90876

Munoz, KD, & Van Duzer, J. (2005). *BlackBoard vs. Moodle: A Comparison of Satisfaction with Online Teaching and Learning Tools.* Humboldt State University.

Panadero, E. (2017). A review of self-regulated learning: six models and four directions for research. *Frontiers in Psychology*, *8*, 422. http://doi.org/10.3389/fpsyg.2017.00422

Panadero, E., Klug, J., & Järvelä, S. (2016). Third wave of measurement in the self-regulated learning field: when measurement and intervention come hand in hand. *Scandinavian Journal of Educational Research, 60,* 723-735. http://doi.org/10.1080/00313831.2015.1066436

Pintrich, P. R. (1991). A manual for the use of the Motivated Strategies for Learning Questionnaire (MSLQ).

Pintrich, P. R. (2000). Multiple goals, multiple pathways: The role of goal orientation in learning and achievement. *Journal of Educational Psychology*, *92*, 544. http://doi.org/10.1037/0022-0663.92.3.544

Pintrich, P. R., McKeachie, W. J., & Lin, Y. G. (1987). Teaching a course in learning to learn. *Teaching of Psychology*, *14*, 81-86. http://doi.org/10.1207/s15328023top1402_3

Rogiers, A.; Merchie, E., & van Keer, H. (2020). Opening the black box of students' text-learning processes: A process mining perspective. *Frontline Learning Research, 8*(3), 40–62. http://doi.org/10.14786/flr.v8i3.527

Schmitz, M., Scheffel, M., van Limbeek, E., van Halem, N., Cornelisz, I., van Klaveren, C., ... & Drachsler, H. (2018). Investigating the Relationships Between Online Activity, Learning Strategies and Grades to Create Learning Analytics-Supported Learning Designs. In *European Conference on Technology Enhanced Learning* (pp. 311-325). Springer, Cham.

Taylor, S. E. & Brown, J. D. (1988). Illusion and well-being: A social psychological perspective on mental health. *Psychological Bulletin*, *103,* 193–210. http://doi.org/10.1037/0033-2909.103.

Tock, J. L., & Moxley, J. H. (2017). A comprehensive reanalysis of the metacognitive self-regulation scale from the MSLQ. *Metacognition and Learning*, *12*, 79-111. http://doi.org/10.1007/s11409-016-9161-y

Veenman, M. (2011). Learning to self-monitor and self-regulate. In R. Mayer & P. Alexander (Eds.), *Handbook of research on learning and instruction (pp. 197–218).* New York: Routledge.

Vriesema, C. C., & McCaslin, M. (2020) Experience and meaning in small-group contexts: Fusing observational and self-report data to capture self and other dynamics. *Frontline Learning Research, 8*(3), 128–141. http://doi.org/10.14786/flr.v8i3.493

Wang, A. Y., & Newlin, M. H. (2000). Characteristics of students who enroll and succeed in psychology web-based classes. *Journal of Educational Psychology*, *92*, 137. http://doi.org/10.1037/0022-0663.92.1.137.

Winne, P. H., & Baker, R. S. (2013). The potentials of educational data mining for researching metacognition, motivation and self-regulated learning. *Journal of Educational Data Mining*, *5*, 1-8. Retrieved from https://jedm.educationaldatamining.org/index.php/JEDM/article/view/28

Winne, P. H., & Perry, N. E. (2000). Measuring self-regulated learning. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of self-regulation.* Academic Press.

Zhou, M., & Winne, P. H. (2012). Modelling academic performance by self-reported versus traced goal orientation. *Learning and Instruction, 22,* 413-419. http://doi.org//j.learninstruc.2012.03.004

Zimmerman, B. J. (2008). Investigating self-regulation and motivation: Historical background, methodological developments, and future prospects. *American Educational Research Journal, 45,* 166–183. http://doi.org/10.3102/0002831207312909

