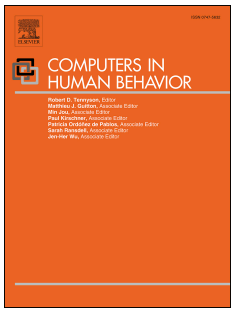
# Accepted Manuscript




Student profiling in a dispositional learning analytics application using formative assessment

Dirk Tempelaar, Bart Rienties, Jenna Mittelmeier, Quan Nguyen

PII: S0747-5632(17)30477-6

DOI: 10.1016/j.chb.2017.08.010

Reference: CHB 5108

To appear in: *Computers in Human Behavior*

Received Date: 10 February 2017

Revised Date: 25 July 2017

Accepted Date: 5 August 2017

Please cite this article as: Tempelaar D., Rienties B., Mittelmeier J. & Nguyen Q., Student profiling in a dispositional learning analytics application using formative assessment, *Computers in Human Behavior* (2017), doi: 10.1016/j.chb.2017.08.010.

# Student profiling in a dispositional learning analytics application using formative assessment

Dirk Tempelaar,

Maastricht University, School of Business and Economics, Netherlands

Bart Rienties,

The Open University, Institute of Educational Technology, Walton Hall, Milton Keynes MK7 6AA, UK

Jenna Mittelmeier,

The Open University, Institute of Educational Technology, Walton Hall, Milton Keynes MK7 6AA, UK

Quan Nguyen,

The Open University, Institute of Educational Technology, Walton Hall, Milton Keynes MK7 6AA, UK

## Abstract

How learning disposition data can help us translating learning feedback from a learning analytics application into actionable learning interventions, is the main focus of this empirical study. It extends previous work (AuthorA, 2015), where the focus was on deriving timely prediction models in a data rich context, encompassing trace data from learning management systems, formative assessment data, e-tutorial trace data as well as learning dispositions. In this same educational context, the current study investigates how the application of cluster analysis based on e-tutorial trace data allows student profiling into different at-risk groups, and how these at-risk groups can be characterized with the help of learning disposition data. It is our conjecture that establishing a chain of antecedent-consequence relationships starting from learning disposition, through student activity in e-tutorials and formative assessment performance, to course performance, adds a crucial dimension to current learning analytics studies: that of profiling students with descriptors that easily lend themselves to the design of educational interventions.

## 1 Introduction

The challenge to design “an optimal sequence of data collection and economic response times …” that includes “the minimum requirements for making valid predictions and creating meaningful interventions” (Ifenthaler, 2015) as one of the challenges to the application of learning analytics (LA), is the main topic of this empirical contribution to dispositional learning analytics. Learning Analytics (LA) is defined as ”the measurement, collection, analysis, and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs” (Gasevic, Dawson, Rogers, & Gasevic, 2016). In the early stages of LA, many scholars focused on building predictive models based on data extracted from both institutional student information systems (SIS) and digital platforms that organize and facilitate learning, such as learning management systems and e-tutorials (LMS, taking them together). While these studies provide important markers on the potential of LA in education, the findings were rather limited to the descriptive functions of LA, which is mostly based on demographics, grades, and trace data. Given the rigidity of SIS and LMS data, educators may encounter difficulties in designing pedagogically informed interventions (Conde & Hernández-García, 2015; Tobarra, Robles-Gómez, Ros, Hernández, & Caminero, 2014; Xing, Guo, Petakovic, & Goggins, 2015).

To overcome this shortcoming, Buckingham Shum and Crick (2012) proposed a Dispositional Learning Analytics (DLA) infrastructure that combines learning data (i.e. those generated in learning activities through the LMS) with learner data (e.g., student dispositions, values, and attitudes measured through self-reported surveys). Learning dispositions represent individual difference characteristics that impact all learning processes and include affective, behavioral and cognitive facets (AuthorB, 2017). Student’s preferred learning approaches are examples of such dispositions of both cognitive and behavioral type; in research on their role in learning, they are often simply labeled as ‘self-report data’ (see e.g. Gašević, Jovanović, Pardo, & Dawson, 2017). Different from LA research, stakeholders of DLA applications are typically restricted to students and teacher/tutors, as these applications can be positioned at both the meso- and micro-level (Ifenthaler, 2015), rather than the mega- or macro-level. Our study is a follow-up of previous research by the authors on the application of LA in a ‘data-rich context’ (AuthorA, 2015). The availability of formative assessment data constitutes a crucial aspect of that data richness, together with learning activity trace data of students practicing in e-tutorial systems in order to be optimally prepared for these formative assessments, and later summative assessments. That data of cognitive type was complemented by learning disposition data to cover all “affective, behavioral and cognitive facets of the ABC framework of student learning” (AuthorB, 2017).

Our previous research indicated a sensitive balance between timing and predictive power of the several data sources in a rich data context. Most informative, but least timely, is typically formative assessment data. Given that formative assessment data is not available until several weeks into a course, trace data from e-tutorial systems are a good second-best. However, it is important to note that the use of e-tutorial trace data is ill-advised at the very start of the course when practicing activities of students have not yet settled into stable patterns. Therefore, learning disposition data are an informative data source next to the trace data in predicting student performance (AuthorA, 2015).

This follow-up study focuses on this very early stage of generating learning feedback at the start of courses that is “personalised, dynamic and timely” (Ifenthaler, 2015). The requirement of learning feedback to be timely implies a crucial role for learning disposition data. The requirement of learning feedback to be actionable too has strong links with the availability of dispositions; learning interventions such as academic counselling are often based on the same social-cognitive frameworks

as the instruments used to measure learning dispositions (such as improving one's learning style, or changing mal-adaptive into adaptive approaches to learning, in case of setbacks) (AuthorA, 2017a).

## 2 Learning Analytics and Dispositional Learning Analytics

### 2.1 Formative Testing and feedback

The classic function of testing is that of summative assessment or assessment of learning: students demonstrate their mastery of a particular subject to their teacher after completing the learning process. Formative assessment or assessment for learning takes place during learning rather than after learning, and has an entirely different function: to provide ongoing feedback to both students, to improve their learning, and teachers, to improve teaching (Spector, Ifenthaler, Sampson, Yang, Mukama, Warusavitarana, …, Gibson, 2016). Thus beyond a different purpose, there are also crucial differences in timing between the two types of testing: formative testing results are especially useful when they become available early in the learning process.

In this regard, feedback plays a crucial part in assisting regulatory learning processes (Hattie, 2009; Lehmann, Hähnlein, & Ifenthaler, 2014). Several alternative operationalizations to support feedback are possible. For example, using two experimental studies with different degrees of generic and directed prompts, Lehmann et al. (2014) found that directed pre-reflective prompts encouraged positive activities in online environments. In a meta-study of 800+ meta-studies, Hattie (2009) found that the way students received feedback was one of the most powerful factors in enhancing their learning experiences, along with self-questioning, concept mapping and problem-solving teaching in the category of teaching and learning approaches. Diagnostic testing directed at adjusting the learning approach to the actual skills and abilities of the student or proper placing the student at the start of the course is one example of this, as is a test-directed learning approach that constitutes a basic educational principle of many e-tutorial systems (AuthorA, 2013).

The setting of this present study is a large-scale classroom covering the most challenging service course students in this international business and economics program will encounter, and it is taught in a problem-based manner. Thus, our application of formative assessment in this study is fully in line with the second recommendation of the Spector et al. (2016, p. 65) report: "formative assessment practices to address learning situations that present difficult challenges (e.g., large and multi-grade classrooms, inquiry- and problem-based learning)". Beyond the important first-order goal of providing students with immediate feedback on their learning progress, formative assessment data is used in this study more indirectly by empowering the LA-based prediction models for signaling students at risk, in line with our previous research (AuthorA, 2015).

### 2.2 Learning Dispositions

Where other DLA research has been based on a single, dedicated and newly designed instrument to measure dispositions (Buckingham Shum & Crick, 2012), we have opted to use well-established and validated instruments to optimize the connection with learning interventions. AuthorB (2017) argue that the single most important question for LA researchers to answer is: "which types of interventions have a positive impact on learners' Attitudes, Behavior and Cognition (ABC) using learning analytics modeling?" (see also AuthorB, 2016).To answer this question, this study includes a very broad range of learning disposition instruments, covering various aspects of affective, behavioral and cognitive antecedents of learning processes. In line with the instructional model of the school, Problem-Based

Learning, we opted for disposition instruments that are based on social-constructivist learning theories, that assume that learning is an active process of learning construction, rather than acquisition, in which collaboration between peers plays an important role, and where not only cognitive, but also affective and behavioral aspects are key to explain learning outcomes. A rich tradition of educational research-designed measurement instruments to observe learner dispositions has emerged over in the last fifty years, which is evidenced by a multiplicity of psychometric survey instruments, including student's self-regulation or goal orientation (Gašević et al., 2017). Given the specific research context of this study in conceptualizing how students learn, we have primarily focused on learning dispositions that can be linked to interventions. These include:

- The expectancy-value framework of learning behavior (Wigfield & Eccles, 2000), encompasses affective, behavioral and cognitive facets. According to the expectancy-value model, students' expectancies for success and the value they contribute to succeeding are important determinants of their motivation to perform achievement tasks. The expectation of success includes two components: belief about one's own ability in performing a task, and a perception of the task demand. Subjective task value constitutes a broad group of factors: attainment values (importance of doing well on a task), intrinsic value (enjoyment gained from doing the task), utility value (usefulness), and costs (spent efforts) belong to it.
- The motivation and engagement framework of learning cognitions and behaviors (Martin, 2007) that breaks down learning cognitions and learning behaviors into four categories of adaptive versus maladaptive types and cognitive versus behavioral types. The classification is based on the theory that thoughts and cognitions can both enable learning, act as boosters, as well as hinder learning: act as mufflers and guzzlers.
- Two aspects of a Student Approaches to Learning (SAL) framework: cognitive processing strategies and metacognitive regulation strategies, from Vermunt's (1996) learning styles instrument, encompassing aspects of cognitions and behaviors. Vermunt's framework of learning approaches distinguishes four main styles or approaches: that of meaning-directed, application-directed, reproduction-directed and undirected learning. Each approach is based on student characteristics in four different domains: cognitive processing strategies (what students do), metacognitive regulation strategies (how students plan and monitor learning), learning orientations (why students learn), and learning conceptions (how students see learning). Learning styles are seen as a specific combination of processing and regulation strategies: meaning-directed learning builds on deep processing and self-regulation, whereas reproduction-directed learning builds on step-wise processing and external regulation (Vermunt, 1996; see also Coffield, Mosely, Hall, Ecclestone, 2004). Although learning styles are subject to debate (Kirschner, 2017), they are of all dispositions closest to intervention when allowing multiple learning strategies in technology-enhanced learning.
- The control-value theory of achievement emotions (CVTAE), both about learning emotions of activity and epistemic types, positions itself at the affective pole of the spectrum (Pekrun, 2012; AuthorB, 2014). 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 while 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).

Learning dispositions that were measured but not incorporated in this study include academic motivations, goal setting behavior, and epistemological views on intelligence and the role of effort. Both collinearity with the included dispositions, as is the case with academic motivations, and lack of possibilities to influence these dispositions in any counseling program led to this choice.

