Tempelaar, D. T., Nguyen, Q., & Rienties, B. (2020). Learning feedback based on dispositional learning analytics. In M. Virvou, E. Alepis, G. Tsihrintzis, & L. Jain (Eds.), *Machine Learning Paradigms. Intelligent Systems Reference Library* (Vol. 158, pp. 69-89). Cham: Springer.

Learning feedback based on dispositional learning analytics

Dirk Tempelaar[a], Quan Nguyen[b], Bart Rienties[b]

[a]Maastricht University, School of Business and Economics, Netherlands

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

ABSTRACT

The combination of trace data captured from technology-enhanced learning support systems, formative assessment data and learning disposition data based on self-report surveys, offers a very rich context for learning analytics applications. In previous research, we have demonstrated how such Dispositional Learning Analytics applications not only have great potential regarding predictive power, e.g. with the aim to promptly signal students at risk, but also provide both students and teacher with actionable feedback. The ability to link predictions, such as a risk for drop-out, with characterizations of learning dispositions, such as profiles of learning strategies, implies that the provision of learning feedback is not the end point, but can be extended to the design of learning interventions that address suboptimal learning dispositions. Building upon the case studies we developed in our previous research, we replicated the Dispositional Learning Analytics analyses in the most recent 17/18 cohort of students based on the learning processes of 1017 first-year students in a blended introductory quantitative course. We conclude that the outcomes of these analyses, such as boredom being an important learning emotion, planning and task management being crucial skills in the efficient use of digital learning tools, help both predict learning performance and design effective interventions.

KEYWORDS

Blended learning; dispositional learning analytics; e-tutorials; learning feedback; learning dispositions; learning strategies.

1. Introduction

Dispositional Learning Analytics (DLA) represents the pendulum of a clock, returning to its neutral position. During many decades, the educational theory advanced by carefully observing learners, using surveys or think-aloud protocols, to reveal preferred modes of learning, or to investigate what learning conditions contribute mostly to efficient learning. The digital age brought Learning Analytics (LA), aiming to advance learning theory by systematically collecting trace data describing learning episodes in digital learning platforms, and moved the pendulum a full swing away from survey data to trace data. In the context of this metaphor, DLA corresponds to the pendulum in the neutral position, where both learning systems-based trace data and survey-based disposition data feed into our models describing learning behaviours.

Buckingham Shum and Crick (2012) defined the DLA infrastructure as a combination of learning data (i.e. generated in learning activities through traces of an LMS) with learner data (i.e. student dispositions, values, and attitudes measured through self-report surveys). The surveys applied in the first applications of DLA, see, e.g. Crick (2017), justified the characterization of learning dispositions: they were focusing on trait-like facets of learning antecedents, such as learner attitudes and values that are of generic nature, not depending on the specific learning context. However, the use of surveys is not restricted to these learning antecedents of a "true" disposition type. As for example clarified in Matzavela, Chrysafiadi and Alepis (2017), questionnaire data can cover the full range of learning antecedents, including cognitive and non-cognitive predictors, learning styles, affective states, learning motivation, satisfaction and curriculum aspects. Examples of empirical studies combining trace and survey data in the area of self-regulated learning are, e.g. Azevedo, HarleyTrevors, Duffy, Feyzi-Behnagh, Bouchet, et al. (2013) and Gašević, Jovanović, Pardo, and Dawson (2017).

With this development, several distinct and overlapping niches in LA seem to converge. The first refers to DLA in relation to Multimodal LA (Ochea, 2017). Multimodal LA is defined as LA combining learning management system (LMS) or intelligent tutoring system (ITS) trace data with data of another mode to derive learning feedback. Although most empirical research focusses on gazing behaviour, body language, action recording, facial expressions, speech, writing and sketching as such alternative modalities (Ochea, 2017), information achieved by administering surveys is another straightforward example of combining LMS/ITS trace data with data of other modality.

A second parallel is between DLA and the area of student or learner modelling. A DLA based prediction model uses preferred learning approaches to understand the choice of learning activities, uses attitudes as interest and affects as boredom and enjoyment to understand the intensity of learning activities. But that is exactly what the discipline of student modelling in expert systems is aiming at (Chrysafiadi & Virvou, 2013): use aspects of students' characteristics to design a student model to provide adaptivity and personalisation in computer-based educational software. One of the issues in student modelling is to distinguish domain dependent from domain-independent students' characteristics, to distinguish static characteristics that can be measured one time, before the learning process takes place, from dynamic features that result from students' interactions with the learning systems (Chrysafiadi & Virvou, 2013). The same considerations are leading in the design of a DLA application: what individual students' learning facets are dispositional in the strict sense, and can be measured in a single survey; what facets are best seen as students' characteristics that develop over time, and might be measured with repeated surveys, and what facets are that strongly context-dependent that continuous measurement, such as by log based trace variables, is appropriate?

In this contribution, we aim to convince the reader of the merits of adding a new dimension to conventional LA data sources. And to demonstrate the added value of students' disposition data beyond the predictive power of LMS or ITS trace data. We will do so in one specific context: first-year university students, learning introductory mathematics and statistics, in a large scale type of education. We choose for this context since it provides very rich data, both from the perspective of the availability of large samples and from the perspective of large diversity in the subjects. Because of this combination of large-scale education with strong diversity in students, the application of LA to derive learning feedback has a lot of potential added value.
The next section describes related research applying a similar learning context, followed by detailed sketch of the characteristics of that learning context in the third section. In the empirical fourth section of this contribution, we analyze data from the current cohort of students, followed by discussion and conclusions in the last section.

2. Related work

In this section, we provide a description of related investigations applying dispositional learning analytics in blended contexts. The first subsection characterizes the context of the learning blend, followed by a discussion of predictive power and availability in time of different types of data in the second subsection. The third subsection focuses on the role of cultural values as an example of a data type that represents a purely fixed trait. Subsection four discusses different types of assessment data: assessment of, assessment for and assessment as learning. The last subsection discusses the relatively recent development of including affective learning dispositions along with dispositions of cognitive and behavioural nature: the role of learning emotions.

2.1 Educational context

The learning context investigated in previous research by the authors is best described as a large-scale introductory mathematics and statistics course, using ‘blended’ or ‘hybrid’ learning, in a business and economics university program in the Netherlands. The main learning component is face-to-face: Problem-Based Learning (PBL), in small groups (14 students), coached by a content expert tutor (Non & Tempelaar, 2016; Williams et al., 2016). Participation in these tutorial groups is required. Optional is the online component of the blend: the use of the two e-tutorials SOWISO and MyStatLab (MSL) (Tempelaar, Rienties, & Giesbers, 2015a; Tempelaar, Rienties, Mittelmeier, & Nguyen, 2018). This choice is based on the philosophy of student-centred education, placing the responsibility for making educational choices primarily on the student. Since most of the learning takes place in self-study outside class, using the e-tutorials or other learning materials, and class time is used to discuss solving advanced problems, the instructional format is best characterized as a flipped-class design (Williams et al., 2016). The use of e-tutorials and achieving good scores in the practising modes of both e-tutorials is stimulated by making bonus points available for good performance in the quizzes: the formative assessments. Quizzes are taken every two weeks, and consist of items that are drawn from the same item pools applied in the practising mode. We chose this particular constellation as it stimulates students with limited prior knowledge to make intensive use of the e-tutorials. The bonus is maximized to 20% of what one can score in the exam.

The student-centred nature of the instructional design requires, first and foremost, adequate actionable feedback to students so that they can 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 of 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.

Subjects of our studies are subsequent cohorts of first-year students, participating in course activities: typically between 1000 and 1100 students each year. A large diversity in the student population is present: only about 20% are educated in the Dutch high school system. Regarding nationality, the largest group, about 40% of the students, is from Germany, followed by about 20% Dutch and between 15% to 20% Belgian students. In most cohorts, no less than 50 nationalities are present, but with a large share of European nationalities: no more than 5% of students are from outside Europe. High school systems in Europe differ strongly, most particularly in the teaching of mathematics and statistics (with, e.g. the Dutch high school system having a strong focus on the topic statistics, whereas that topic is completely missing in high school programs of many other countries). Therefore, it is crucial that the first module offered to these students is flexible and allows for individual learning paths (Non & Tempelaar, 2016; Williams et al., 2016). In the investigated cohorts, students work an average of 25 to 30 hours in SOWISO and a similar amount of time in MSL, 30% to 40% of the available time of 80 hours for learning on both topics.

