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Adding dispositions to create pedagogy-based Learning Analytics

Abstract

This empirical study aims to demonstrate how Dispositional Learning Analytics (DLA) can provide a strong connection between Learning Analytics (LA) and pedagogy. Where LA based models typically do well in predicting course performance or student drop-out, they lack actionable data in order to easily connect model predictions with educational interventions. Using a showcase based on learning processes of 1080 students in a blended introductory quantitative course, we analysed the use of worked-out examples by students. Our method is to combine demographic and trace data from learning-management systems with self-reports of several contemporary social-cognitive theories. Students differ not only in the intensity of using worked-out examples but also in how they positioned that usage in their learning cycle. These differences could be described both in terms of differences measured by LA trace variables and by differences in students' learning dispositions. We conjecture that using learning dispositions with trace data has significant advantages for understanding student's learning behaviours. Rather than focusing on low user engagement, lessons learned from LA applications should focus on potential causes of suboptimal learning, such as applying ineffective learning strategies.

Keywords

Dispositional Learning Analytics, actionable data

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1 Dispositional Learning Analytics

In order to use Learning Analytics (LA) "*to evaluate different pedagogical strategies and their effects on learning and teaching through the analysis of learner data*" (GRELLER & DRACHSLER, 2012, p. 48), we will need to move beyond mere collection of traces of student activity in Learning Management Systems (LMS). Beyond the issue of the low predictive power of some of these logged activity data (TEMPELAAR, RIENTIES & GIESBERS, 2015), the more important issue is the lack of 'actionable data' for educators (GASEVIC, DAWSON, & SIEMENS, 2015). In order to design effective pedagogy-based learning interventions in case predictions signal the need to intervene, it should be possible to link LA data to pedagogical theory.

In this contribution, we conjecture and provide first evidence that Dispositional LA (DLA, see BUCKINGHAM SHUM & DEAKIN CRICK, 2012; BUCKINGHAM SHUM & FERGUSON, 2012) has the potential to provide a pedagogy-based LA framework. Elsewhere (TEMPELAAR, RIENTIES & NGUYEN, 2016) we argued that a DLA infrastructure that combines learning data (i.e. generated in learning activities through traces of an LMS) with learner data (e.g., student dispositions, values, and attitudes measured through self-report surveys) may generate data that is actionable. DLA applications not only provide prediction models that help identify students at risk, but do so using pedagogical descriptors, such as students high in deactivating negative learning emotions, or students using the suboptimal cognitive processing strategies of step-wise learning. Such pedagogical descriptors are easily linked with pedagogical theories, and hence, enable concrete actions, such as counselling activities directed at discovering where the negative learning emotions stem from or practicing the use of deep learning processing strategies.

In this showcase study, we will focus on one specific trace variable: students requesting fully worked-out solutions. What different pedagogical scenarios apply to fully worked-out solutions? And what learning dispositions act as an antecedent of these scenarios? In answering these questions, we intend to demonstrate the pedagogical advantage of extending LA into DLA.

2 Use of fully worked-out solutions

The manner in which students seek feedback in their self-regulated learning activities constitutes one aspect of pedagogic behaviour (GRELLER & DRACHSLER, 2012). Worked-out examples represent one of the several feedback formats in computer-enhanced environments (DUFFY & AZEVEDO, 2015), formats that amongst others differ in the amount of guidance or assistance provided to students. Pedagogics has identified four main instructional approaches for assisting learners in problem-solving (MCLAREN, VAN GOG, GANOE, KARABINOS & YARON, 2016), with varying degrees of learner support. First, the problem-solving approach is positioned in the low guidance end of the continuum, offering little or no feedback to learners. Second, tutored problem solving provides learners with feedback and hints to solve the problem or construct the schema when a learner is stuck. This approach intervenes in the learning process only when help is needed; hence, it ensures learners will actively attempt to solve the problems. Third, erroneous examples present learners with flawed examples and instruct them to find, explain, and fix errors. Finally, at the high end of learner support MCLAREN et al. (2016) position the use of worked-out examples. The use of worked-out solutions in multi-media based learning environments stimulates gaining deep understanding (RENKL, 2014). When compared to the use of erroneous examples, tutored problem solving, and problem-solving in computer-based environments, the use of worked-out examples may be more efficient as it reaches similar learning outcomes in less time and with less learning efforts (MCLAREN et al., 2016).