### 2.3 Blended learning of quantitative methods using e-tutorials

Our empirical contribution focuses on first-year undergraduate students learning quantitative methods (mathematics and statistics) in a blended learning environment. With problem-based learning as the face-to-face component, the digital component consists of Blackboard as the LMS to share basic course information and two external e-tutorials: SOWISO (mathematics) and MyStatLab (statistics). Both e-tutorials follow a test-directed learning and practicing approach. Each step in the learning process is initiated by a question, and students are encouraged to (attempt to) answer each question. If a student does not master a question (completely), she/he can either ask for hints to solve the problem step-by-step, or ask for a fully worked example. These two functionalities are examples of Knowledge of Result/Response (KR) and Knowledge of the Correct Response (KCR) types of feedback (see Narciss, 2008; Narciss and Huth, 2006). After receiving feedback, a new version of the problem loads (parameter based) to allow the student to demonstrate his/her newly acquired mastery. When a student provides an answer and calls for an evaluation, Multiple-Try Feedback (MTF) (Narciss, 2008) is provided. Students' revealed learning feedback preferences are related to their learning dispositions, as we demonstrated in previous research (AuthorD, 2016). For instance, the negative epistemic emotion Frustration is positively associated with the frequent calling of complete exercise solutions, whereas the processing strategy Concrete processing is negatively associated with calling solutions.

### 2.4 Research questions

The ultimate goal of any LA application is to generate such 'personalised, dynamic and timely' learning feedback (Ifenthaler, 2015) so that the learning process is facilitated to the maximum extent. In previous research (AuthorA, 2013, 2015), we demonstrated the crucial role of formative assessment and learning disposition data in such an endeavor. Building on such rich data, we derived predictions models (AuthorD, 2016; AuthorA, 2017 a, b) focusing on 'actionable data' (Gasevic et al., 2016). An example of such application is the investigation of how learning feedback preferences of students depend on their dispositions (AuthorsD, 2016). This however still does not include the full range of affective, behavioral and cognitive antecedents of learning processes. This study aims to make that last step by answering the following research questions:

- What can the antecedent-consequence relationships learning depositions – trace data - formative assessment - course performance tell us about the role of affective, behavioral and cognitive factors in how students learn difficult topics, such as mathematics and statistics?
- What opportunities are there for pedagogical interventions triggered by LA-based feedback, based on student profiling by e-tutorial trace data?

The research design of this study can be summarized in the following schematic overview, Figure 1.

**→ Insert Figure 1 about here**

**Fig. 1.** Schematic overview of research design, with investigated relationships in single-line arrows, cluster construction in double-line arrows

# 3 RESEARCH METHODS

## 3.1 Context of the empirical study

This study takes place in a large-scale introductory mathematics and statistics course for first-year undergraduate students in a business and economics program in the Netherlands. The educational system is best described as 'blended' or 'hybrid.' The main component is face-to-face: Problem-Based Learning (PBL), in small groups (14 students), coached by a content expert tutor (see AuthorA, 2016 and Williams et al., 2016 for further information on PBL and the course design). Participation in tutorial groups is required. Optional is the online component of the blend: the use of the two e-tutorials -- SOWISO and MyStatLab (MSL) (AuthorA, 2015). This design is based on the philosophy of student-centered education, placing the responsibility for making educational choices primarily on the student. Since most of the learning takes place during self-study outside class through the e-tutorials or other learning materials, class time is used to discuss solving advanced problems. Thus, the instructional format is best characterized as a flipped-classroom design (Williams et al., 2016). Using and achieving good scores in the e-tutorial practice modes is incentivized by providing bonus points for good performance in the quizzes (i.e. the formative assessment), worth up to 20% of what one can score in the exam. Quizzes are taken every two weeks, and consist of items that are 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.

The student-centered nature of the instructional design requires, first and foremost, adequate actionable feedback to students so that they can appropriately monitor their study progress and topic mastery. The provision of relevant feedback starts on the first day of the course when students take two diagnostic entry tests for mathematics and statistics. Feedback from these entry tests provides a first signal for the importance of using the e-tutorials. Next, the SOWISO and MSL-environments take over the monitoring function: at any time, students can see their performance in the practice sessions, their progress in preparing for the next quiz, and detailed feedback on their completed quizzes, all in the absolute and relative (to their peers) sense. Profiting from the intensive contact between students and their tutors of the pbl tutorial groups, learning feedback is directed at students and their tutors, who carry first responsibility for pedagogical interventions.

The subject of this study is the full 2016/2017 cohort of students (i.e. all students who enrolled the course and/or the final exam: in total, 1093 students). A large diversity in the student population was present: only 19% were educated in the Dutch high school system. Regarding nationality, the largest group, 44% of the students, was from Germany, followed by 23% Dutch and 19% Belgian students, which is representative of the larger university student population. In total, 50 nationalities were present. A large share of students was of European nationality, with only 3.9% of students from outside Europe. High school systems in Europe differ strongly, most particularly in the teaching of mathematics and statistics. For example, the Dutch high school system has a strong focus on the topic of statistics, whereas statistics are completely missing in high school programs of many other countries. Therefore, it is crucial that this present introductory module is flexible and allows for individual learning paths (AuthorA, 2016; Williams et al., 2016). In this course, students spend on average 24 hours in SOWISO and 32 hours in MSL, which is 30% to 40% of the available time of 80 hours for learning on both topics.

## 3.2 Instruments and procedure

In this study, we will investigate the relationships between course performance measures, LMS system trace variables, SIS based variables, and learning disposition variables measured in self-report surveys. As suggested by Winne's taxonomy of data sources (Winne, 2013; Zhou & Winne, 2012), our study applies self-report survey data and trace data through the logging of study behaviors and the specific choices students make in the e-tutorials.

The self-report surveys applied in this study (described in sections 3.2.4 through 3.2.9) are all long-existing instruments, well described and validated in decades of empirical research into educational psychology. Most were administered at the start of the course. The exception is the instrument quantifying emotions by participating in learning activities (described in section 3.2.5), which was administered halfway through the course. This was done to allow students sufficient experiences with the learning activities, while simultaneously avoiding the danger that an approaching exam might strongly impact learning emotions. In the subsections that follow, our data sources are described in detail to provide the response and predictor variables for our modeling. Due to the compulsory nature of the self-report surveys (part of a required individual, a statistical project in which students analyze personal disposition data), the response covers all students (except for about 15 students dropping out).

Although trace data is available for both e-tutorial systems, in this paper, we will focus on the trace data from the mathematics e-tutorial: SOWISO. In contrast to many common LMS systems like Blackboard and Desire2Learn, the SOWISO system allows full insights into all learning activities by providing complete logs of any student click, including time-stamps, in contrast to the MSL system, which limits activity reports to a limited set of predefined formats.

### 3.2.1 Course Performance Measures

The ultimate aim of the learning analytics application is to get insight, as early as possible, in which students are at risk of failing the course, to allow timely intervention. To assess who is failing the course, four course performance measures are relevant: performance in the exam, both for mathematics (MathExam) and statistics (StatsExam), and the aggregated performance in the three quizzes for both topics: MathQuiz and StatsQuiz. Because of missing good trace data for the MSL e-tutorial, see the previous section, predictive modeling will be limited to the two mathematical performance variables.

### 3.2.2 LMS Trace Data

Three digital systems have been used to organize the learning of students and to facilitate the creation of individual learning paths: the LMS BlackBoard and the two e-tutorials SOWISO and MSL. As indicated previously, this study focuses on the learning of mathematics, one of the two topics covered in the course, and subsequently, on trace data derived from the SOWISO platform. The following SOWISO trace variables relate to a different aspect of student learning:

- SOWISOMastery: the proportion of exercises in SOWISO correctly solved.
- SOWISOAttempt: the total number of attempts solving the exercises.
- SOWISOHours: total connect time in hours.
- SOWISOViews: the number of views of theory pages called for by students while solving SOWISO exercises; these pages provide a clarification of the mathematical methods.
- SOWISOSolutions: the number of complete solutions, or worked-out examples, called for by students while solving SOWISO exercises.

- SOWISOHints: the number of hints called for by students while solving SOWISO exercises.
- SOWISODiagnTests: the number of tries of the seven weekly diagnostic tests.
- SOWISODiagnTestsAv: average score in all tries of the seven weekly diagnostic tests.
- SOWISODiagnTestsMax: average best score in all tries of the seven weekly diagnostic tests.

From the MSL e-tutorial, we take one trace variable:

- MSLMastery: the proportion of exercises in MSL correctly solved.

To improve approximate normality of these data, Mastery, Hours and Hints data were log-transformed, and the number of Attempts, Views, Solutions and Diagnostic Tests were square-root transformed (the usual transform for count data). To these trace data, seven logs from the BlackBoard LMS were added:

- BBHours: total connect time in hours.
- BBClicks: the total number of clicks in BB.
- BBKhanVideo: the number of times students clicked an external link to a video on the Khan Academy website explaining a mathematical concept.
- BBOverviewLecture: the total number of times students called for the slides of the begin-of-the-week overview lecture.
- BBRecapLecture: the total number of times students called for the slides of the end-of-the-week recap lecture.
- BBOverviewLectureVideo: the total number of times students called for the taped recordings of the begin-of-the-week overview lecture.
- BBRecapLecture: the total number of times students called for the taped recordings of the end-of-the-week recap lecture.

To improve the approximate normality of the data, calling for the slides as well as recordings of the recap lectures were transformed into square roots.

### 3.2.3 SIS System Data

Our university SIS provided several further predictor variables. Standard demographic variables are Gender (with an indicator variable for female students), International (with an indicator for non-Dutch high school education), and MathMajor (with an indicator for the advanced mathematics track in high school). Distinguishing between domestic and international students is relevant, given the strong focus on statistics in the Dutch high school system (with large variations in other countries, but never as extreme as the Dutch case). The MathMajor indicator is constructed based on distinguishing prior education preparing for either sciences or social sciences. Students in the sample are from 50 different national and international high school systems, all being very different but in all cases differentiating between advanced and intermediate level math tracks (students of basic math track are not admitted in the program). The Nationality of students is available but problematic to use in any model since in 43 cases, the number of representative students is 10 or less. For that reason, we did not use nationality itself but instead included scores on six national cultural values, based on the research of Hofstede (Hofstede, 1986; Hofstede, Hofstede, & Minkov, 2010). This has been successfully applied in our previous LA research (AuthorC, 2016). Since these are national measures, all students with the same nationality are assigned the same scores, based on the research by Hofstede. These six national culture values are:

- Power distance (PDI): the extent to which less powerful members of organizations and institutions accept and expect unequal distribution of power.
- Uncertainty avoidance (UAI): society's tolerance for uncertainty and ambiguity, indicating the extent to which members of a culture feel threatened by ambiguous and uncertain situations.
- Individualism versus collectivism (IND): the degree to which individuals are integrated into groups, from loose ties between individuals and self-agency to integrated and strong, cohesive societies.
- Masculinity versus Femininity (MAS): the degree to which emotional gender roles being rather distinct (masculine) or overlapping (feminine).
- Long-term orientation (TOWVS): the degree to which societies are directed towards future rewards or the fulfillment of present needs and desires.
- Indulgence versus Restraint (IVR): the degree to which a culture allows or suppresses gratification of needs and human drives.

Finally, students were required upon entering the course to complete two diagnostic entry tests, one for mathematics (MathEntry), and one for statistics (StatsEntry).These scores were additionally added to the SIS data.

#### 3.2.4 Dispositions on Self-Regulated Learning

Learning processing and regulation strategies which shape self-regulated learning are based on Vermunt's Inventory of Learning Styles (ILS) instrument (AuthorA, 2015; Vermunt, 1996). In an extensive review of research on learning styles (Coffield et al., 2004), the ILS was found to be one of the few learning styles instruments of sufficient rigor for research applications. Our study focuses on two out of four domains of the ILS: cognitive processing strategies and metacognitive regulation strategies. The other two domains of the instrument, learning conceptions, and learning orientations, were not included, since these are more distantly related to the learning processes, and less susceptible to learning interventions. Both included domains are composed of five scales. The five processing strategies scales shaping the first domain can be 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
- Analyzing: students investigate step by step,
- Memorizing: students learn by heart.