Learning dispositions measured at the start of the course were of affective, behavioural, and cognitive types (Rienties, Cross, & Zdrahal, 2017). The surveys had a prime role to supply students with an individual data set required for doing a statistical project, resulting in a full response.

2.2 The crucial predictive power of cognitive data

Early LA applications focused on the development of predictive models, with the central question: what is the predictive power of the data at hand, can we signal students at risk with sufficient reliability by, e.g. LMS learning activity data. The best context to answer such question about predictive power is the context where a wide range of alternative learning data is available, allowing for comparative analyses of the predictive power of different types of data. We did so in a couple of studies (Tempelaar et al., 2015a; Tempelaar, Rienties, Mittelmeier et al., 2018; Tempelaar, Rienties, & Nguyen, 2017a, b), where we analysed LMS student activity data, e-tutorial trace data of both process and product types (Azevedo et al., 2013), formative assessment data, and learning disposition data. The conclusions of these studies can be adequately summarized as cognitive formative assessment data dominating all other types of data in terms of predictive power. Whether signalling students at risk or predicting course performance: as soon as quiz data became available, learning activity data or dispositions do not add explained variation anymore. However, that brings a timing issue: the availability of such formative assessment data is typically restricted to later moments, limiting the opportunity to use that data for learning interventions (in our case: the first assessment data became available in the fourth week of an eight-week course). The second outcome of our studies was that early intervention is best based on the combination of e-tutorial trace data and learning dispositions, available early in the course. LMS activity trace data has similar availability, but did not add any predictive power beyond e-tutorial trace data.

2.3 An unexpected source of variation: national cultural values

In a discussion on the antecedents of learning processes and the trait/state nature of these antecedents, one group of antecedents takes the most polar position one can think of: national cultural values. These values, as is clear from their name, represent dimensions of preferences that distinguish countries, rather than individuals. In their influential work, Hofstede, Hofstede, and Minkov (2010) identified six major dimensions on which cultures in the workplace differ: power distance, uncertainty avoidance, individualism versus collectivism, masculinity versus femininity, long-term versus short-term orientation, and indulgence versus restraint. Power distance refers to the extent to which less powerful members of organisations and institutions accept and expect unequal distribution of power. Uncertainty avoidance refers to 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 signals the degree to which individuals are integrated into groups: from loose ties between individuals, and everyone expected to look after oneself and immediate family, to people being integrated into strong, cohesive in-groups. In masculine societies, emotional gender roles are rather distinct, whereas in feminine societies, these roles overlap. The fifth culture dimension of long-term orientation distinguishes societies in being directed towards future rewards, or the fulfilment of present needs and desires. The sixth and most recently added culture dimension is that of indulgence versus restraint and signals the degree to which a culture allows or suppresses gratification of needs and human drives related to hedonism and consumerism. And although these national cultural values are defined at the country level, assigning these country scores on the six dimensions to individual subjects in an attempt to investigate has proven to be an effective way to model country differences in a wide range of applications. In our context, dealing with the large diversity in European national cultures at the one hand, and small national subsamples at the other hand, it is an adequate solution to include more than 50 nationalities into one parsimonious prediction model.

In a series of studies (Mittelmeier, Rienties, Tempelaar, Hillaire, & Whitelock, 2018; Tempelaar, Rienties, Giesbers, & Schim van der Loeff, 2013a, b; Tempelaar, & Verhoeven, 2016), we investigated the role of national cultural values in learning processes, assigning national dimension scores from the Hofstede et al. (2010) study to individual students. The effects we found are nowhere larger than medium-sized, explaining up to 5% of the variation in outcome measures, but the effects were quite generic. Two national culture dimensions tended to have positive impacts on learning: Long-Term Orientation and Masculinity, with the strongest role for orientation. Two other dimensions tended to have negative impacts: Power Distance and Indulgence (implying that Restraint has a positive impact). Weak or absent impacts were found for Individualism and Uncertainty Avoidance. Those impacts do not restrict to the prediction of learning performance and learning activity but extend to the prediction of other student characteristics that act as antecedents in our prediction model. For instance, masculinity, uncertainty avoidance, orientation and restraint are predictors of several learning emotions: boredom, hopelessness, and enjoyment. And of learning motivation and engagement variables, both adaptive and maladaptive types. That is: the relationships between cultural values and learning activity and performance is both of direct type, and of indirect type, through the mediation of learning dispositions. In a sample of such international composition as ours, cultural values thus serve two different functions: to create parsimonious prediction models, and to better understand the nature of country differences.

2.4 LA, formative assessment, assessment of learning and feedback preferences

LA is about having rich data, and in many cases, richness is about the cognitive nature of the available data: see the second subsection. Formative assessments, or 'assessments for learning', are the first source of such cognitive data about student mastery in relevant topics. There are, however, two issues with formative assessment: a timing issue, and an incentivisation issue. The first issue is discussed before: formative assessment data is often available only late in the course, limiting its use for educational interventions. That late availability is related to the issue of incentivisation: to get a reliable impression of student mastery; one needs to get rid of any non-committal nature. That requires incentivising the assessment, making it a kind of midterm test. But midterm feedback is indeed late feedback.

'Assessment as learning' data replacing formative assessment data suggests being an alternative. In our studies (Nguyen, Tempelaar, Rienties, & Giesbers, 2016; Tempelaar, 2014; Tempelaar, Cuypers, Van de Vrie, Heck, & Van der Kooij, 2013; Tempelaar, Mittelmeier et al., 2018; Tempelaar, Rienties, & Giesbers, 2014, 2015b, Tempelaar, Rienties, & Nguyen 2018a, 2018b), we analysed the roles of both types of assessment data, assessment for and assessment as learning, and linked these with students' preferences for feedback. From an LA perspective, the great advantage of assessment as learning data is that these data are derived from trace data generated by test steered e-tutorial or intelligent tutoring systems, and beyond registering student mastery in these learning environments, these systems also log revealed learning approaches by students. Such as learning feedback modes students use most often when the choice is theirs: worked-examples, tutored problem-solving or untutored problem-solving (Nguyen et al., 2016; Tempelaar, Rienties, & Nguyen, 2018a). Another facet of revealed learning preferences refers to timing decisions: to what extent learn students just in time, and what events (tutorial session, midterm, final exam) are most important to learn for (Tempelaar, Rienties, & Nguyen, 2018b). Enabled by the DLA nature, the last step of this analysis is to connect these revealed preferences with learning dispositions, to derive learning feedback of the nature of: 'learning as a preparation for tutorial sessions represents the most effective timing of learning; learning emotions are strongly related with timing decisions'.

2.5 LA and learning emotions

A relatively recent development in LA applications is the integration of affective antecedents of learning, along with the more standard behavioural and cognitive antecedents (Rienties, Cross, & Zdrahal, 2017). That development is stimulated by the availability of wearables that allow continuous measurement of emotions. Nonetheless, even more traditional surveys generating cross-sectional affect data offer great opportunities to account for trait-like learning emotions in the provision of learning feedback. In several studies (Tempelaar, Niculescu, Rienties, Giesbers, & Gijselaers, 2012; Tempelaar, Rienties, & Nguyen, 2017a, b, 2018b), we investigated the role of two different types of learning emotions: epistemic emotions and activity emotions (Pekrun & Linnenbrink-Garcia, 2012). Epistemic emotions represent real traits: what affects do students encounter when confronted with academic disciplines. Activity emotions are dependent on the learning context, on the learning tasks that shape the learning process. We found strong interrelations between both types of learning emotions and activity of students in the learning environments. Those interrelations should impact the type of learning feedback and learning interventions we derive from our prediction model. For instance, we found that learning boredom is one of the affects most strongly related (in a negative manner) to the learning activity. Where in general a message telling a student that (s)he is lagging behind peers, and is advised to catch up by doing some specific learning task, might be effective, such a message will have little impact when the reason of lagging behind is feeling bored about the typical learning activity. So another type of feedback may be needed, such as offering alternative learning activities.