Most of the above-cited studies are nested in laboratory settings, with students assigned to one of the several experimental conditions, each representing one unique pedagogical feedback scenario. In authentic settings, students mix and match diverse pedagogical feedback scenarios, and do so in different orders. For example, some students will avoid using worked-out examples; other students use worked-out examples at the start of a new learning cycle, whereas others use worked-out examples at the very end of their learning cycle.

Beyond detecting individual differences in preferences for pedagogical feedback scenarios, a next step is to explain these based on differences in learning dispositions. For example, studies in gender differences in learning mathematics suggest that female students would profit more from having worked-out examples available at the very start of learning new mathematical concepts (BOLTJENS, 2004). As suggested by KOEDINGER, MCLAUGHLIN, ZHUXIN JIA & BIER (2016), LA-based models that encompass traces of all relevant pedagogical scenarios may not only lead to knowledge of preferred pedagogical scenarios and their relationship to learning dispositions but also to their efficiency.

Any attempt to solve an exercise can have three different outcomes: the student successfully solves the exercises, provides an incorrect answer, or does not provide any answer, but calls for a worked-out solution. In each of these cases, a student can call for a supportive Hint. These functionalities are examples of Knowledge of the Correct Response (KCR) and Knowledge of Result/response (KR) types of learning feedback; see NARCISS (2008). As indicated before, individual differences exist both in the intensity of using worked-out examples and their timing. For example, in our context students undertake on average 1.35 attempts per exercise, using one hint per eight exercises, and ask on average 0.37 worked-out solutions per exercise. As an approximation of the specific stage in the learning cycle in which students use the feedback mode of fully worked-out solution, we constructed a SolutionOrder variable indicating the position of the call of the solution in the series of attempts of any exercise. The variable ranges from zero to one, with lower values indicating that the call takes place in the initial learning phase, and higher values indicating that the call is positioned at the end of the learning process, such as the last attempt preparing for a quiz.

3 Methods

3.1 Context of the empirical study

This empirical study is based on a large-scale course introductory mathematics and statistics, using an educational system 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 (SCHMIDT, VAN DER MOLEN, TE WINKEL & WIJNEN, 2009). Participation in these tutorial groups is required. Optional is the online component of the blend: the use of the two e-tutorials SOWISO for mathematics, MyStatLab for statistics (TEMPELAAR et al., 2015). This choice is based on the philosophy of student-centred education placing the responsibility for making educational choices primarily on the student. The use of e-tutorials and achieving good scores in the practicing modes of the digital environments is stimulated by making bonus points available for good performance in the quizzes. Quizzes are taken every two weeks and consist of items that are drawn from the same item pools applied in the practicing mode. We chose this particular constellation as it stimulates students with less prior knowledge to make intensive use of the digital platforms. The bonus is maximized to 20% of what one can score in the exam.

The subject of this study is the 2015/2016 cohort of first-year students, who in some way participated in learning activities in the SOWISO digital tool: 1080 students. We restrict this study to learning activities in the SOWISO tool, because of the richness of trace data generated by the tool. A large diversity in the student population is present: only 23.8% were educated in the Dutch high school system, 45.7% of the students were educated according to the German Abitur system. In the investigated course, students work an average 9.7 hours in SOWISO, 12% of the available time of 80 hours for learning on both topics.

The study profits from the circumstance that students conduct a required statistical project, in which they analyse a personal data set, built from their own disposition data. That is: answering all surveys in an honest way is crucial for fulfilling all course requirements. Nonresponse is therefore limited to dropout from the course (the last survey counting a response of 1021).

3.2 Instruments and procedure

Our study combines two different data sources: trace data of the SOWISO learning environment, and self-report survey data measuring learning dispositions. Trace data is both of product and process type (AZEVEDO et al., 2013). SOWISO reporting options of trace data are very broad, requiring making selections from the data. First, all dynamic trace data were aggregated over time, to arrive at static, full course period accounts of trace data. Second, from the large array of trace variables, a selection was made by focusing on process variables most strongly connected to alternative pedagogical behaviours of students. These include the alternative feedback modes preferred by students. In total, six trace variables were selected:

- Mastery in the tool, the proportion of exercises successfully solved as product indicator;
- Time in the tool: total connect time;
- #Attempts: total number of attempts of individual exercises;
- #Solutions: total number of worked-out solutions called;
- SolutionOrder: indicator of the phase in the learning process where worked-out solution is called for;
- #Hints: the total number of Hints called for.