Likewise, the five metacognitive regulation strategies that constitute the second domain describe how students regulate their learning processes. Students are positioned in the spectrum from self-regulation as the main mechanism of 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.

#### 3.2.5 Dispositional Attitudes Data

Attitudes towards learning of mathematics and statistics were assessed with the SATS instrument (AuthorA, 2007), based on the expectancy-value theory (Wigfield & Eccles, 2000). The instrument contains six quantitative methods-related attitudes:

- Affect: students' feelings concerning mathematics and statistics
- CognComp: students' self-perceptions of their intellectual knowledge and skills when applied to mathematics and statistics
- Value: students' attitudes about the usefulness, relevance, and worth of mathematics and statistics in their personal and professional life
- NoDifficulty: students' perceptions that mathematics and statistics as subjects are not difficult to learn
- Interest: students' level of individual interest in learning mathematics and statistics
- Effort: the amount of work students are willing to undertake to learn the subjects

#### 3.2.5 Dispositional Learning Emotions Data

The Control-Value Theory of Achievement Emotions (CVTAE; Pekrun 2000, 2012) 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 about an achievement activity (e.g. boredom experienced while 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, we made a selection of four scales measuring learning emotions, found to be most strongly related to course performance, from the Achievement Emotions Questionnaire (AEQ; Pekrun, Götz, Frenzel, Barchfeld, & Perry, 2011), next to Academic Control as the common antecedent of all learning emotions:

- LEnjoyment: positive, activating learning emotion,
- LAnxiety: negative, activating learning emotion,
- LBoredom: neutral, deactivating learning emotion,
- LHopelessness: negative, deactivating learning emotion,
- Academic Control: antecedent of all learning emotions.

#### 3.2.6 Dispositional Epistemic Emotions Data

While achievement emotions, described in the previous section, arise from doing learning activities, like doing homework, epistemic emotions are related to cognitive aspects of the task itself (Pekrun, 2012). Prototypical epistemic emotions are curiosity and confusion. In this study, epistemic emotions were measured with the Epistemic Emotion Scales (EES; Pekrun & Meier, 2011). That instrument includes 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.

### 3.2.7 Dispositional Goal Setting Data

The framework applied in this study is based on the common framework that distinguishes a valence dimension of goals, the approach–avoidance distinction, and a definition dimension of goals. Where that definition dimension is often operationalized as a mastery–performance distinction (Elliot & Murayama, 2008), we follow two contemporary developments: that of distinguishing two separate evaluation standards in the mastery definition, focus on the attainment of task-based as well as self-based competence, whereas the performance goal is identified with the attainment of other-based competence (Elliot, Murayama, & Pekrun, R2011), and the addition of the dimension of future potentials (Elliot, Murayama, Kobeisy, & Lichtenfeld, 2015). That results into the following eight scales:

- Task-approach goals: focus on the attainment of task-based competence,
- Task-avoidance goals: focus on the avoidance of task-based incompetence,
- Self-approach goals: focus on the attainment of self-based competence,
- Self-avoidance goals: focus on the avoidance of self-based incompetence,
- Other-approach goals: focus on the attainment of other-based competence,
- Other-avoidance goals: focus on the avoidance of other-based incompetence,
- Potential-approach goals: focus on the attainment of potential-based competence,
- Potential -avoidance goals: focus on the avoidance of potential -based incompetence.

### 3.2.8 Dispositional Help Seeking Data

Help seeking can be conceptualized as a general problem-solving strategy that allows learners to cope with academic difficulties by gaining the assistance of others. Nelson-Le Gall (1985) draws a distinction between executive help seeking and instrumental help seeking. The former refers to those instances in which the student's intention is to have someone else solve a problem or attain a goal on his or her behalf; the latter refers to seeking assistance needed for the student to solve the problem independently. Avoidance of help-seeking is a situation in which help is needed, but the student refuses to seek help. Perceived benefits of help seeking are students' beliefs about the outcomes of help-seeking activities, such as interest or learning. Also, the source of help can also be distinguished between formal and informal sources. The former refers to institutional resources such as instructors, or tutors, while the latter refers to non-institutional resources such as classmates, friends, and family members (Knapp & Karabenick, 1988). These help seeking frameworks result in the following scales (Pajares, Cheong, Oberman, 2004):

- Instrumental help seeking,
- Executive help seeking,
- Avoidance of help seeking,
- Interest as help seeking benefit,
- Learning as help seeking benefit,
- Formal vs. informal help seeking.

### 3.2.9 Dispositional Motivation and Engagement Data

The 'Motivation and Engagement Wheel' framework (Martin, 2007) includes both behaviors and thoughts, or cognitions, that play a role in learning. Both are subdivided into adaptive and maladaptive (or obstructive) forms:

- Self-Belief: adaptive cognition,
- Value of School: adaptive cognition,
- Learning Focus: adaptive cognition,
- Planning: adaptive behavior,
- Task management: adaptive behavior,
- Persistence: adaptive behavior,
- Anxiety: maladaptive cognition,
- Failure avoidance: maladaptive cognition,
- Uncertain Control: maladaptive cognition,
- Self-sabotage: maladaptive behavior,
- Disengagement: maladaptive behavior.

As a result, the four quadrants are adaptive behavior and adaptive cognitions (the 'boosters'), mal-adaptive behavior (the 'guzzlers') and obstructive cognitions (the 'mufflers').

### 3.3 Data analysis

The data analysis steps of this study are all based on linear, multivariate models, making use of hierarchical regression analysis and k-means cluster analysis. In the first step, we focused on a chain of three antecedent-consequence relationships: formative assessments (Quiz scores) being the antecedents of course performance (exam scores); tool intensity trace data (SOWISO traces) being the antecedents of formative assessment scores; and lastly, disposition data being antecedents of tool trace data. Rather than looking at these separate relationships, we could eliminate the in between stages and investigate, for instance, the role that dispositions play in a prediction model of course performance. We opted for investigating the indirect relationships, and not the direct ones, for two reasons. First, there is a timing issue: disposition data is available at the start of the course, while trace data in e-tutorials starts building from the first week on, but needs one or two weeks to settle to somewhat stable figures. At the same time, formative assessment data is not available until half way into the course, and performance data only after finishing the course. Therefore, when providing students with LA-based learning feedback in an online manner, one cannot but follow the subsequent links for timing reasons. Second, information about the separate links provides more actionable data; knowing that learning boredom has a negative impact on learning activity levels in the e-tutorial, for instance, provides more intervention options than knowing that boredom is negatively related to course performance. In this first analysis step, we use regression as a variable-oriented method to establish that our data set of dispositions has sufficient predictive power to start doing the second step.

In this second step, we switch from variable-oriented modeling to person-oriented modeling by profiling students on the basis SOWISO trace data. The aim of this profiling is to assign students to clusters of students that demonstrate similar learning behaviors. Such similarity is the basis of designing a limited number of learning interventions. This profiling was done using k-means cluster analysis, where the number of clusters was chosen as to have maximum variability in profiles without going into very small clusters. Thus, the smallest cluster contains 45 students.

Gibson & Ifenthaler (2017) highlight the following methods for applying LA applications: prediction, clustering, relationship mining, distillation of data for human judgement, and discovery via models. The focus of our contribution is on the first three of these by deriving optimal prediction models and applying clustering of students based on trace data to find relationships between these cluster compositions and their learning dispositions. In our analysis, we applied linear modeling only, after transforming variables where needed to fit linearity.

## 4. Results

In this section, we will demonstrate the existence of the chain of three antecedent – consequence links: from learning depositions to traces in learning systems; from these traces to the outcomes of formative assessment; and from the outcomes of formative assessment to course performance. Demonstrating the last two of these links is a replication of our AuthorA (2015) study, with a different class year of students, and a different learning tool. In that study, we derived that the application of LA models profits strongly from having trace data from e-tutorial systems, together with formative assessment data. Early in the course, lacking formative assessment data and trace data not yet being very representative, learning dispositions have the potential to fill the gap of lacking predictive power. After replicating these broad outcomes in the first section, we will continue with the second step of profiling students on the basis of e-tutorial trace variables, and interpreting these clusters in terms of differences in learning dispositions.

### 4.1 LA prediction models

When expressing the cycle of antecedent-consequence relationships (in reverse order), the following hierarchical regression equations are in place (beta's or standardized regression coefficients, all significant at the .001 level):

- MathExam = 0.60*MathQuiz + 0.15*StatsQuiz ($R^2$ = 0.50)
- MathQuiz = 0.50*SOWISOMastery + 0.14*MSLMastery + 0.35*SOWISOAttempts – 0.43*SOWISOSolutions ($R^2$ = 0.53)
- SOWISOMastery = 0.20*LEnjoyment + 0.18*AcadControl + 0.12*TaskAppr + 0.14*HofstedeMas + 0.09*MathMajor– 0.12*ConcreteProc –0.15*Self-sabotage ($R^2$ = 0.24)

The last equation results from a step-wise regression applying all dispositional antecedents described in the following sections.

### 4.2 Student profiling based on e-tutorial trace data

E-tutorial trace data constitutes a mixture of pure activity data (i.e., number of Attempts, connect time Hours, number of Views of theory pages, number of Solutions called for, number of Hints called for, number of Diagnostic Tests practiced) and learning outcome data (i.e., Mastery level, Average and Maximum scores in the diagnostic tests). When profiling students by these data, six clusters provide an insight into variations in observed learning approaches of students in the e-tutorial. Figure 2 depicts cluster means of the six clusters for all nine trace variables. Clusters are ordered by Mastery score, the main predictor of formative assessment scores and course performance. To include all trace variables in one figure, all variables are standardized. Differences in cluster means are strongly significant (p-values below .001), with eta squared effect sizes of 2.6% and 3.2% for gender and prior education, respectively.

**→ Insert Figure 2 about here**

**Fig. 2.** Cluster means for SOWISO trace data

The three smaller clusters represent rather unique learning approaches. Cluster 1 students strongly outperform all other students in terms of the three learning outcome variables. They spend the most

hours in SOWISO, view the most theory pages, and start the most diagnostic tests, but hardly ask for any worked-out solution. In stark contrast, Cluster 2 students spend less time in SOWISO, but do much more attempts, many of which call a full solution. At the other side of the spectrum, Cluster 6 students are by far the least active and the least productive of all clusters, with differences being smallest for the use of diagnostic tests. The three larger clusters positioned in between these extremes differ primarily in terms of overall activity, with one exception: differences in calling solutions and total attempts. Cluster 3 students mirror Cluster 2 students in this respect, with a high number of called solutions and attempts. Cluster 5 students are characterized by an opposite pattern: relative low levels of activity, but especially low levels of attempts, and called solutions. Altogether, this analysis demonstrates that there are wide variations in student behaviors and activities within the online learning system.

### 4.3 Profiles and SIS data

When relating cluster membership with SIS data, we find the first part of the explanation of why Cluster 1 students are such efficient learners, reaching high Mastery levels in SOWISO, in comparison to Cluster 2 students, who demonstrate relatively few Attempts. The greatest difference between the cluster means is in the MathMajor variable, indicating mathematics prior education at an advanced level. Approximately 53% of students in Cluster 1 have been trained at this high level compared to only 35% for the complete cohort. Next, female students are overrepresented in Cluster 1, with 60% female compared to 42% of overall proportion. Students with an international education are also overrepresented, but with smaller differences (see the left panel of Figure 3). Differences in cluster means are strongly significant (p-values below .001), with eta squared effect sizes of 2.6% and 3.2% for gender and prior education, respectively.