3. The current study

In the empirical part of this contribution, we will investigate the potentials of DLA applied to the current '17/'18 cohort of first-year students in our program, who just finished their introductory mathematics and statistics course. It is best seen as a replication study: are the several empirical findings we distilled from previous research as reviewed in the second section, invariant over time? To what extent do they repeat themselves in new cohorts of international students, with the somewhat different composition of nationalities? These are the research questions we will focus on in the remainder of this section.

The first subsection defines the participants of the current study, whereas the next three subsections describe the different types of data: trace data in subsection two, learning performance data in subsection three, and disposition data in subsection four. We close the section with a description of the statistical methods in subsection five.

3.1 Participants.

We included 1017 first-year students in this study: students in the introductory mathematics and statistics course who have been active in both digital learning platforms SOWISO and MSL (30 students chose to concentrate their learning outside one or both platforms). Of these students, 42% were female, 58% male, 21% had a Dutch high school diploma, and 79% were international students (including a small group of students of Dutch nationality but high school education of international type).

3.2 E-tutorial trace data

In both e-tutorial systems, we investigated one process variable: connect time in the tool, and one product variable: mastery in the tool. Average values of *MathTime* is 28 hours, *StatsTime* 24 hours. Crucial differences exist in the way both e-tutorials measure connect time, resulting in noisy measures for *StatsTime*: the tool does not correct for the idle time. Mastery, expressed as the percentage of learning activities successfully finished, is on average: *MathMastery*: 69%, *StatsMastery*: 77%. These are mastery levels at the very end of the course when writing the final exam. To investigate the timing decisions of students, we also looked at two intermediate mastery levels: the tutorial session and the quiz. These mastery levels were on average: *MathTutS*: 21%, *MathQuiz*: 41%, *StatsTutS*: 40%, *StatsQuiz*: 71%.

3.3 Performance data

Two different performance indicators, Exam and Quiz for both academic topics, result in four performance variables: *MathExam*, *StatsExam*, *MathQuiz*, *StatsQuiz*. The course starts with a diagnostic entry test, producing *MathEntry* and *StatsEntry* measures of prior knowledge.

3.4 Disposition data

Several sources of disposition data have been applied, all documented in full detail in previous studies (Tempelaar et al., 2015a, 2017a). For space limitations, we limit the current description to the identification of survey scales adopted and refer to the above sources for a full elaboration.

National cultural values are adopted form Hofstede et al. (2010). We use six dimensions: power distance (*PowerDist*), uncertainty avoidance (*UncertAvoid*), individualism–collectivism (*Individual*), masculinity-femininity (*Masculine*), long-term–short-term orientation (*LongTermOrient*), and indulgence–restraint (*Restraint*; this last scale is reverted, to have its direction in line with the other national values).

Individual approaches to cognitive learning processing strategies and metacognitive learning regulation strategies are based on Vermunt's (1996) learning styles instrument. Processing strategies can be ordered from surface to deep learning approaches: *Memorising* and rehearsing, *Analysing*, *Relating* and structuring, and *Critical* processing, with *Concrete* processing as a separate category. Regulation strategies are decomposed into self and external regulation: Self-regulation of learning processes and results (*SelfRegProc*), Self-regulation of learning content (*SelfRegCont*), External regulation of learning processes (*ExtRegProc*), and External regulation of learning results (*ExtRegRes*), with Lack of regulation (*LackReg*) indicating lack of regulation of any type.

Attitudes and beliefs toward learning quantitative topics are assessed with the SATS instrument (Tempelaar, Gijselaers, Schim van der Loeff, & Nijhuis, 2007). It distinguishes *Affect*, cognitive competence (*CognComp*), *Value*, expected difficulty in learning, reversed (*NoDifficulty*), *Interest* and planned *Effort*.

Measurements of learning emotions, both of epistemic and activity type, are based on the research by Pekrun (Pekrun & Linnenbrink-Garcia, 2012). Epistemic emotions are composed of positive emotions *Curiosity* and *Enjoyment*, negative emotions *Confusion*, *Anxiety*, *Frustration*, and *Boredom*, and neutral emotion *Surprise*. Three activity emotions share the same focus as a corresponding epistemic emotion: *Enjoyment*, *Anxiety* and *Boredom*. A fourth activity emotion is the negative emotion *Hopelessness*. Academic control (*AcadControl*) is hypothesised being the main direct antecedent of activity emotions.

The instrument Motivation and Engagement Wheel (Martin, 2007) breaks down learning cognitions and learning behaviours into four categories of adaptive versus maladaptive types and cognitive versus behavioural types. *Self-belief*, value of school (*ValueSchool*), and learning focus (*LearnFocus*) shape the adaptive, cognitive factors, or cognitive boosters. *Planning*, task management (*TaskManagm*), and *Persistence* shape the behavioural boosters. Mufflers, the maladaptive, cognitive factors are *Anxiety*, failure avoidance (*FailAvoid*), and uncertain control (*UncertainCtrl*), while self-sabotage (*SelfSabotage*) and *Disengagement* are the maladaptive, behavioural factors or guzzlers.

A recently developed 4x2 achievement goal framework by Elliott and coauthors (Elliot, Murayama, Kobeisy & Lichtenfeld, 2015) was applied to include self-perceived goal setting behaviour of students. The instrument distinguishes two valence dimensions: approach and avoid, and four goal definition dimensions: task-based, self-based, other-based and potential-based competence, resulting in eight scales: *TaskApproach*, *TaskAvoid*, *SelfApproach*, *SelfAvoid*, *OtherApproach*, *OtherAvoid*, *PotentApproach* and *PotentAvoid* achievement goals.

3.5 Analyses

The main aim of the analyses is to demonstrate the role different learning dispositions may have in the explanation of learning activities and learning outcomes. For that reason, rather than deriving simultaneous prediction models, we will focus on bivariate relationships between learning antecedents and their consequences, and apply correlational analyses. Given the sample size in this study, correlations of the absolute size of .11 and beyond are statistically significant at the .01 level.

4. Results

In the results section, we will follow the same route as in section two, and describe in several subsections the relationships between e-tutorial trace variables of both product and process type, and different types of other learning related variables. We start by describing relationships between trace variables and performance variables in the first subsection and continue with the relationships between trace variables and national culture dimensions in subsection two. Subsections three and four continue with both facets of learning strategies: processing strategies and learning regulation. Followed by learning attitudes (subsection five), epistemic and activity type learning emotions (subsections six and seven), and closing with adaptive and maladaptive motivation and engagement (subsections eight and nine).

4.1 Performance

In order to find out what role learning in the e-tutorials had played in gaining mathematical and statistical knowledge, we investigated relationships between eight trace variables from the two e-tutorials, and six performance variables: the two quiz results (*MathQuiz* and *MathStats*), the two final exam results (*MathExam* and *StatsExam*), and the outcomes of the two diagnostic entry tests administered at day 1 (*MathEntry* and *StatsEntry*). Figure 1 gives insight into these bivariate relationships.