In this study, we will make an additional selection with regard to the self-report surveys measuring student learning dispositions. More than a dozen were administered, ranging from epistemological conceptions about the role of intelligence in learning, to academic buoyance in the learning itself. We will focus here on a selection of six instruments measuring aspects of self-regulated learning (SRL), feedback seeking, achievement goal setting and learning emotions, since these dispositions have been investigated in recent LA studies (see AZEVEDO et al., 2012; DUFFY & AZEVEDO, 2015, and references therein). All disposition surveys are measured using seven-point Likert scales; no transformations of variables were required.

Applications of achievement goal theory in LA studies typically employ the two*two framework of goals, distinguishing two goal definitions, mastery goals against performance goals, and two goal valences, approach goals against avoiding goals (see e.g. DUFFY & AZEVEDO, 2015, and references therein). In this study, we apply an extended version of this framework using four different goal definitions: Task, Self, Other, and Potential goal types (ELLIOT, MURAYAMA, KOBEISY & LICHTENFELD, 2015). Task, Self, and Potential goals use as a basic standard to define competence the task itself, oneself in the past, and one's own future potential, respectively. Other goals are normative of character, using a standard based on the comparison with others.

Self-regulated learning dispositions decompose into preferred processing strategies of students, and metacognitive regulation strategies (VERMUNT, 1996). Processing strategies allow for an ordinal classification from two deep learning orientations, Critical processing, and Relating, through Concrete processing, to two surface or step-wise learning orientations: Analysing and Memorising.

The second component of SRL is the metacognitive component, specifying students' preferences in the regulation of the learning (VERMUNT, 1996). The two main types are a preference for self-regulation versus a preference for regulation by others, or external regulation. Both distinguish two aspects: the regulation of the learning process and the learning content. A third main type is that of lack of regulation.

A further facet of SRL is the help-seeking behaviour of students: of Instrumental type, of Executive type, or Avoiding help-seeking type (PAJARES, CHEONG & OBERMAN, 2004). Here, both students who avoid help-seeking at all and students who seek help with the main goal that someone else solves the problem for them, labelled as executive help-seeking, represent the mal-adaptive types of help-seeking. Instrumental help-seekers search for help as part of their own learning process.

Learning emotions of epistemic type distinguish in emotions with positive, negative and neutral valence (PEKRUN & MEIER, 2011).

4 Results

This first reporting of the empirical research intends to verify that our case satisfies the requirement of a traditional LA application: that trace data are informative for the relevant performance indicators of the course, implying that trace-based prediction models have a potential to signal students at risk. Fig. 1 contains bivariate correlations of the three performance indicators MathExam, the score in the final exam on the Math questions, MathQuiz, the total score in the three Math quizzes, and CourseScore, the final total score for the course, built from quiz scores and final exam scores, and containing both Math and Statistics as topics. A fourth variable added to Fig. 1 is the indicator variable Female, as to check the existence of differences in revealed preferences in using alternative pedagogical scenarios. The six different trace variables are described in the previous section.

The full correlation matrix and descriptive statistics of all variables are contained in the statistical supplementary material, including the significance of all bivariate correlations. However, with the current sample size, all correlations larger than .06 are significant at 5% level, and all correlations larger than .08 are significant at 1% level, in all figures.

In total, the digital tool contained 60 lessons, each counting five to twelve exercises, spread over seven weeks of education. Every exercise in all lessons contains the option of calling a worked-out example or hints. For all these lessons, average mastery level were .51 and an average number of attempts per exercise equalled 1.35, indicating that exercises are attempted on average 2.7 times. In 28% of all attempts, students called for a solution, and in 9% of the attempts, students called for a hint.

Reading the correlations for Female in Fig. 1 signals the absence of gender effects in LMS trace data, in contrast to what previous studies suggest. All other correlations, referring to course performance, are strongly significant; these correlations confirm the prospect of LA: trace variables are crucial building blocks for predictive models of course performance.