**→ Insert Figure 3 about here**

**Fig. 3.** Cluster composition (left panel) and cluster means for Hofstede culture scores (right panel)

The right panel of Figure 3 looks at differences in cultural traits, expressed by means of the six national Hofstede culture dimensions. Four of them signal strongly significant cluster mean differences: the Individualism versus Collectivism score, the Masculinity versus Femininity score, Long-term orientation and the Indulgence versus Restraint score (all p-values<.001, eta squared effect sizes were small, ranging between 2.1% and 2.4%). Cluster 1 students score highest on Collectivism (i.e. the prioritization of the collective society over the individual), Masculinity (characterized by a drive for achievement and success) and Restraint (characterized by a suppression of personal desires). In our sample, this combination is most common amongst students from Germanistic cultures. In contrast, Cluster 6 students score high in Femininity (characterized by reference for cooperation and modesty) and Indulgence (characterized by a free gratification of human desires), and a low score in Long-term planning (characterized by a focus on current needs and desires). These combinations are more typical for the Dutch culture. Altogether, the results of this analysis highlight that differences in cultural traits are an important influence on student behaviors.

### 4.4 Profiles and LMS data

Although an important part of students' learning activities for learning mathematics in our study took place in SOWISO, not all of them were hosted in the e-tutorial system. Additional materials, such as links to relevant Khan Academy videos, old exams to allow preparation for the final written exam, and weekly lecture slides and recordings are available in the BlackBoard LMS. The question of

whether students tend to substitute or complement their use of the e-tutorial with the use of these other learning aids can be answered by looking into differences between cluster means in regards to BlackBoard trace data, as visible in Figure 4 (trace data standardized to account for differences in scales).

→ **Insert Figure 4 about here**

**Fig. 4.** Cluster means for BlackBoard LMS trace data

The answer is straightforward: BlackBoard use intensity, as signaled by the cluster means, is ordered in exactly the same way as the SOWISO use intensity across each cluster. The relatively efficient way of learning of Cluster 1 students is apparent from having the same Hours and Clicks, but viewing more videos, slides and recordings than Cluster 2 students. Another deviation from the dominant pattern that higher clusters show uniformly less activity is in the use of recap lecture-related learning materials. In this regard, Cluster 2 students are less strong in activities that finish the weekly learning cycle, as they are in the early in the week learning activities. All cluster mean differences are significant beyond the .001 level, and eta squared effect sizes range from 3.8% (use of recap lecture materials) to 11.5% (clicks in BlackBoard).

4.5 Profiles and learning styles

Students' approaches to learning frameworks distinguish between prototypical preferred learning approaches in specific contexts. Deep learning is one approach, where students search for true understanding by making connections with concepts previously learned. The opposite of deep learning is surface or stepwise learning, where students are inclined to learn by heart. In these frameworks, it is often assumed that these types are exclusive: one cannot be a deep and surface learner at the same time. Figure 5 suggests that this is not the case. Only Cluster 2 students score low on the two deep learning scales, Critical processing and Relating and structuring, but high on the two surface learning scales, Analyzing and Memorizing. Cluster 1 students score relatively high on all scales. Four of the clusters, and with it the large majority of students, seem to be Concrete learners, who are characterized by searching to apply their knowledge. Significant differences beyond levels of .001 exist for surface learning scales Memorizing and Analyzing, with however small eta squared effect sizes: 4.6% and 2.4%.

→ **Insert Figure 5 about here**

**Fig. 5.** Cluster means for cognitive processing strategies of ILS, Inventory Learning Styles

Within the student approaches to learning framework, cognitive learning processing strategies are assumed to be linked with metacognitive learning regulation strategies: deep learners apply self-regulation, while surface learners depend on external regulation. Although Cluster 1 students score higher than the other clusters on Self-regulation of learning process and learning content and these students also score lowest on the Lack of regulation scale, all clusters score highest on one of the external regulation scales: External regulation of learning content. Differences between cluster means, except for External regulation of learning content, are strongly significant, but eta squared effect sizes are small: between 1.7% and 2.7%.

4.6 Profiles and learning attitudes

Larger effect sizes are visible when we consider learning attitudes of students. Most students enter the course with very positive attitudes. Only the attitude score for NoDifficulty is slightly below the neutral benchmark of four, which indicates that students expect (some) difficulties in mastering mathematics and statistics. Remarkably, all clusters regard the topics as equally difficult. Indeed, this is one of the few scales without mean differences. In all other attitude facets, Affect, Cognitive Competence, Value, Interest and Effort, Cluster 1 students score highest, Cluster 6 students score lowest, with significance beyond .001, and eta squared effect sizes between 2.9% and 5.3%.

### 4.7 Profiles and epistemic learning emotions

Except for the Surprise and Curiosity, the two most neutrally valence epistemic emotions, large cluster mean differences are visible in positive and negative epistemic emotions, with significance levels beyond .001 (see Figure 6). The most striking aspect of the differences is that the order of the clusters in the negative emotions Confusion and Anxiety deviates from the 'natural' order. Cluster 2 and Cluster 4 students score relatively high compared to Cluster 3 and Cluster 5 students. Eta squared effect sizes are modest and range from 1.9% (Confusion, Enjoyment) to 2.5% (Frustration, Anxiety).

**→ Insert Figure 6 about here**

**Fig. 6.** Cluster means for epistemic learning emotions

### 4.8 Profiles and learning achievement emotions

All cluster mean differences in achievement emotions, related to doing specific learning activities rather than the general nature of the topic to be learned, are larger than those in epistemic emotions. All are significant beyond .001; eta squared effect sizes are 4.5% for Academic control, 3.6% for learning Anxiety, 6.4% for learning Boredom, 5.5% for learning Helplessness, and 6.3% for learning Enjoyment: see Figure 7. Also different from the epistemic emotions: Cluster 1 students achieve the consistently the 'best' scores (high on academic control and positive emotion enjoyment, low on the negative emotions), with Cluster 6 students scoring 'worst', and the other clusters taking an intermediate position.

**→ Insert Figure 7 about here**

**Fig. 7.** Cluster means for achievement learning emotions

### 4.9 Profiles and goal setting behavior

Cluster means for achievement goals are consistently ordered by cluster number: lower cluster numbers correspond with higher levels of goal attainment, be it that levels of self-based goal attainment, doing better than one did in the past, are basically equal. With regard to the other-based goal attainments, doing better than other students, it is only Cluster 1 that stands out. Cluster mean differences of the two Task-based goals, being successful in the task, and the two Potential-based goals, doing better in the future, are significant beyond .001; eta squared effect sizes range from 1.8% (PAV) to 4.0% (PAP).

### 4.10 Profiles and help seeking behavior

Help-seeking behavior of students between different clusters is very similar: all students seek help first for instrumental reasons (i.e. in order to learn). Scores for help seeking out of interest are neutral,

as are the scores for formal versus informal channels of help. The single difference between the clusters is in Executive help seeking, using others to help you solve the task, where Cluster 1 students score much lower than all other clusters, and in Avoidance of help seeking, where Cluster 6 score higher than all other students (see Figure 8). Cluster mean differences of Executive help seeking and Avoidance of help seeking are significant beyond .001; eta squared effect sizes are 3.4% and 1.7%, respectively.

→ **Insert Figure 8 about here**

**Fig. 8.** Cluster means for help seeking behavior

4.11 Profiles and the motivation and engagement wheel

Adaptive motivation and engagement constructs exhibit cluster mean differences in line with the general tendency of lower ordered clusters to contain students with more adaptive dispositions. This is most clearly visible in the Cluster 1 scores, which is higher than any other cluster in all three adaptive cognitions, and one of the adaptive behaviors: Persistence (see Figure 9). All differences except Self-belief and Valuing school are significant beyond .001; eta squared effect sizes are between 2.1% and 5.0%, the case of Persistence.

→ **Insert Figure 9 about here**

**Fig. 9.** Cluster means for adaptive scales of the motivation and engagement wheel

Maladaptive cognitions and behaviors exhibit, as expected, the opposite pattern: the lower numbers clusters are described by lower cluster means, with again the difference between Cluster 1 students and all other students being largest. Mean differences in the two maladaptive cognitions Anxiety and Failure avoidance do not reach .001 significance level, as the other constructs do. Eta squared effect sizes are 2.3% for Uncertain control, 2.6% for Disengagement, and 4.2% for Self-sabotage.

4.12 Profiles and student performance

In this last subsection, we close the chain of antecedent-consequence relationships by linking the profiles directly to student performance in mathematics: the Exam and Quiz scores. Performance differences accentuate the good performance of Cluster 1 students and poor performance of Cluster 6 students, with small differences between the central clusters: see Figure 10. Quiz scores exhibit larger cluster differences than exam scores, as demonstrated by the eta squared effect sizes: 8.3% and 23.2% respectively, with significance levels below .001.

→ **Insert Figure 10 about here**

**Fig. 10.** Cluster means for mathematics performance

5 Discussion

The first outcome section confirms results of previous research on the role of formative assessment in learning and LA applications. Formative assessment outcomes constituted crucial feedback to learners about where they stand in their learning process (Spector et al., 2016), and constituted the most important predictors in LA-based prediction equations (AuthorA, 2015). Next, formative assessment outcomes were well explained by trace variables of student activity in e-tutorials. In the third step, we

found a somewhat weaker relationship: learning dispositions explained about a quarter of the variation in student mastery levels in the practicing mode of the e-tutorial. We looked in-depth at the relationships between learning dispositions in the following sections after making student profiles based on e-tutorial trace data. The clustering application resulted in six different profiles of tool activity that mainly differ in two respects: overall activity level and the use of worked-out solutions. Cluster 2 and Cluster 4 students called for many worked-out solutions, and by doing so, also scored high in the number of Attempts, whereas Cluster 1 and Cluster 5 students demonstrated an opposite pattern. The importance of the use of worked-out examples in distinguishing different learning approaches corresponds with the outcomes of previous research by the authors (Nguyen et al., 2016), where not only the frequency of using worked-out examples but also the timing of the use (early or late in the learning cycle) was investigated.

The selection of learning dispositions incorporated in this study has been based on the role the dispositions play in main stream learning theory, and how connected they are with learning interventions. The underlying motive being the wish to design models that are both predictive and actionable. Would we have focused solely on the goal of prediction, an alternative choice for learning dispositions, such as Deakin Crick's learning power (Deakin Crick & Goldspink, 2014; Shum & Crick, 2012), might have been the better choice. However, at the cost of the potential of educational interventions (Deakin Crick & Goldspink, 2014). As a concrete example of the link between DLA and learning interventions, we will focus on the case of learning strategies, and learning styles based on preferred learning strategies (see also Gašević et al., 2017, for a description of this case). Both Hattie (2009, 2012) and Coffield et al. (2004) call on to be careful in the selection of instruments and types of interventions, but the instrument we adopted from the Vermunt (1996) study is one of the few that has the potential of sound applications: '*On the grounds of robustness and ecological validity, we recommend that the concepts … of deep, surface and strategic approaches to learning, and by Vermunt … of meaning-directed, application-directed and reproduction-directed learning styles, be adopted for general use in post-16 learning*' (Coffield et al., 2004, p. 134). Next, although not as effective as other types of interventions, such as the provision of feedback, interventions based on learning styles score in the range of medium sized effect sizes (Hattie, 2009, p. 195). Potential interventions can be of different types, and best described with Vermunt's (1996) terms of constructive and destructive friction (see also Coffield et al., 2004). When the content to be learned is challenging, and substantial cognitive frictions make learning demanding, interventions should focus on the avoidance of destructive frictions. Allowing the student to apply the individual preferred or dominant learning style by supporting different learning strategies is an example of such intervention focusing on avoiding destructive frictions. The other type of intervention is based on constructive friction: in cases where less cognitive barriers exist, there is space to improve the use of learning strategies by the student, moving from more reproduction-oriented styles to meaning-directed styles (or '*working at +1 beyond where the student is working now*', Hattie, 2012, p. 95). For both of these types of interventions, profiling information of students and the ability to support multiple learning strategies, are crucial.