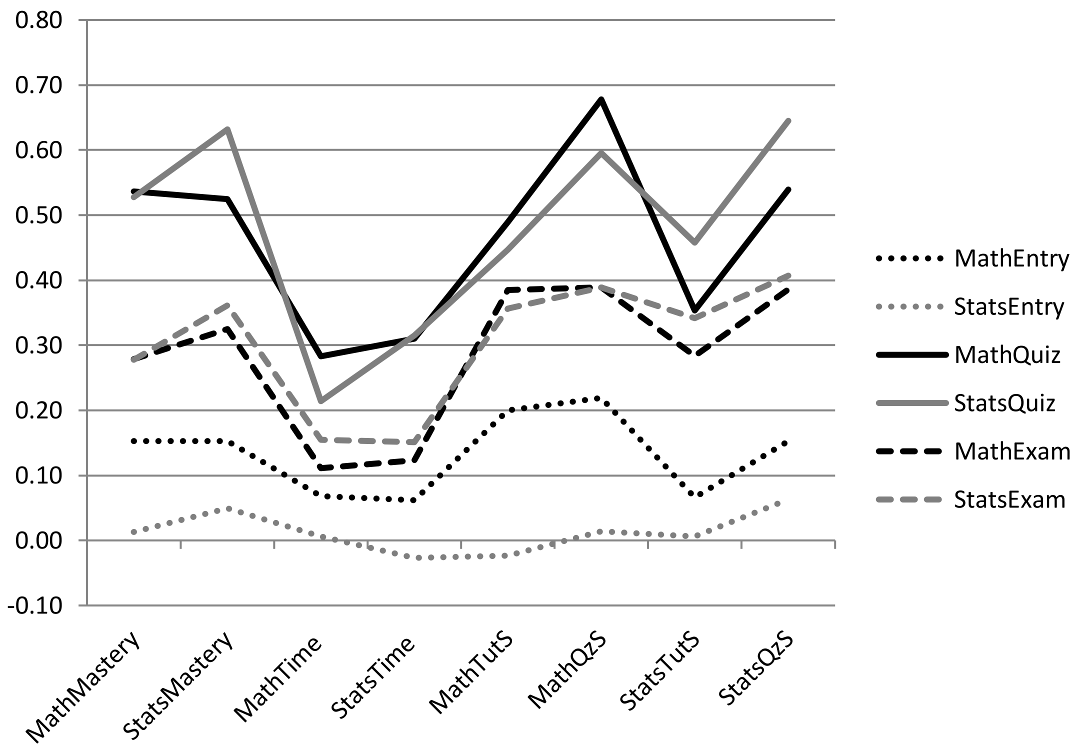

Figure 1: correlations between e-tutorial trace data, and performance indicators.

Quiz performance has by far the strongest relationship with the e-tutorial product and process data, followed by exam performance. Entry test scores are only weakly related to e-tutorial trace data. The dominant role of quiz scores is not surprising: quizzes share the same item bank as the materials students see in the practising mode. With regard to the two types of e-tutorial data, tool mastery and tool time: the cognitive product variable mastery is a much stronger predictor of course performance than the process variable connect time in the tool. Regarding the timing of learning, we do not find any differences between the exam performance of students with different timing strategies. That is not true for quiz performance: the highest correlations are achieved by students who prepare just in time for the quiz sessions, not for students who prepare timely for the tutorial sessions.

4.2 National cultural values

Three of the cultural dimensions interrelate e-tutorial trace data, as visible from Figure 2: *Masculine*, the *Restraint* pole of the indulgence-restraint dimensions, and the *Long-Term Orient*ation pole of the long-term versus short-term orientation dimension. Different from the performance correlations discussed above, correlations of e-tutorial time data and e–tutorial mastery data are not very far apart.

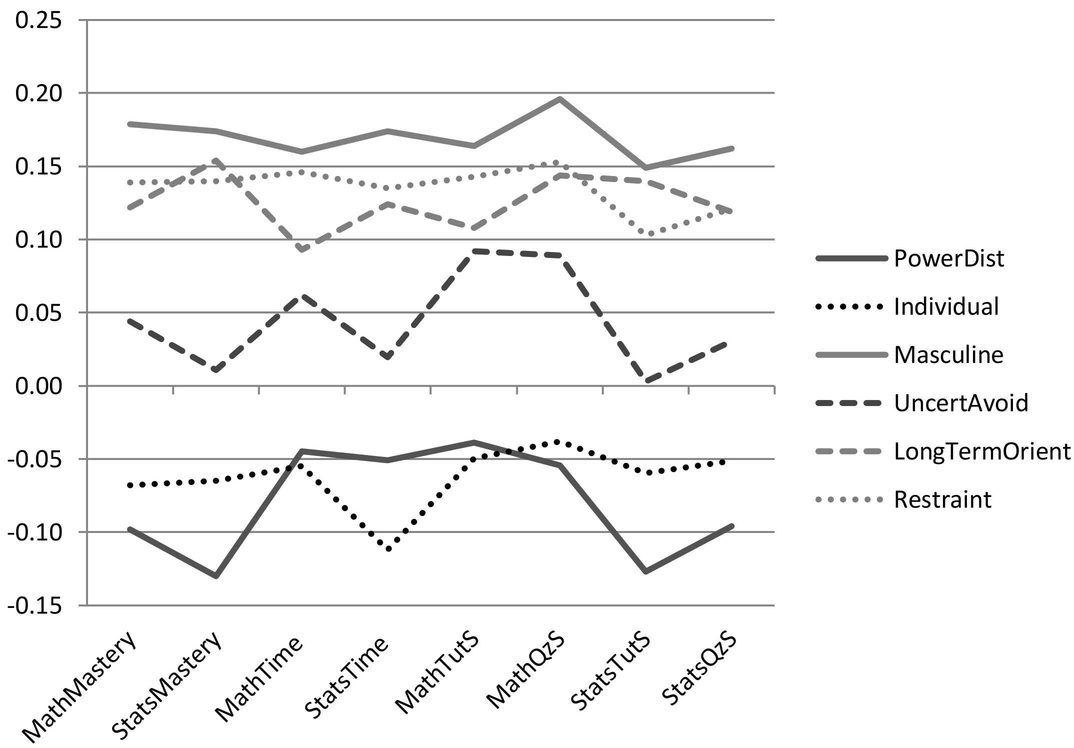

Figure 2: correlations between e-tutorial trace data, and national cultural values.

4.3 Cognitive learning processing strategies

The processing strategies demonstrate a clear picture: deep learning, the composition of *Critical* processing and *Relating* and structuring, is uncorrelated to the use of the e-tutorials. Against the strict benchmark of .01 significance, the strategy of *Concrete* learning also is unrelated to learning in the digital mode; if anything, these correlations tend to be negative. Positive correlations show up for the two stepwise or surface learning strategies: *Memorising* and rehearsing, and *Analysing*. Correlations are of limited size, and beyond final math mastery and quiz math mastery, not significant beyond .01: see Figure 3.

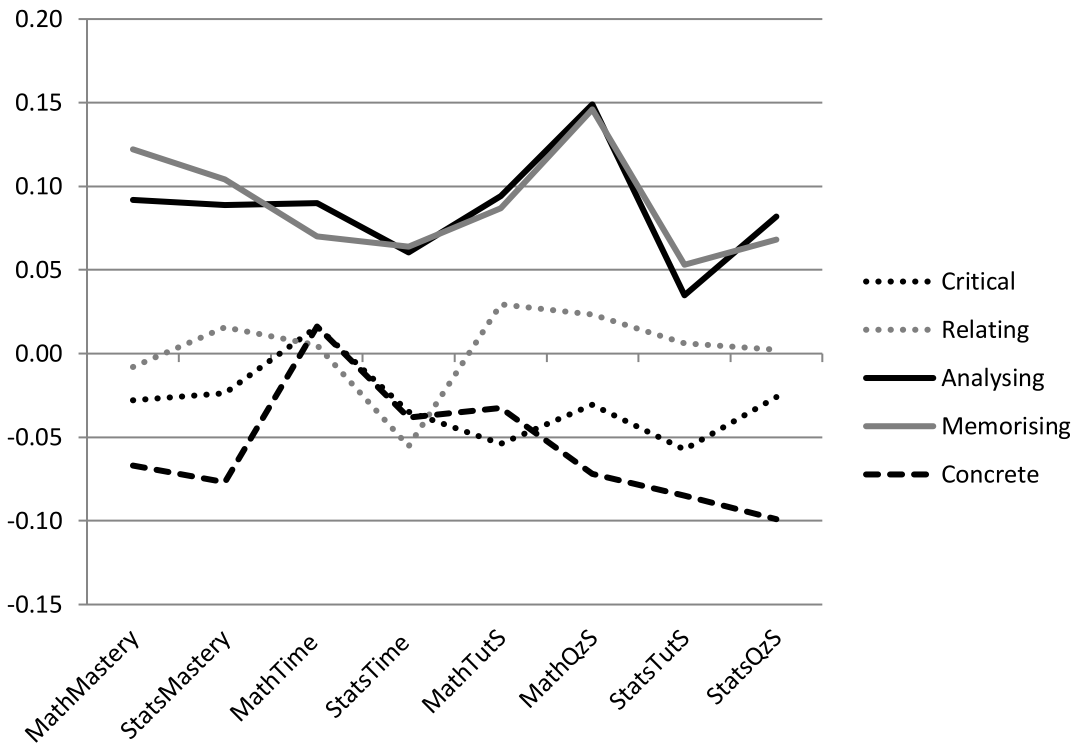

Figure 3: correlations between e-tutorial trace data, and cognitive learning processing strategies.