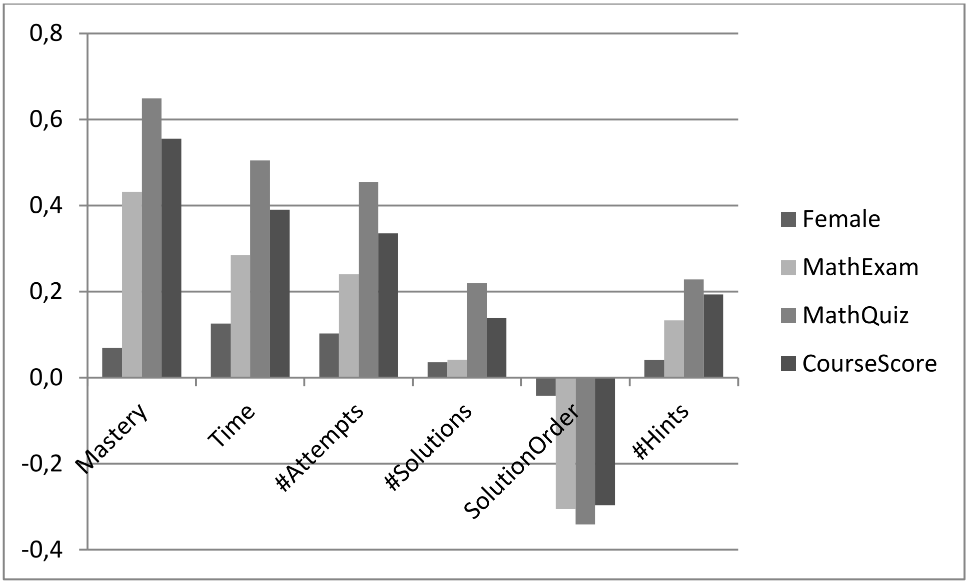

Figure 1: Task, Self, Other, & Performance achievement goals as antecedents

4.1 Achievement goals as pedagogic antecedents

The main part of the empirical analysis focuses on the relationships between trace variables and student dispositions. We perform this analysis in five steps, starting with goal setting behaviour related dispositions. Both cognitive or product traces (Mastery in the tool) and activity or process traces (Time in the tool, #Attempts, #Solutions, #Hints) are positively related to all goal setting types, see Fig. 2. Strongest relationships are for the classical Task goals and for future directed self-related goals: Potential. Within these definitions, stronger impacts exist for the Approach rather than Avoid valence of goals.

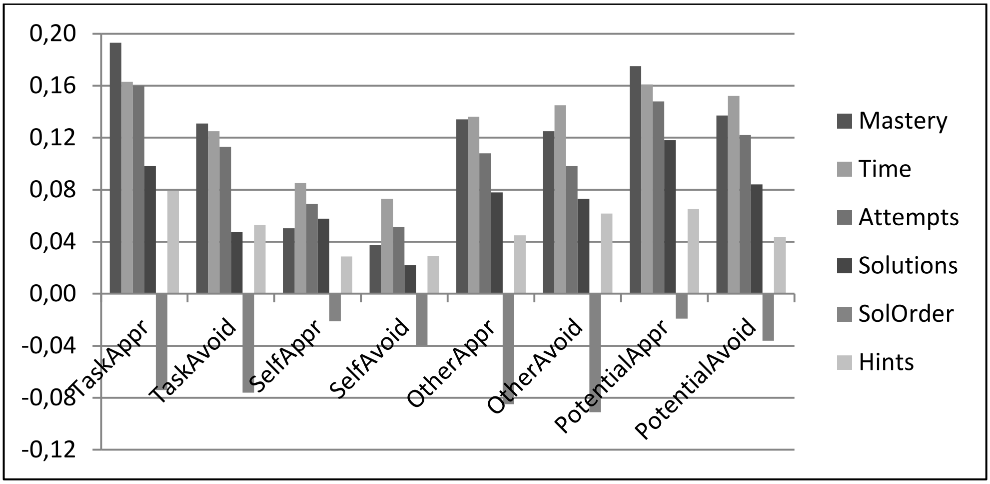

Figure 2: Task, Self, Other, & Potential achievement goals as antecedents

The negative relationships with SolutionOrder indicate that students scoring high on the Task and Other achievement goals, of both Approach and Avoid valences make use of the worked-out solutions in an earlier stage of the learning process, relative to students scoring high on the two Self-related goals, both of past and future (Potential) type.