If we include the role of dispositions in the analysis of the use of worked-out examples, we see that Cluster 2 and Cluster 4 students (i.e. those who used worked-out examples more frequently) differ in two main respects from the other students. First, they have the lowest scores on the two deep learning processing strategies: Critical processing, and Relating. Next, they differ from the other students regarding having highest scores on the epistemic Anxiety scale (i.e. related to the cognitive aspect of the learning task). That is different from the achievement Anxiety scale (i.e. related to course progression), which is dominated by Cluster 6. Thus, passive use of the e-tutorial can be explained by

anxiety for mathematics and statistics as academic topics, in combination with the inability to apply deep learning processing strategies. Rather than solving the problems themselves, these students walk through the solutions the system provides. Other studies distinguish categories of learning emotions in line with the classification of epistemic versus achievement type. For instance, Järvenoja and Järvela (2005) distinguish five different emotions when learning in technology enhanced environments: self, task, performance, context and social. Their task emotion is congruent to epistemic emotion, while performance emotion is overlapping achievement emotion. Remarkably, task and performance emotions were dominated by self and context emotions regarding frequency of appearance (Järvenoja & Järvela, 2005).

The students most clearly at risk are those in Cluster 6. Their activity levels in the e-tutorial system are by far the lowest of all students. At the same time, their prior education is at an average level, which indicates they have the capacity to participate on par with their more active peers. At the same time, males and domestic students in Cluster 6 are overrepresented. When dispositional aspects were added to the model, we found that Cluster 6 students are Concrete processors who score low on surface learning and all learning regulation scales. Relative to the other clusters, these students are extremely bored with their learning materials and seem to lack the goal-setting behavior relevant for learning.

If this study had been limited to predictive modeling using trace and SIS data only, the outcome of our analysis would have merely highlighted that domestic, male students are most at risk. This finding would have been specific, but not actionable, as descriptors such as gender and nationality do not lend much to intervention. However, that story changes when adding the dispositional descriptors. Knowing that these students are easily bored, and tend to learn by applying a concrete approach, does constitute actionable feedback with multiple intervention options. For instance, one potential intervention is enriching the learning materials to better support learners with a concrete processing approach. A second consideration is training learners not to depend on one single processing strategy, but rather to apply multiple strategies depending on the context.

The merits of clustering students by revealed learning activities and comparing these clusters about learning dispositions is not limited to discovering students at (immediate) risk. This model can be similarly applied to the scaffolding of other students, as demonstrated in the marked differences between Cluster 1 and Cluster 2 students. Both clusters are populated by very active and highly motivated students. The main difference is that Cluster 1 students possess more or less the ideal dispositions for studying in a student-centered program designed according to the problem-based learning principles. They are deep-learners who can self-regulate both learning content and learning processes, with high affect and cognitive competence levels and low levels of negatively valenced epistemic and achievement emotions. Cluster 2 students demonstrate opposite dispositions: lowest levels of all students of Critical processing and Relating (the two scales shaping deep learning), the highest level of all students of the most surface oriented scale, Memorizing, relative high levels of epistemic emotions Confusion and Anxiety, the highest level of all students of Executive help-seeking. These maladaptive dispositions mirror themselves in ‘over-activity’ in the e-tutorial for Cluster 2. They demonstrate a high number of Attempts, with many of them looking at complete Solutions. Due to this very high activity level, any LA based ‘traffic light system’ for signaling students at risk would miss these students. In the short term, after all, they are not at risk, given that their maladaptive dispositions are amply compensated by their high activity levels. In the long run, however, these students might be in danger, due to the external scaffolding of learning being dismantled over time in light of the expectation that mature students can self-regulate their study in a deep learning manner. Being able to signal these behaviors in an early stage to identify potential

interventions is of crucial importance to prevent these maladaptive dispositions from developing into relative stable and difficult-to-change preferred approaches to learning.

One of the main contributions of this study is that learning behaviors of students show marked differences, e.g. regarding the use of worked-out examples and that these marked differences are associated with differences in learning dispositions. Deep learners who are strong in Critical processing and Relating are less inclined to use worked examples than surface learners. But the most important contribution relates the application of DLA: the crucial merit of adding dispositions to LA applications is that it brings actionable data, as becomes clear from the above learning processing strategies example. Designing learning interventions directed at changing surface learning approaches into more deep learning approaches has more potential than just telling students they are using more worked out examples than the best students in their class are doing. As the next step in our research project, we intend to broaden the scope of learning behaviors included in our DLA research: beyond the use of worked examples, also include the use of hints in solving exercises.

In this study, we opted for clustering students by trace data of LA type and demonstrated that these clusters bring about differences in levels of dispositional variables. The main goal for following this procedure was to provide evidence of the merits of DLA beyond applying LA: once our LA application can distinguish different clusters of students that learn in different ways, combining these outcomes with disposition data provides a psychological perspective on these differences, and links to educational interventions. From an intervention perspective, an alternative clustering approach might be even more attractive: cluster by learning dispositions, and investigate whether these clusters come with meaningful differences in learning processes (as measured by trace variables) and learning outcomes. To the extent this analysis proves itself to be fruitful, it will allow for interventions that take place very early in the learning process. And allow designing each individual student's learning process as a series of constructive frictions, rather than a mixture of constructive and destructive frictions.

## 6 Limitations and Conclusions

The finding that self-reported disposition data are an important data source in this LA application does not come with the conjecture that these data are true, unbiased accounts of not directly observable dispositions. The scientific debate on whether self-reports, or trace-data, better approximate true levels of learning dispositions (Gasevic et al., 2017) is not touched upon in this paper. The only criterion we have taken into consideration is that of predictive power, rather than unbiasedness. In fact, we even profit from the fact that some self-report data tend to be biased: relatively high levels of inactivity of Cluster 6 students may partly be explained by their (too) optimistic view about managing to pass this course. For instance, their NoDifficulty score is no higher than that of any other cluster. By connecting self-report data and student activity trace data, however, DLA studies can contribute in the undertaking to merge both approaches to measuring learning (Gasevic et al., 2017).

The limitations of our analysis lie in the specificity of the context. The availability of a broad range of disposition measurements with the full response is exceptional; in that sense, this study serves primarily as a showcase of what can be done with rich disposition data, where the way of getting such rich data may not be easily generalizable. The most important facet of the richness of the data is having a full response of all students, where typically response rates of self-report surveys tend to be low and, typically, the missed cases represent students low in motivation and high in drop-out risk,

exactly those students it is crucial to have data about. It is, however, our experience that providing students with feedback from these surveys (rather than limiting the use of the data to predictive modeling only) has a favorable impact on response rates.

Another contextual limitation is to be found in the instructional design: the small group aspect of PBL with intensive student-tutor contact enables pedagogical interventions to take the form of discussing LA generated feedback in these private contacts, where other instructional designs may need to find different forms of intervention. At the same time, the easy interventions in tutor-student contacts come at a cost: tutors will act in different ways upon this information, and most importantly, their interventions take place in the tutorial group sessions and are not laid down, limiting the possibility to investigate their effect.

Nonetheless, we have demonstrated in this study the strong potential for learning dispositions to be used in combination with learning analytics trace data to provide better predictions and intervention handles for students at risk of failure in both the short and long term. Although the feedback function of informing students about the outcomes of LA-based prediction models is one of the most efficient interventions (Hattie, 2009), other interventions that focus on students' learning dispositions do have an effect on achievement, such as improving study skills. Therefore, we encourage learning analytics research to combine the predictive power of formative assessment and the strong links to interventions of learner dispositions to truly help and support our learners to succeed.

References

Buckingham Shum, S., & Crick, R. D. (2012). Learning dispositions and transferable competencies: pedagogy, modelling and learning analytics. In S. Buckingham Shum, D. Gasevic, & R. Ferguson (Eds.), *Proceedings of the 2nd international conference on learning analytics and knowledge* (pp. 92–101). New York, NY: ACM. doi: 10.1145/2330601.2330629

Buckingham Shum, S., & Ferguson, R. (2012). Social Learning Analytics. *Journal of Educational Technology & Society, 15*(3), 3-26. Doi: 10.1145/2330601.2330616

Coffield F., Moseley D., Hall E., & Ecclestone K. (2004). *A Critical Analysis of Learning Styles and Pedagogy in post-16 learning. A systematic and critical review*. London, England: Learning & Skills Research Centre.

Conde, M. Á., & Hernández-García, Á. (2015). Learning analytics for educational decision making. *Computers in Human Behavior, 47*, 1-3. Doi: 10.1016/j.chb.2014.12.034

Deakin Crick, R. & Goldspink, C. (2014). Learner Dispositions, Self-Theories and Student Engagement. *British Journal of Educational Studies, 62*, 19-35. doi: 10.1080/00071005.2014.904038

Elliot, A.J. & Murayama, K. (2008). On the Measurement of Achievement Goals: Critique, Illustration, and Application, *Journal of Educational Psychology, 100*, 613–628. doi: 10.1037/0022-0663.100.3.613

Elliot, A., Murayama, K., Kobeisy, A., & Lichtenfeld, S. (2015). Potential-based achievement goals, *British Journal of Educational Psychology, 85*, 192–206. doi: 10.1111/bjep.12051

Elliot, A., Murayama, K., & Pekrun, R. (2011). A 3X2 Achievement Goal Model. *Journal of Educational Psychology*, *103*(3), 632– 648. doi: 10.1037/a0023952

Author B. (2016). [details removed for peer review].

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

Gašević ,D., Jovanović, J., Pardo, A., & Dawson, S. (2017). Detecting learning strategies with analytics: Links with self-reported measures and academic performance, *Journal of Learning Analytics*, (in press), https://goo.gl/RD4pwT.

Gibson, D. C., & Ifenthaler, D. (2017). Preparing the next generation of education researchers for big data in higher education. In B. Kei Daniel (Ed.), *Big data and learning analytics: Current theory and practice in higher education* (pp. 29–42). Cham: Springer International Publishing. doi: 10.1007/978-3-319-06520-5_4

Hattie, J. (2009). *Visible Learning: A synthesis of over 800 meta-analyses relating to achievement*. New York: Routledge.

Hattie, J. (2012). *Visible Learning for Teachers: Maximizing impact on learning*. London and New York: Routledge.

Hofstede, G. (1986). Cultural differences in teaching and learning. *International Journal of Intercultural Relations*, *10*, 301-320. doi: 10.1016/0147-1767(86)90015-5

Hofstede, G., Hofstede, G. J., & Minkov, M. (2010). *Cultures and Organizations: Software of the Mind* (3rd ed.): McGraw-Hill.

Ifenthaler, D. (2015). Learning Analytics: Benefits and Challenges for Higher Education. In *Food For Thought, The Academic Eye*, by The Council on Business & Society. https://councilcommunity.com/2015/05/23/learning-analytics-benefits-and-challenges-for-higher-education/

Järvenoja, H. & Järvela, S. (2005). How students describe the sources of their emotional and motivational experiences during the learning process: A qualitative approach. *Learning and Instruction*, *15*, 465-480.