4.4 Metacognitive learning regulation strategies

The patterns in the regulation strategies are quite similar to those in the processing strategies: see Figure 4. The two self-regulation scales, the self-regulation of the process (*SelfRegProc*) and the content (*SelfRegCont*), are uncorrelated to the several indicators of e-learning, as were the two deep-learning processing scales. The absence of learning regulation, represented by the *Lack* of *Reg*ulation scales, tends to be negatively related, without reaching the .01 benchmark of statistical significance, and except the two time-related traces variables. Positive correlations are there for the two external regulation scales, external regulation of the learning process (*ExtRegProc*) and learning results (*ExtRegRes*). The effect is again strongest for final math mastery and quiz math mastery, but more correlations go beyond the .01 significance benchmark.

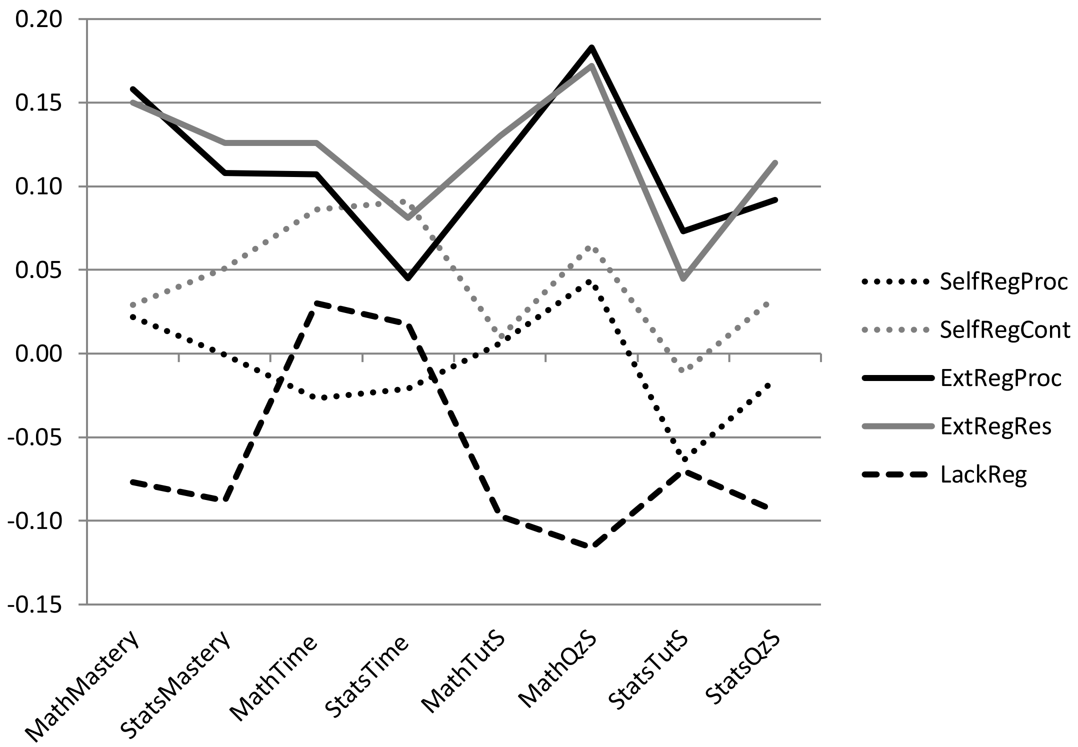

Figure 4: correlations between e-tutorial trace data, and metacognitive learning regulation strategies.

4.5 Attitudes and beliefs towards learning quantitative methods

Three of the attitudinal variables are basically unrelated to learning in the digital mode: *Value*, the absence of expected difficulty, *NoDifficulty,* and *Interest,* with two exceptions: the correlations of interest with the timely preparation of mathematics, *MathTutS* and *MathQzS:* see Figure 5. Stronger correlations exist for *Effort*, *Affect*, and *CognComp*, the self-perceived level of quantitative competence. The three attitudes share that time correlations are dominated by mastery correlations, and that correlations for math dominate those for stats. They differ regarding the impact on the timing of learning. Correlations between *Affect*, *CognComp* and *MathTutS, MathQzS* are higher than correlations with *MathMastery*. That is, students who like mathematics, and feel more competent, prepare their sessions more timely. That is not true for statistics: correlations with *StatsMastery* are higher than correlations with *StatsTutS, StatsQzS,* implying that positive attitudes do not help students to opt for timely learning of stats in the same way as it does for math.

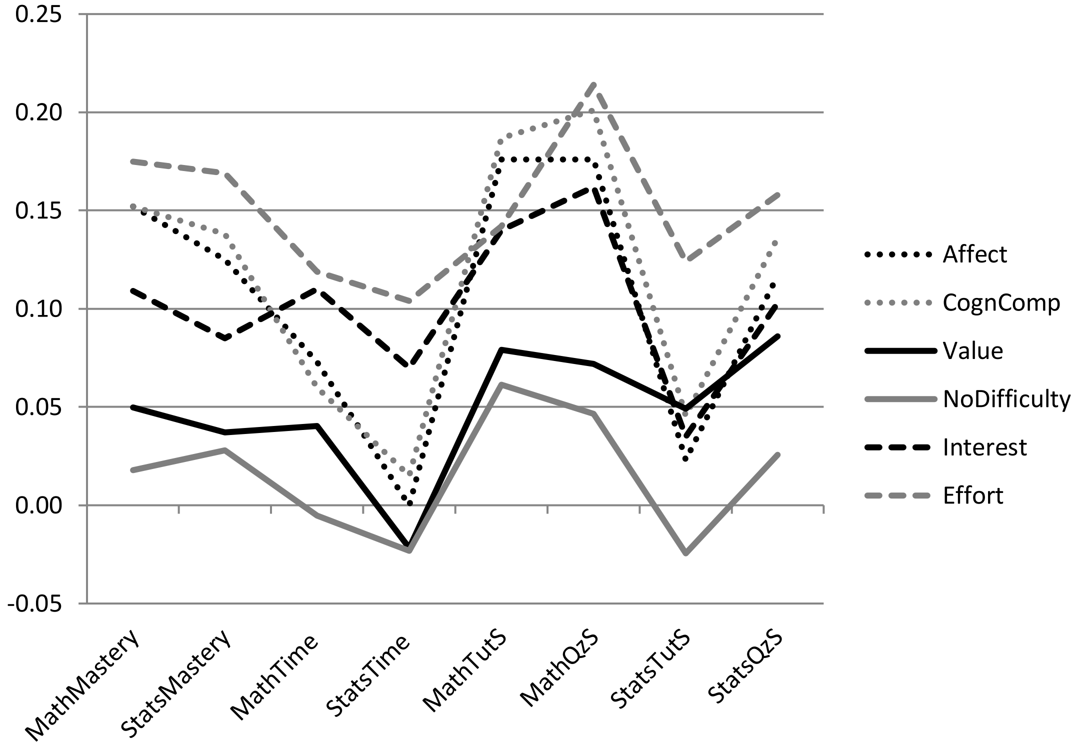

Figure 5: correlations between e-tutorial trace data, and attitudes and beliefs towards learning quantitative methods.

4.6 Epistemic learning emotions

The valence dimension of epistemic emotions splits the correlational outcomes into two mirrored patterns. Positive emotions *Curiosity* and *Enjoyment* are positively related to all trace variables, be it that correlations are weak, and only significant beyond the .01 level for timely preparation of math: *MathTutS* and *MathQzS*. *Surprise*, hypothesized as a neutral emotion, acts as a positive emotion, be it nowhere passing the .01 level of significance: see Figure 6.