An alternative operationalization of achievement goals that avoids the use of the avoidance valence for goal setting is based on the learning and appearance achievement goal framework proposed by GRANT & DWECK (2003). Correlations depicted in Fig. 3 demonstrate that Outcome goal setting provides the strongest stimulus to be active in SOWISO, followed by the second appearance goal of non-normative type: Ability goal setting. Lower scores are visible for both the normative versions of the appearance goals and the two types of learning goals.

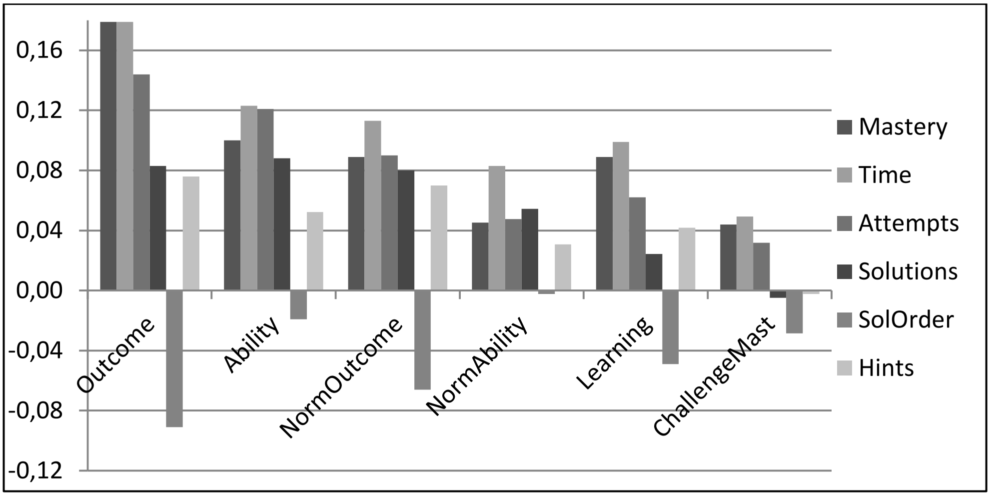

Figure 3: Learning and Appearance achievement goals as antecedents

4.2 Cognitive processing strategies as pedagogic antecedents

In the second step, the role of different levels of cognitive processing strategies is investigated, ranking these from deep learning strategies (critical processing, relating) to surface strategies (analysing, memorising). Fig. 4 demonstrates the relationships of these student dispositions and tool trace data. Higher order processing strategies appear to be unrelated to process type of trace data, in contrast to lower order processing strategies. Especially students scoring high on Memorising as preferred strategy distinguish from other users in high levels of activity, and subsequently high levels of mastery. These students differ also in the way they use solutions: early in the learning cycle for students scoring high on the deeper strategies, equally spread out for students with the memorising strategy.