Kirschner, P. A. (2017). Stop propagating the learning styles myth. *Computers & Education*, *106*, pp. 166-171. doi: org/10.1016/j.compedu.2016.12.006

Knapp, J. R., & Karabenick, S. A. (1988). Incidence of formal and informal academic help-seeking in higher education. *Journal of College Student Development*, *29*(3), 223–227.

Lehmann, T., Hähnlein, I., & Ifenthaler, D. (2014). Cognitive, metacognitive and motivational perspectives on preflection in self-regulated online learning. *Computers in Human Behavior*, *32*, 313-323. doi: 10.1016/j.chb.2013.07.051

Martin, A. J. (2007). Examining a Multidimensional Model of Student Motivation and Engagement Using a Construct Validation Approach, *British Journal of Educational Psychology*, *77*(2), pp. 413-440. doi: 10.1348/000709906X118036

Author C. (2016). [details removed for peer review].

Narciss, S. (2008). Feedback strategies for interactive learning tasks. In J. M. Spector, M. D. Merrill, J. J. G. van Merrienboer & M. P. Driscoll (Eds.), *Handbook of Research on Educational Communications and Technology* (3 ed., pp. 125-144). Mahaw, NJ: Lawrence Erlbaum Associates.

Narciss, S., & Huth, K. (2006). Fostering achievement and motivation with bug-related tutoring feedback in a computer-based training for written subtraction. *Learning and Instruction*, *16*(4), 310-322. doi: 10.1016/j.learninstruc.2006.07.003

Nelson-Le Gall, S. (1985). Help-seeking behavior in learning. *Review of Research in Education*, *12*(1), 55–90.

Author D. (2016). [details removed for peer review].

Author A. (2016). [details removed for peer review].

Pajares, F. , Cheong, Y.F., Oberman, P. (2004). Psychometric Analysis of Computer Science Help-Seeking Scales, *Educational and Psychological Measurement*, *64*(3), 496-513. doi: 10.1177/0013164403258447

Pekrun, R. (2000). A social-cognitive, control-value theory of achievement emotions, in Motivational psychology of human development: Developing motivation and motivating development (pp. 143–163). New York, NY US: Elsevier Science

Pekrun, R. (2012). Emotions as drivers of learning and cognitive development, in Rafael A. Calvo & Sidney K. D'Mello (eds.), *New perspectives on affect and learning technologies* (pp. 23–39). New York: Springer. doi: 10.1007/978-1-4419-9625-1_3

Pekrun, R. , Götz, T., Frenzel, A.C., Barchfeld, P., & Perry R.P. (2011). Measuring emotions in students' learning and performance: The Achievement Emotions Questionnaire (AEQ), *Contemporary Educational Psychology*, *36*, 36–48. doi: 10.1016/j.cedpsych.2010.10.002

Pekrun, R. & Meier, E. (2011).*Epistemic Emotion Scales (EES)*. Unpublished manuscript, Department of Psychology, University of Munich, Munich, Germany.

Author B. (2017). [details removed for peer review].

Author B. (2014). [details removed for peer review].

Spector, J. M., Ifenthaler, D., Samspon, D., Yang, L., Mukama, E., Warusavitarana, A., Lokuge Dona, K., Eichhorn, K., Fluck, A., Huang, R., Bridges, S., Lu, J., Ren, Y., Gui, X., Deneen, C. C., San Diego, J., & Gibson, D. C. (2016). Technology Enhanced Formative Assessment for 21st Century Learning. *Educational Technology & Society*, *19*(3), 58–71.

Siemens, G. (2013). Learning Analytics: The Emergence of a Discipline. *American Behavioral Scientist*, *57*(10), 1380-1400. doi: 10.1177/0002764213498851

Author A. (2013). [details removed for peer review].

Author A. (2007). [details removed for peer review].

Author A. (2015). [details removed for peer review].

Author A. (2017a). [details removed for peer review].

Author A. (2017b). [details removed for peer review].

Tobarra, L., Robles-Gómez, A., Ros, S., Hernández, R., & Caminero, A. C. (2014). Analyzing the students' behavior and relevant topics in virtual learning communities. *Computers in Human Behavior*, *31*, 659-669. doi: 10.1016/j.chb.2013.10.001

Vermunt, J.D. (1996). Metacognitive, cognitive and affective aspects of learning styles and strategies: A phenomenographic analysis, *Higher Education*, *31*, 25–50. doi: 10.1007/BF00129106

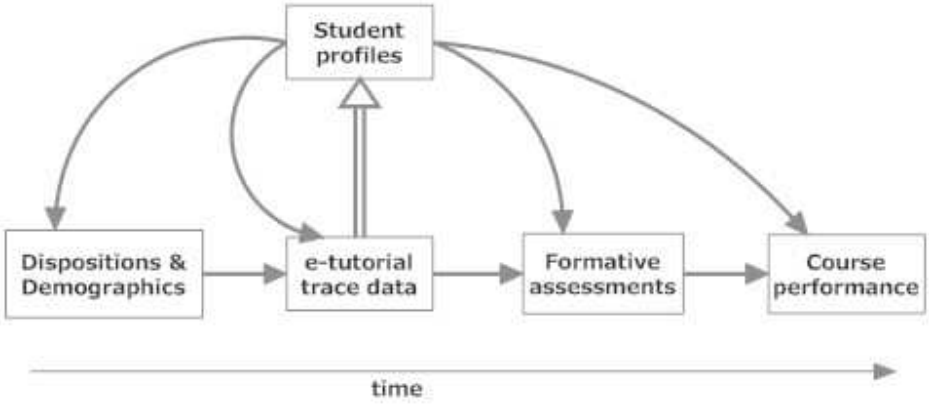
Xing, W., Guo, R., Petakovic, E., & Goggins, S. (2015). Participation-based student final performance prediction model through interpretable Genetic Programming: Integrating learning analytics, educational data mining and theory. *Computers in Human Behavior*, *47*, 168-181. doi: 10.1016/j.chb.2014.09.034

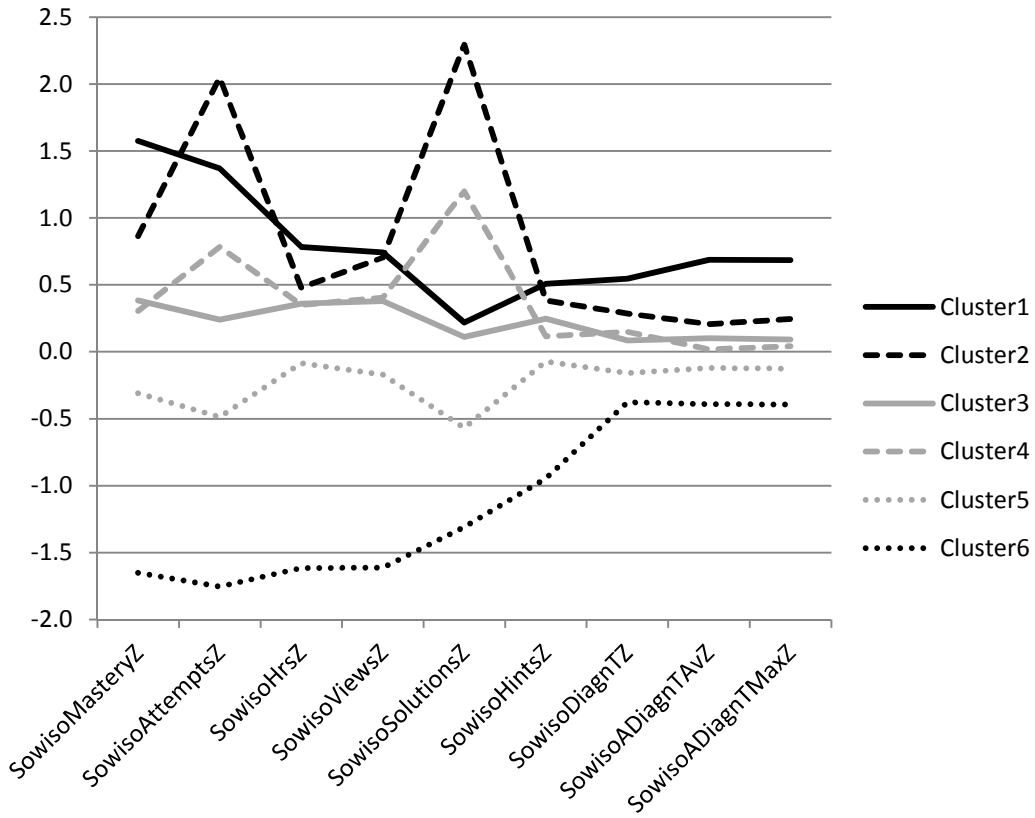
Williams, A., Sun, Z., Xie, K., Garcia, E., Ashby, I., Exter, M., Largent, D., Lu, P., Szafron, D., Ahmed, S., Onuczko, T., Smith, J., Tempelaar, D. T., Bitting, K. S., Olcott Marshall, A., Christensen, E., Tseng, H., & Walsh, J. (2016). Flipping STEM. In L. Santos Green, J. Banas, R. Perkins (Eds.), *The Flipped College Classroom, Conceptualized and Re-Conceptualized, Part II* (pp. 149-186). Switzerland: Springer International Publishing. doi: 10.1007/978-3-319-41855-1_8

Wigfield, A. & Eccles, J. S. (2000). Expectancy -- Value Theory of Achievement Motivation, *Contemporary Educational Psychology*, *25*, 68-81. doi: 10.1006/ceps.1999.1015

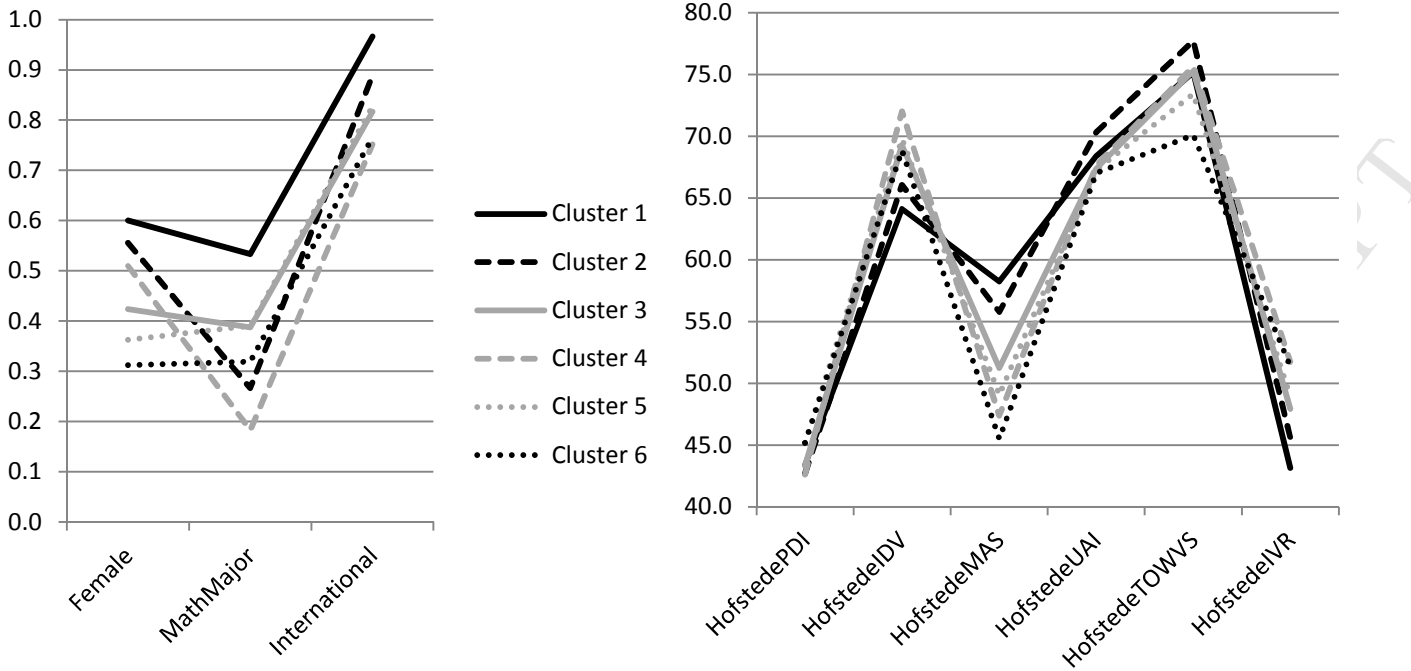
Winne, P. H. (2013). Learning strategies, study skills and self-regulated learning in postsecondary education. In M. B. Paulsen (Ed.), *Higher education: Handbook of theory and research, Volume 28* (pp. 377–403). Netherlands, Dordrecht: Springer. doi: 10.1007/978-94-007-5836-0_8