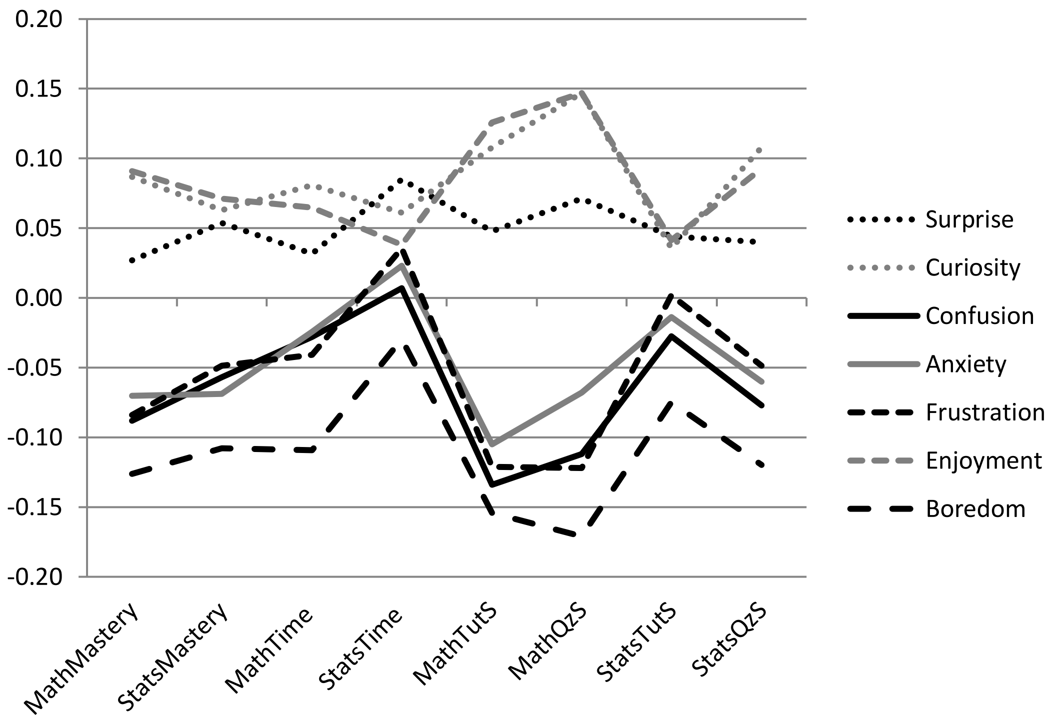

Figure 6: correlations between e-tutorial trace data, and epistemic learning emotions.

Negative emotions *Frustration*, *Anxiety*, and *Confusion*, all demonstrate negative correlations (except for *StatsTime*), of modest size, except again the two correlations indicating timely preparation of math: *MathTutS* and *MathQzS*. Strongest correlations overall are for the negative emotion *Boredom*, indicating that this learning emotion forms an obstacle for both the amount of digital learning and the proper timing of digital learning.

4.7 Activity learning emotions

Patterns in epistemic emotions repeat in activity emotions, and academic control (*AcadControl*), the self-efficacy variable acting as a direct antecedent of the activity emotions: see Figure 7.

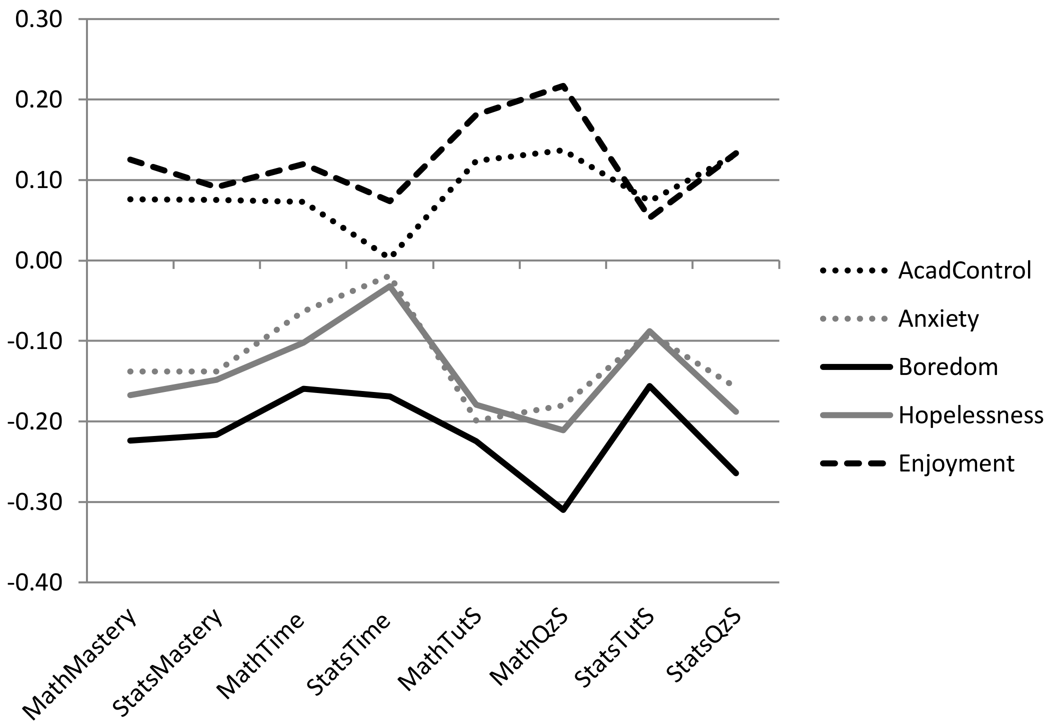

Figure 7: correlations between e-tutorial trace data, and activity learning emotions.

It is again timely preparation for mathematics, represented by *MathTutS* and *MathQzS*, where the largest correlations are found. *Anxiety*, hypothesised as an activating negative emotion, follows the same pattern as the other negative emotions: no activation is visible, neither with regard to time and mastery. Regarding the size of the effect, it is again *Boredom* dominating the other emotions.

4.8 Adaptive motivation and engagement

Cognitive and behavioural motivation and engagement constructs demonstrate different correlational patterns. The cognitive scales *Self-belief*, *Value School*, and *LearnFocus* are no more than weakly related to the trace variables. The behavioural constructs *Planning*, *TaskManagm*, and *Persistence* are much stronger positively related to learning in the digital platform: see Figure 8.

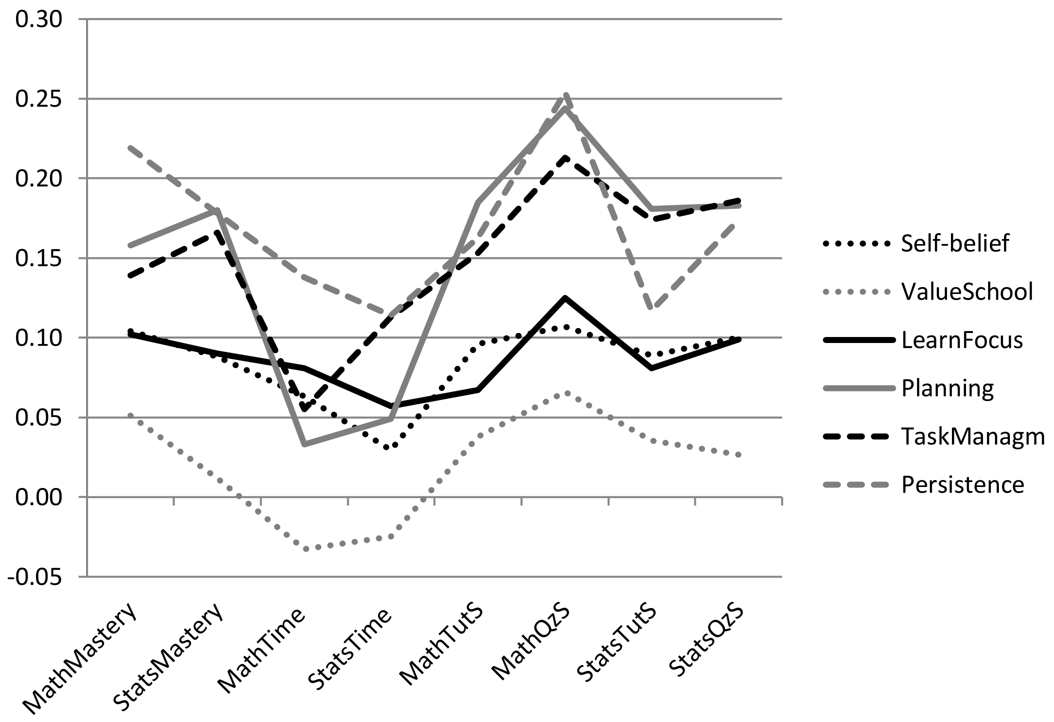

Figure 8: correlations between e-tutorial trace data, and adaptive motivation and engagement scales.