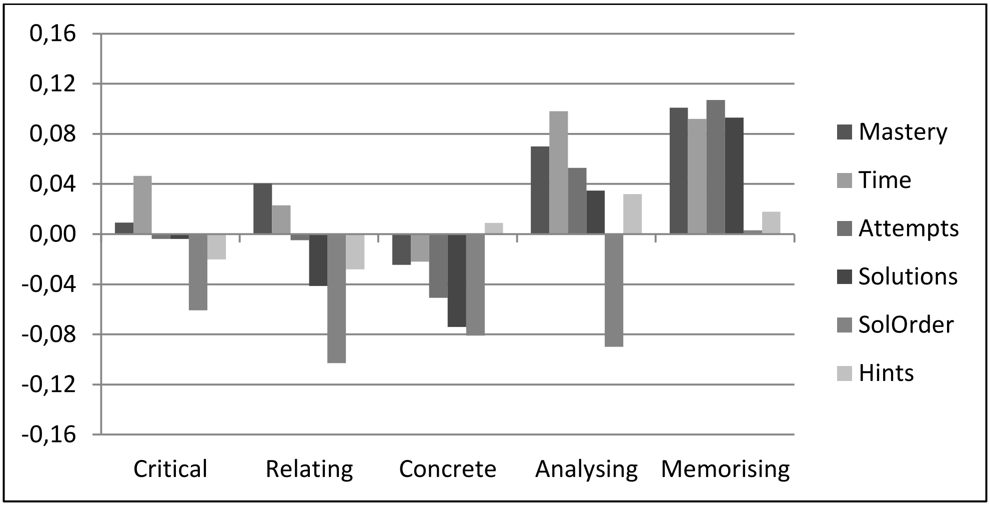

Figure 4: Cognitive learning processing strategies as antecedents

4.3 Metacognitive regulation as pedagogic antecedents

The specific learning strategies that students apply are linked to their metacognitive learning regulation strategies that allow once again a ranking: from stronger self-regulation to stronger external regulation. Fig. 5 exhibits the relationships between these five dispositions and the tool trace data. Self-regulation is only very weakly related to tool trace data, in contrast to external regulation. Students who need external help in regulating their learning profit from the support by SOWISO. These students are more active than others and reach higher mastery levels. At the same time, these students use the worked-out solutions primarily at the start of the learning cycle. The opposite position is taken by students who lack regulation: they are low on mastery and activity levels but high on the SolutionOrder score.

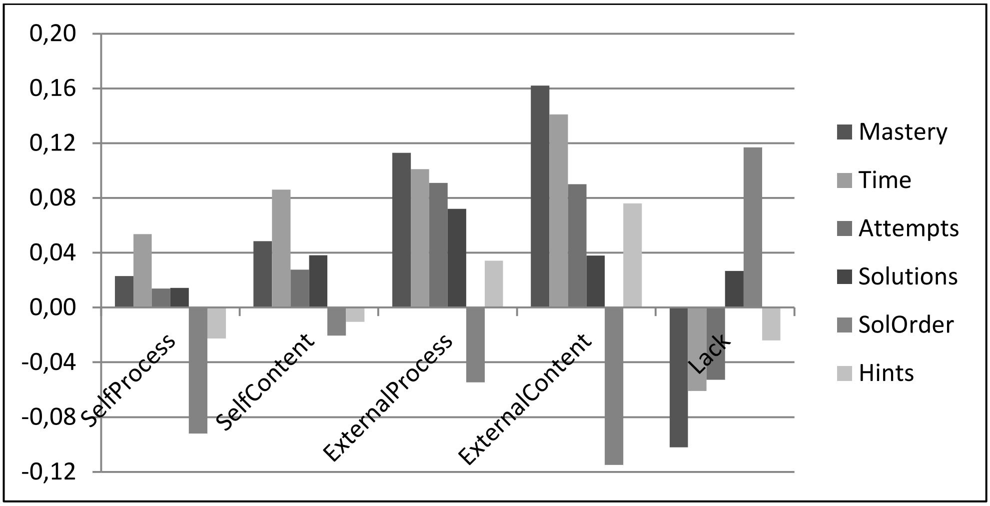

Figure 5: Metacognitive learning regulation strategies as antecedents

4.4 Help-seeking behaviour as pedagogic antecedents

A separate aspect of metacognitive learning regulation is how students proceed with help-seeking. How differences in preferred help-seeking behaviour impact the tool use is visible from Fig. 6. The tendency to avoid help-seeking blocks students both from using the tool and from building mastery in the tool. When students with such tendency use the tool, they are inclined to use it in a suboptimal way: to let the tool find the solutions. Seekers of executive help demonstrate a similar pattern, although less outspoken, while finally seekers of instrumental help demonstrate the opposite pattern.