Zhou, M. & Winne, P.H. (2012). Modeling academic achievement by self-reported versus traced goal orientation. *Learning and Instruction*, *22*, 413–419. doi: 10.1016/j.learninstruc.2012.03.004



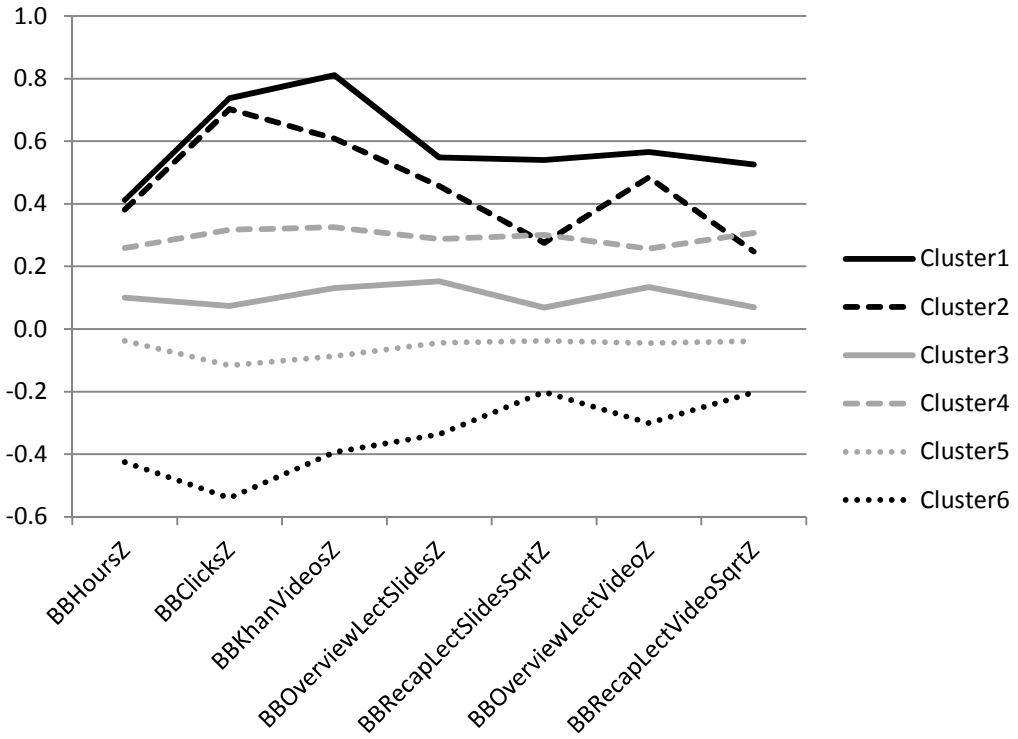


| | SowisoMasteryZ | SowisoAttemptsZ | SowisoHrsZ | SowisoViewsZ | SowisoSolutionsZ | SowisoHintsZ | SowisoDiagnTZ | SowisoADiagnTAvZ | SowisoADiagnTMaxZ |
|---|---|---|---|---|---|---|---|---|---|
| Cluster1 | 1.5754 | 1.3699 | .7832 | .7432 | .2189 | .5081 | .5472 | .6885 | .6860 |
| Cluster2 | .8652 | 2.0489 | .4782 | .7047 | 2.2944 | .3849 | .2846 | .2078 | .2446 |
| Cluster3 | .3841 | .2414 | .3599 | .3789 | .1114 | .2479 | .0844 | .1006 | .0926 |
| Cluster4 | .3059 | .7841 | .3501 | .4044 | 1.2004 | .1147 | .1486 | .0188 | .0407 |
| Cluster5 | -.3090 | -.4863 | -.0851 | -.1703 | -.5681 | -.0729 | -.1590 | -.1213 | -.1267 |
| Cluster6 | -1.6518 | -1.7550 | -1.6150 | -1.6140 | -1.3095 | -.9451 | -.3776 | -.3900 | -.3930 |

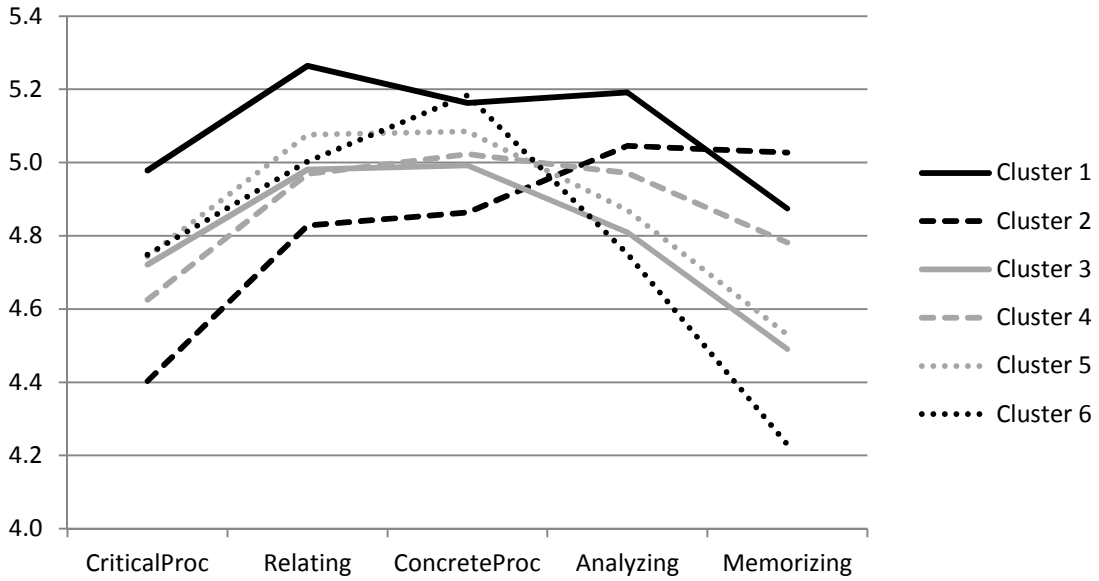


| | Female | MathMajor | International |
|---|---|---|---|
| Cluster 1 | 0.6 | 0.533333 | 0.966667 |
| Cluster 2 | 0.555556 | 0.266667 | 0.888889 |
| Cluster 3 | 0.423823 | 0.387812 | 0.817175 |
| Cluster 4 | 0.509804 | 0.183007 | 0.751634 |
| Cluster 5 | 0.362676 | 0.390845 | 0.827465 |
| Cluster 6 | 0.312057 | 0.319149 | 0.765957 |

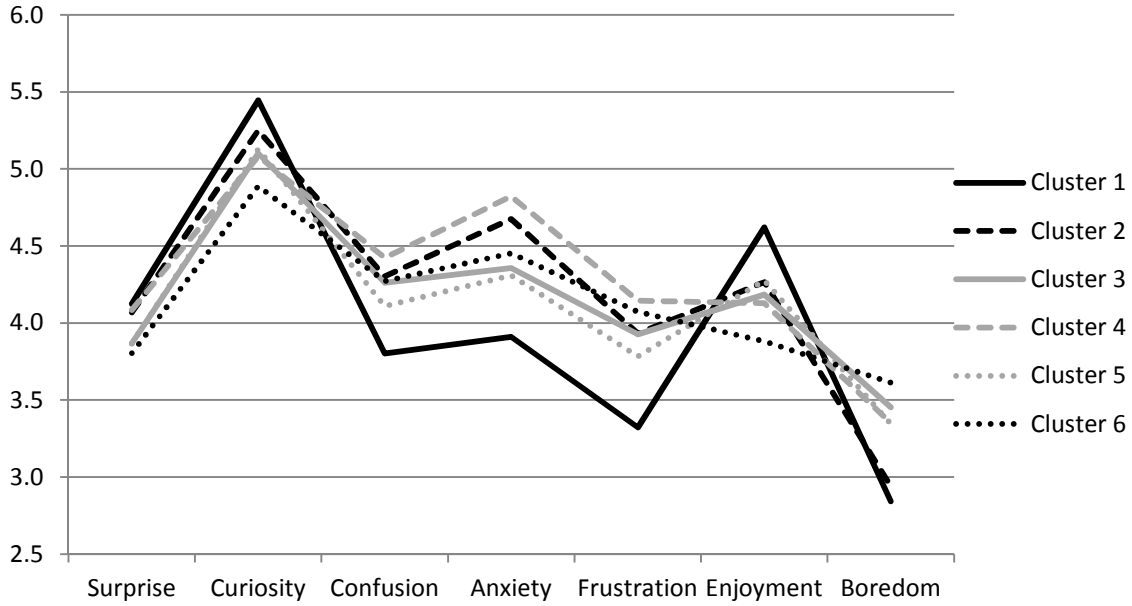
| Cluster | Nu | HofstedePI | HofstedeID | HofstedeM/ | HofstedeUA | HofstedeTC | HofstedeIVR |
|---|---|---|---|---|---|---|---|
| Cluster 1 | 43.38983 | 64.10169 | 58.22034 | 68.38983 | 75.16373 | 43.15104 | |
| Cluster 2 | 42.68889 | 66.04444 | 55.77778 | 70.33333 | 77.70501 | 45.62004 | |
| Cluster 3 | 43.30362 | 69.26462 | 51.24234 | 67.37604 | 75.2709 | 47.91551 | |
| Cluster 4 | 42.61842 | 72 | 47.36184 | 67.63158 | 75.64907 | 51.72707 | |
| Cluster 5 | 45.1773 | 69.76241 | 49.0461 | 67.2766 | 73.40122 | 48.93125 | |
| Cluster 6 | 45.17021 | 68.84397 | 45.51773 | 67.02128 | 70.09129 | 51.38013 | |



| | BBHoursZ | BBClicksZ | BBKhanVid | BBOverviev | BBRecapLe | BBOverviev | BBRecapLectVideoSqrtZ |
|---|---|---|---|---|---|---|---|
| Cluster1 | 0.412662 | 0.737072 | 0.811439 | 0.547669 | 0.540453 | 0.565131 | 0.525255 |
| Cluster2 | 0.381809 | 0.702614 | 0.608386 | 0.457458 | 0.275175 | 0.484587 | 0.247279 |
| Cluster3 | 0.100662 | 0.073462 | 0.130506 | 0.152278 | 0.068412 | 0.133633 | 0.069307 |
| Cluster4 | 0.258603 | 0.316802 | 0.325414 | 0.287627 | 0.301151 | 0.256546 | 0.307322 |
| Cluster5 | -0.03729 | -0.11651 | -0.08667 | -0.0443 | -0.03776 | -0.04458 | -0.03921 |
| Cluster6 | -0.42569 | -0.53967 | -0.39382 | -0.3365 | -0.20181 | -0.3006 | -0.2028 |