It is again timely learning for math, but this time also timely learning for stats, that profits from planning and task-management skills of the students. Remarkably, students having those skills can achieve these high mastery levels in a very efficient way: they hardly need more time on average to reach much higher mastery levels than on average. Apparently, self-perceptions on planning and task-management do provide a reliable impression of actual skills.

4.9 Maladaptive motivation and engagement

The same breakdown of cognitive and behavioural correlations is visible in the last figure, Figure 9, providing patterns for maladaptive motivation and engagement constructs. The impacts of the maladaptive cognitive constructs, *Anxiety*, *FailAvoid*, and *UncertainCtrl*, tend to be negative, but small in size. The sign of the Anxiety correlations is even undetermined, tending to be positive for the two time variables, negative for the mastery variables. The behavioural constructs have a much stronger, consistently negative, impact: *SelfSabotage* and *Disengagement* predict both final mastery as well as timely preparation. Their impact on learning time is much smaller, implying that these are the students making inefficient use of their learning time, mirroring the positions of students high in planning and task-management.

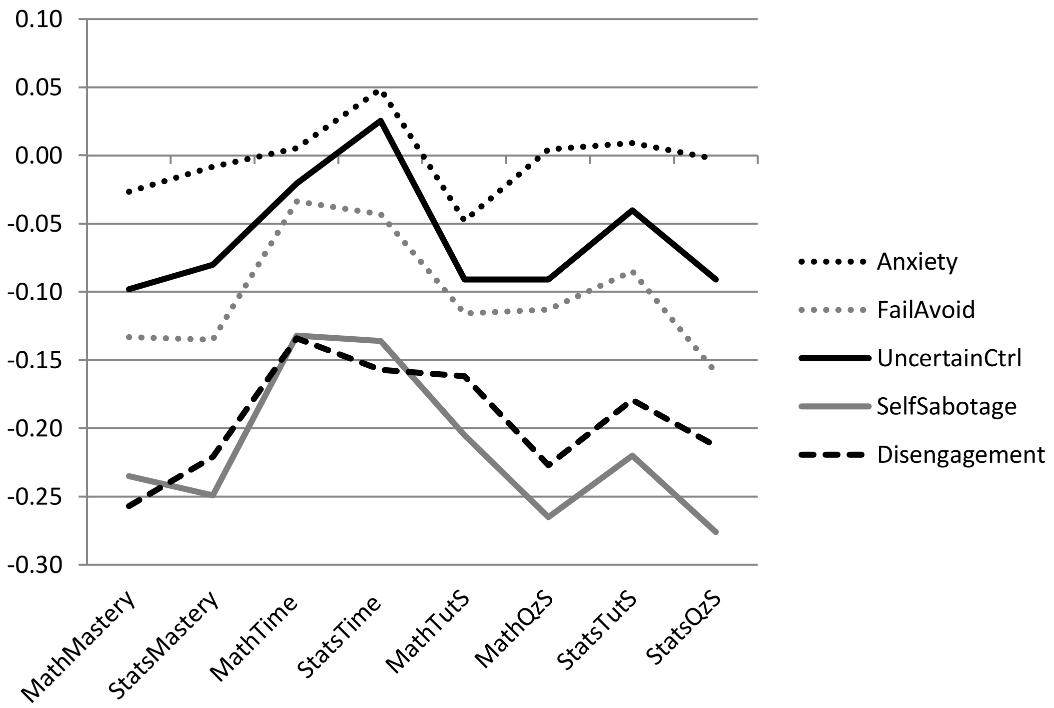

Figure 9: correlations between e-tutorial trace data, and maladaptive motivation and engagement scales.

5. Discussion and conclusion

By and large, the outcomes of the empirical analyses reproduced the findings from previous studies. LA needs rich data: measuring student activity in a learning management system may not be the best data set to build a prediction model. In all our studies, we find formative assessment data being the key facet of rich data. This immediately gives rise to the dilemma of timely data versus informative data. It takes time to collect formative assessment data, maybe too much for being in time to intervene aiming the prevention of dropout or improve study success. So we might have to opt for somewhat less informative, but timelier data. In our context, assessment as learning data, trace data from e-tutorial systems representing mastery of students in the practice modes, in combination with learning disposition data collected through surveys, suggest being alternative data sources for LA applications: a good “second best” with regard to predictive power, early available in the course as to allow ample time for intervention. In answering the question of what type of intervention is most helpful in assisting students, we find another advantage of including dispositions into an LA application. If a traditional LA application using click and connect time type of trace data derived from LMS use comes to a prediction of drop-out, it is not that obvious what type of intervention is adequate. If the prediction results from low levels of student activity, a simple call to become more active is likely to have little effect, if boredom is the underlying cause of low activity. Or in case the student lacks planning and/or task management skills, offering a training to improve those skills may be a more productive intervention than again this simple call to become more active in the LMS.

The availability of such a broad range of disposition measurements as available in our study will be the exception rather than the rule. From that perspective, this study serves more 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. An 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 on. A less crucial facet of the richness of data is the multitude of different disposition surveys. Disposition data tends to be collinear, that is, students with less favourable attitudes will tend to follow less adaptive learning strategies, or depend strongly on external types of motivation. The availability of specific interventions will govern in such a situation the choice of what type of survey instruments to apply: the ultimate goal is to prevent drop-out, rather than predict drop-out.

REFERENCES

Azevedo, R., Harley, J., Trevors, G., Duffy, M., Feyzi-Behnagh, R., Bouchet, F., et al. (2013). Using trace data to examine the complex roles of cognitive, metacognitive, and emotional self-regulatory processes during learning with multi-agents systems. In R. Azevedo & V. Aleven (Eds.), *International handbook of metacognition and learning technologies*, 427–449. Amsterdam, The Netherlands: Springer.

Buckingham Shum, S. & Deakin Crick, R. (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*, 92-101. ACM, New York, NY, USA. DOI: 10.1145/2330601.2330629

Chrysafiadi, K. & Virvou, M. (2013). Student modeling approaches: A literature review for the last decade. *Expert Systems with Applications*, 40, 4715–4729. DOI: 10.1016/j.eswa.2013.02.007

Crick, R. (2017). Learning Analytics: Layers, Loops and Processes in a Virtual Learning Infrastructure. In C. Lang, G. Siemens, A. Wise, & D. Gašević (Eds.), *Handbook of Learning Analytics*, Ch. 25, pp. 291-308. Solar: Society for Learning Analytics Research. DOI: 10.18608/hla17

Gašević, D., Jovanović, J., Pardo, A., & Dawson, S. (2017). Detecting learning strategies with analytics: Links with self-reported measures and academic performance. In *Journal of Learning Analytics*, 4(1), 113–128 DOI: 10.18608/jla.2017.42.10

Hofstede, G., Hofstede, G. J., & Minkov, M. (2010). *Cultures and organizations: Software of the mind*. Revised and expanded third edition. Maidenhead: McGraw-Hill.

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), 413-440. DOI: 10.1348/000709906X118036

Matzavela, V., Chrysafiadi, K., & Alepis, E. (2017). Questionnaires and artificial neural networks: A literature review on modern techniques in education. In *Proceedings 2017 IEEE Global Engineering Education Conference (EDUCON)*, 25-28 April 2017, Athens, Greece. DOI: 10.1109/EDUCON.2017.7943077

Mittelmeier, J., Rienties, B., Tempelaar, D.T., Hillaire, G. & Whitelock, D. (2018). The influence of internationalised versus local content on online intercultural collaboration in groups: A randomised control trial study in a statistics course, *Computers & Education*, 118(1), 82-95. DOI: 10.1016/j.compedu.2017.11.003

Nguyen, Q., Tempelaar, D.T., Rienties, B., & Giesbers, B. (2016). What learning analytics based prediction models tell us about feedback preferences of students. In Amirault, R., & Visser, Y., (Eds.). (2016). e-Learners and Their Data, Part 1: Conceptual, Research, and Exploratory Perspectives. *Quarterly Review of Distance Education*. 17(3).