APPENDIX A

Cronbach's Alpha per subscale of the MSLQ per cohort

		Cohort 2016		Cohort 2017	
Subscale	**Definition (adapted from Duncan & McKeachie, 2015)**	N	α	N	α
Intrinsic Goal Orientation	Goal orientation refers to the student's perception of the reasons why she is engaging in the course. Having intrinsic goal orientation means participation is an end all to itself, rather than participation being a means to an end. Sample item: In a class like this, I prefer course material that really challenges me so I can learn new things.	341	.65	466	.58
Extrinsic Goal Orientation	Extrinsic goal orientation complements intrinsic goal orientation, with the degree to which the student perceives herself to be participating in a task for reasons such as grades, rewards, performance, evaluation by others, and competition; meaning engaging in the course is the means to an end. Sample item: Getting a good grade in this class is the most satisfying thing for me right now.	347	.73	465	.59
Task Value	Task value differs from goal orientation in that task value refers to the student's evaluation of the how interesting, how important, and how useful the course is. Sample item: I think I will be able to use what I learn in this course in other courses.	342	.81	458	.79
Self-Efficacy	Self-efficacy is a self-appraisal of one's ability to master a task. Self-efficacy includes judgments about one's ability to accomplish a task as well as one's confidence in one's skills to perform that task. Sample item: I believe I will receive an excellent grade in this class.	341	.86	462	.92
Test Anxiety	Test anxiety refers to students' negative thoughts that disrupt performance, and the affective and physiological arousal aspects of anxiety. Sample item: When I take a test, I think about how poorly I am doing compared with other students.	345	.82	464	.82
Control of Learning Beliefs	Control of learning concerns the belief that outcomes are contingent on one's own effort, in contrast to external factors such as the teacher. If students believe that their efforts to study make a difference in their learning, they should be more likely to study more strategically and effectively. Sample item: If I study in appropriate ways, then I will be able to learn the material in this course.	345	.65	470	.69
Metacognitive Self-Regulation	Metacognitive self-regulation refers to planning, monitoring, and regulating. Planning activities such as goal setting and task analysis help to activate, or prime, relevant aspects of prior knowledge that make organizing and comprehending the material easier.	331	.71	375	.74

	Monitoring activities include tracking of one's attention as one read, and self-testing and questioning: these assist the learner in understanding the material and integrating it with prior knowledge. Regulating refers to the fine-tuning and continuous adjustment of one's cognitive activities. Sample item: When reading for this course, I make up questions to help focus my reading.				
Rehearsal	Basic rehearsal strategies involve reciting or naming items from a list to be learned. These strategies are best used for simple tasks and activation of information in working memory rather than acquisition of new information in long-term memory. Sample item: When I study for this class, I practice saying the material to myself over and over.	338	.65	377	.65
Elaboration	Elaboration strategies help students store information into long-term memory by building internal connections between items to be learned. Elaboration strategies include paraphrasing, summarizing, creating analogies, and generative note taking. Sample item: When I study for this class, I pull together information from different sources, such as lectures, readings, and discussions.	335	.66	371	.68
Organization	Organization strategies help the learner select appropriate information and also construct connections among the information to be learned. Examples of organizing strategies are clustering, outlining, and selecting the main idea in reading passages. Organizing is an active, effortful endeavour, and results in the learner being closely involved in the task. Sample item: When I study the readings for this course, I outline the material to help me organize my thoughts.	339	.64	381	.66
Critical Thinking	Critical thinking refers to the degree to which students report applying previous knowledge to new situations in order to solve problems, reach decisions, or make critical evaluations with respect to standards of excellence. Sample item: I often find myself questioning things I hear or read in this course to decide if I find them convincing.	337	.77	380	.79
Time and Study Environment	Time management involves scheduling, planning, and managing one's study time. This includes not only setting aside blocks of time to study, but the effective use of that study time, and setting realistic goals. Time management varies in level, from an evening of studying to weekly and monthly scheduling. Study environment management refers to the setting where the student does her class work. Sample item: I usually study in a place where I can concentrate on my course work.	341	.85	375	.79
Effort Regulation	Effort regulation is self-management in the face of distractions and uninteresting tasks and reflects a commitment to completing one's study goals.	341	.70	375	.73

	Sample item: I work hard to do well in this class even if I don't like what we are doing.				
Peer Learning	Peer learning involves peer collaboration and dialogue, which can help a learner reach insight one may not have attained on one’s own. Sample item: When studying for this course, I often try to explain the material to a classmate or a friend.	339	.66	380	.68
Help Seeking	Help seeking involves knowing when one doesn’t know something and being able to identify someone to provide them with some assistance. Sample item: I ask the instructor to clarify concepts I don't understand well.	338	.71	378	.63

APPENDIX B

Example questions from the 2016-2017 exam

An example of a knowledge question:*
Fill in the blanks: The ….I…. test is used for testing the difference in proportions between dependent samples and the ….II…. test for testing the difference in proportions between small independent samples.

a.	I: Binomial,	II: Chi-squared
b.	I: Chi-squared,	II: binomial
c.	**I: McNemar,**	**II: Fisher's exact**
d.	I: Fisher's exact,	II: McNemar

An example of an insight question:
In order to evaluate differences in study success across different programs offered at the VU, an equal number of students are randomly selected from each program and asked to participate in the research. This is an example of:
a. Systematic random sampling
b. Cluster sampling
c. Stratified random sampling
d. Multi-stage sampling

An example of a calculation question:
Research results have revealed that intelligence in the Netherlands is normally distributed. The mean IQ score is 100 with a standard deviation of 15. John has an IQ-score of 122.5. What percentage of people in the Netherlands will have an IQ lower than that of John?
a. 3.34 %
b. 6.68 %
c. 93.32 %
d. 96.66 %

*The correct answer is provided in bold.