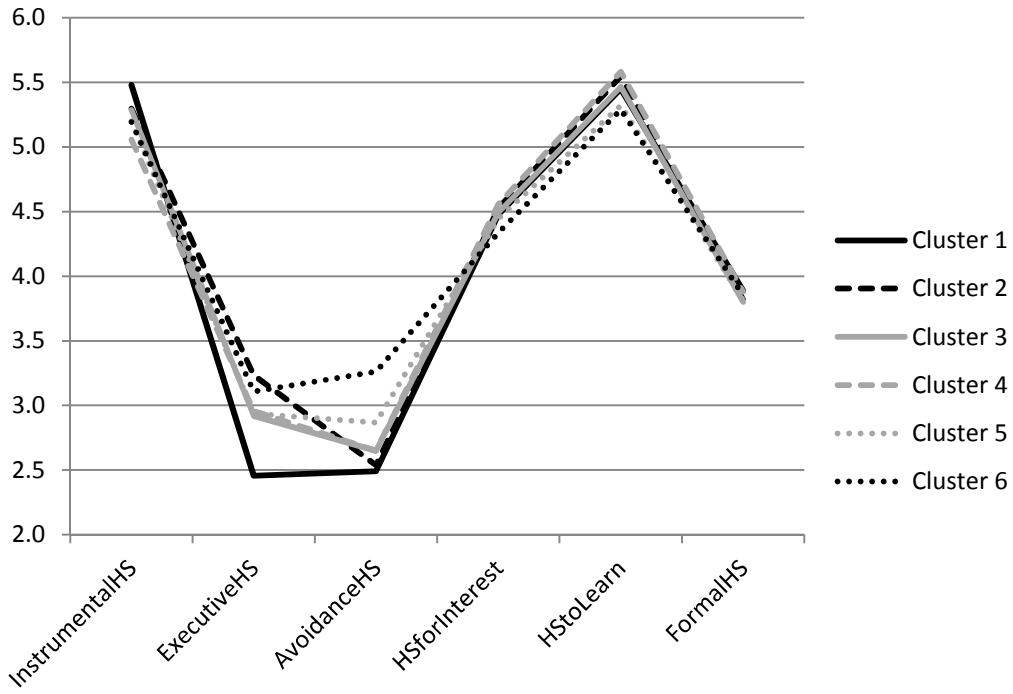


| | CriticalProc | Relating | ConcretePr | Analyzing | Memorizing |
|---|---|---|---|---|---|
| Cluster 1 | 4.978814 | 5.263923 | 5.162712 | 5.19209 | 4.874576 |
| Cluster 2 | 4.403409 | 4.827922 | 4.863636 | 5.045455 | 5.027273 |
| Cluster 3 | 4.721347 | 4.980761 | 4.991977 | 4.809933 | 4.490544 |
| Cluster 4 | 4.625 | 4.968571 | 5.022667 | 4.971111 | 4.781333 |
| Cluster 5 | 4.743659 | 5.076087 | 5.084783 | 4.869565 | 4.52971 |
| Cluster 6 | 4.748134 | 5.003198 | 5.183582 | 4.751244 | 4.229851 |

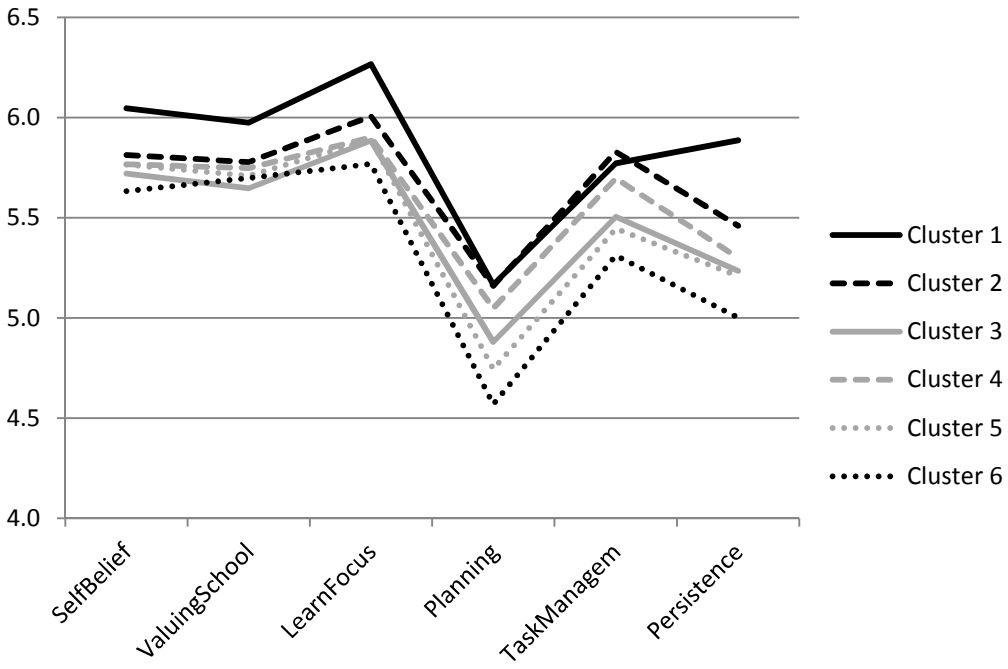


| | Surprise | Curiosity | Confusion | Anxiety | Frustration | Enjoyment | Boredom |
|---|---|---|---|---|---|---|---|
| Cluster 1 | 4.124294 | 5.446328 | 3.80226 | 3.909605 | 3.322034 | 4.621469 | 2.841808 |
| Cluster 2 | 4.068182 | 5.25 | 4.30303 | 4.674242 | 3.931818 | 4.265152 | 2.939394 |
| Cluster 3 | 3.866285 | 5.100287 | 4.260745 | 4.356256 | 3.927412 | 4.185291 | 3.452722 |
| Cluster 4 | 4.084444 | 5.082222 | 4.422222 | 4.822222 | 4.144444 | 4.128889 | 3.351111 |
| Cluster 5 | 3.865455 | 5.128485 | 4.110303 | 4.309091 | 3.784242 | 4.275152 | 3.344242 |
| Cluster 6 | 3.804688 | 4.888021 | 4.270833 | 4.453125 | 4.072917 | 3.880208 | 3.611979 |

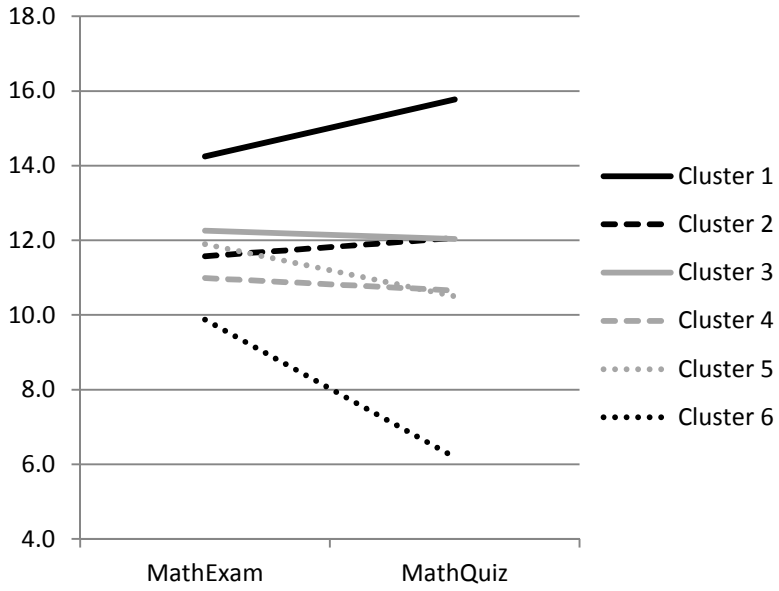
| | AcadContrc | LAnxiety | LBoredom | LHelpless | LEnjoyment |
|---|---|---|---|---|---|
| Cluster 1 | 5.025424 | 3.386749 | 2.252696 | 2.33282 | 4.923729 |
| Cluster 2 | 4.832386 | 3.985537 | 2.456612 | 3.10124 | 4.643182 |
| Cluster 3 | 4.787966 | 3.914301 | 2.934618 | 2.948164 | 4.351003 |
| Cluster 4 | 4.680833 | 4.161818 | 2.901818 | 3.325455 | 4.312667 |
| Cluster 5 | 4.707273 | 3.956694 | 3.072066 | 3.077686 | 4.301091 |
| Cluster 6 | 4.515 | 4.365091 | 3.512727 | 3.603636 | 3.8896 |



| | InstrumentH | ExecutiveH | AvoidanceH | SforInterH | StoLearnH | FormalHS |
|---|---|---|---|---|---|---|
| Cluster 1 | 5.480226 | 2.457627 | 2.491525 | 4.474576 | 5.446328 | 3.887006 |
| Cluster 2 | 5.295455 | 3.234848 | 2.537879 | 4.522727 | 5.545455 | 3.818182 |
| Cluster 3 | 5.286533 | 2.918816 | 2.64852 | 4.491882 | 5.465138 | 3.800382 |
| Cluster 4 | 5.055556 | 2.955556 | 2.648889 | 4.555556 | 5.58 | 3.88 |
| Cluster 5 | 5.199262 | 2.937269 | 2.868389 | 4.445264 | 5.322263 | 3.814268 |
| Cluster 6 | 5.191667 | 3.108333 | 3.261111 | 4.336111 | 5.288889 | 3.85 |



| | SelfBelief | ValuingSch | LearnFocus | Planning | TaskManag | Persistence |
|---|---|---|---|---|---|---|
| Cluster 1 | 6.04661 | 5.974576 | 6.266949 | 5.165254 | 5.771186 | 5.885593 |
| Cluster 2 | 5.8125 | 5.778409 | 6.005682 | 5.159091 | 5.829545 | 5.460227 |
| Cluster 3 | 5.72063 | 5.646132 | 5.88467 | 4.880372 | 5.504298 | 5.234957 |
| Cluster 4 | 5.766667 | 5.746667 | 5.9 | 5.048333 | 5.696667 | 5.3 |
| Cluster 5 | 5.765511 | 5.708942 | 5.889599 | 4.744526 | 5.446168 | 5.208942 |
| Cluster 6 | 5.632231 | 5.698347 | 5.768595 | 4.568182 | 5.311983 | 5.002066 |



| | MathExam | MathQuiz |
|---|---|---|
| Cluster 1 | 14.25 | 15.77306 |
| Cluster 2 | 11.56818 | 12.05865 |
| Cluster 3 | 12.2549 | 12.03682 |
| Cluster 4 | 10.99346 | 10.65568 |
| Cluster 5 | 11.89493 | 10.49884 |
| Cluster 6 | 9.874016 | 6.189108 |

Formative assessment data have high predictive power in generating learning feedback.

Learning disposition data are most actionable: triggering educational interventions.

Dispositional LA is instrumental in chaining dispositions, traces, performance.

Student profiling based on traces allows characterization in terms of dispositions.