Non, A. & Tempelaar, D. (2016). Time preferences, study effort, and academic performance. *Economics of Education Review*, 54, 36–61. DOI: 10.1016/j.econedurev.2016.06.003.

Ochea, X. (2017). Multimodal Learning Analytics. In C. Lang, G. Siemens, A. Wise, & D. Gašević (Eds.), *Handbook of Learning Analytics*, Ch. 11, pp. 129-141. Solar: Society for Learning Analytics. DOI: 10.18608/hla17

Pekrun, R., & Linnenbrink-Garcia, L. (2012). Academic Emotions and Student Engagement. In S. L. Christenson, A. L. Reschly, & C. Wylie (Eds.), *Handbook of Research on Student Engagement* (pp. 259–282). Springer US. DOI: 10.1007/978-1-4614-2018-7_12

Rienties, B., Cross, S., & Zdrahal, Z (2017). Implementing a Learning Analytics Intervention and Evaluation Framework: What Works? In B. Kei Daniel (Ed.), *Big data and learning analytics: Current theory and practice in higher education*, 147–166. Cham: Springer International Publishing. DOI: 10.1007/978-3-319-06520-5_10

Tempelaar, D. T. (2014). Learning Analytics And Formative Assessments In Blended Learning Of Mathematics And Statistics. *Innovative Infotechnologies for Science, Business and Education*, 2(17), 9-13.

Tempelaar, D. T., Cuypers, H., Van de Vrie, E., Heck, A., Van der Kooij, H. (2013). Formative Assessment and Learning Analytics. In D. Suthers & K. Verbert (Eds.), *Proceedings of the 3rd International Conference on Learning Analytics and Knowledge*, 205-209. New York: ACM. DOI: 10.1145/2460296.2460337.

Tempelaar, D.T., Gijselaers, W.H., Schim van der Loeff, S., & Nijhuis, J.F.H., (2007). A structural equation model analyzing the relationship of student achievement motivations and personality factors in a range of academic subject-matter areas, *Contemporary Educational Psychology*, 32(1), 105-131. DOI: 10.1016/j.cedpsych.2006.10.004

Tempelaar, D. T., Mittelmeier, J., Rienties, B., & Nguyen, Q. (2018). Student profiling in a dispositional learning analytics application using formative assessment, *Computers in Human Behavior*, 78, 408-420. DOI: 10.1016/j.chb.2017.08.010

Tempelaar, D. T., Niculescu, A., Rienties, B., Giesbers, B., & Gijselaers, W. H. (2012). How achievement emotions impact students' decisions for online learning, and what precedes those emotions. *Internet and Higher Education*, 15 (2012), 161-169. DOI information: 10.1016/j.iheduc.2011.10.003.

Tempelaar, D. T., Rienties, B., & Giesbers, B. (2014). Computer Assisted, Formative Assessment and Dispositional Learning Analytics in Learning Mathematics and Statistics. In M. Kalz and E. Ras (Eds.), *Computer Assisted Assessment. Research into E-Assessment*, pp. 67-78. Berlin, Springer: Communications in Computer and Information Science, Volume 439. DOI: 10.1007/978-3-319-08657-6_7

Tempelaar, D. T., Rienties, B., & Giesbers, B. (2015a). In search for the most informative data for feedback generation: Learning analytics in a data-rich context. *Computers in Human Behavior*, 47, 157-167. Special Issue Learning Analytics. DOI: 10.1016/j.chb.2014.05.038

Tempelaar, D. T., Rienties, B., & Giesbers, B. (2015b). Understanding the role of time on task in formative assessment: the case of mathematics learning. In E. Ras and D. Joosten-ten Brinke (Eds.), *Computer Assisted Assessment -- Research into E-Assessment.*

Communications in Computer and Information Science, Vol. 571, 120-133. Zug, Switzerland: Springer. DOI: 10.1007/978-3-319-27704-2_12

Tempelaar, D. T., Rienties, B., & Giesbers, B. (2016). Verifying the Stability and Sensitivity of Learning Analytics Based Prediction Models: An Extended Case Study. In S. Zvacek, M. T. Restivo, J. Uhomoibhi and M. Helfert (Eds.), *Computer Supported Education*, pp. 256-273. Switzerland: Springer, Communications in Computer and Information Science, Vol. 583. DOI: 10.1007/978-3-319-29585-5_15

Tempelaar, D. T., Rienties, B., Giesbers, B., & Schim van der Loeff, S. (2013a). How Cultural and Learning Style Differences Impact Students' Learning Preferences in Blended Learning. In E. Jean Francois (Ed.), *Transcultural Blended Learning and Teaching in Postsecondary Education*, Pages 30-51, DOI: 10.4018/978-1-4666-2014-8.ch003. Hershey PA: IGI Global.

Tempelaar, D. T., Rienties, B., Giesbers, B., & Schim van der Loeff, S. (2013b). Cultural differences in learning approaches. In P. Van den Bossche, W. H. Gijselaers and Richard G. Milter (Eds.), *Facilitating Learning in the 21st Century: Leading through Technology, Diversity and Authenticity*, 1-28, DOI 10.1007/978-94-007-6137-7_1. Dordrecht: Springer-Verlag.

Tempelaar, D. T., Rienties, B., Mittelmeier, J., & Nguyen, Q. (2018). Student profiling in a dispositional learning analytics application using formative assessment. *Computers in Human Behavior*, *78*, 408-420. DOI: 10.1016/j.chb.2017.08.

Tempelaar, D. T., Rienties, B., & Nguyen, Q. (2017a). Towards actionable learning analytics using dispositions. *IEEE Transactions on Education*, 10(1), 6-16. DOI:10.1109/TLT.2017.2662679

Tempelaar, D.T., Rienties, B., & Nguyen, Q. (2017b). Adding dispositions to create pedagogy-based Learning Analytics. *Zeitschrift für Hochschulentwicklung, ZFHE*, 12(1), 15-35.

Tempelaar, D., Rienties, B. & Nguyen, Q. (2018a). Investigating learning strategies in a dispositional learning analytics context: the case of worked examples. In *Proceedings of the International Conference on Learning Analytics and Knowledge*, Sydney, Australia, March 2018 (LAK'18), p. 201-205. DOI: 10.1145/3170358.3170385

Tempelaar, D., Rienties, B. & Nguyen, Q. (2018b). A multi-modal study into students' timing and learning regulation: time is ticking. *Interactive Technology and Smart Education* (in press).

Tempelaar, D. T. & Verhoeven, P. (2016). Adaptive and maladaptive emotions, behaviours and cognitions in the transition to university: The experience of international full degree students. In D. Jindal-Snape and B. Rienties (Eds.), *Multi-dimensional transitions of international students to higher education*, Chapter 12, 334-358. Routledge: New York, NY.

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

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. (2017). 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.

CVs

Dr Dirk T. Tempelaar is an associate professor at the Department of Quantitative Economics at the Maastricht University School of Business and Economics. His research interests focus on modelling student learning, and students' achievements in learning, from an individual difference perspective. That includes Dispositional learning analytics: 'big data' approaches to learning processes, with the aim to find predictive models for generating learning feedback, based on computer-generated trace data, and learning dispositions.

Quan Nguyen is a Leverhulme fundedPh.D. candidate in Learning Analytics at the Institute of Educational Technology, The Open University, UK. He graduated with a Master (cum laude) of Economics and Information Management at Maastricht University. Quan had considerable experience in teaching Quantitative Methods and Management of Information System, and working as a data analyst in several projects. In his PhD (2016-2019) under the supervision of Prof. Bart Rienties, Prof. Denise Whitelock, and Prof. Zdenek Zdrahal, he is focusing on the use of Learning Analytics to understand and improve how teachers design their course in Virtual Learning Environment.

Dr Bart Rienties is Professor of Learning Analytics at the Institute of Educational Technology at the Open University UK. He is programme director Learning Analytics within IET and head of Data Wranglers, whereby he leads a group of learning analytics academics who conduct evidence-based research and sense-making of Big Data at the OU. As an educational psychologist, he conducts multi-disciplinary research on work-based and collaborative learning environments and focuses on the role of social interaction in learning, which is published in leading academic journals and books. His primary research interests are focussed on Learning Analytics, Computer-Supported Collaborative Learning, and the role of motivation in learning.