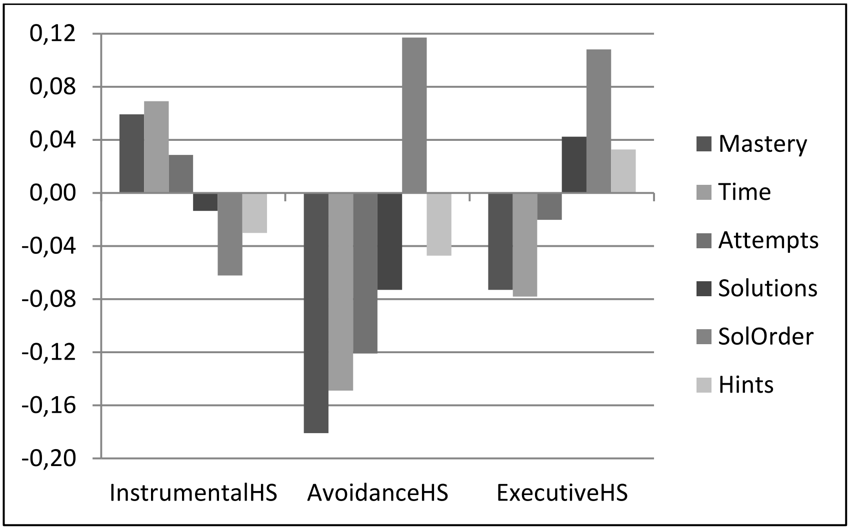

Figure 6: Help-seeking behaviour as antecedents

4.5 Epistemic learning emotions as pedagogic antecedents

In the last step of our empirical investigations, we looked into epistemic learning emotions. Emotions with positive valence, Enjoyment, and Curiosity, are positively related to all tool trace data, with the exception of SolutionOrder. Emotions with negative valence, Anxiety, Frustration, Confusion, and Boredom, exhibit the opposite pattern, whereas the emotion with neutral valence, Surprise, is unrelated to tool trace data: see Fig. 7.

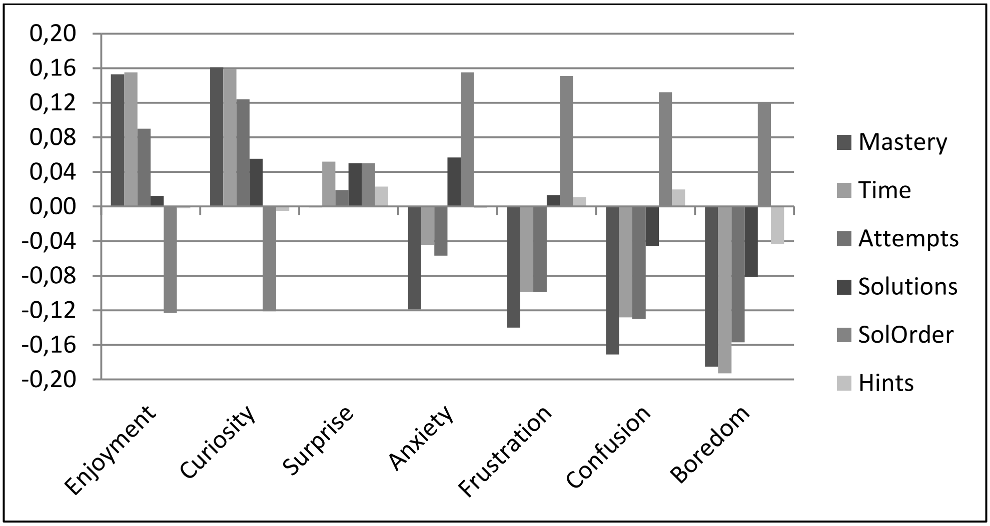

Figure 7: Epistemic learning emotions as antecedents

5 Discussion and conclusion

‘Traditional’ LA applications focus on discovering relationships between trace data and course performance in order to provide learning feedback. In this study, we focussed on how students made use of worked-out examples, how their learning dispositions influenced the intensity of this activity, and at what stage this took place in the learning cycle. Our findings indicated that calling for worked-out examples improved performance in general, but the timing of that call made a strong difference. Looking at worked-out examples at the start of a new learning cycle appeared being a more effective learning strategy than calling that same worked-out example at the end of the learning cycle.

Different from previous research, all taken place under laboratory conditions with tightly controlled opportunities to use pedagogical scenarios, our authentic setting did allow us to differentiate between two alternative ways of using worked-out examples. Some students used the worked-out examples early in the learning cycle, most probably as the first encounter with a new mathematical topic. This variant of the worked-out examples pedagogical scenario proved to be an efficient one, corroborating the findings achieved in laboratory research (RENKL, 2014; MCLAREN et al., 2016). However, another usage of this pedagogical scenario is one whereby students use the worked-out examples late in the learning cycle, mostly just before upcoming quizzes. This specification of the scenario appeared being ineffective, given the negative correlations of the SolutionOrder variable with all performance indicators (Fig. 1).

Our results indicated that particular learning behaviours are linked to using worked-out examples in a suboptimal way. Amongst students setting achievement goals using own performance, either in the past or in the future, as a standard, correlations were basically zero. But students adopting a Mastery goal or a performance goal whilst taking peers as their standards, the Other goal, tended to postpone the use of worked-out examples. The alternative goal setting framework of GRANT & DWECK (2003) confirmed this finding: it is the Outcome goal, both in non-normative and normative versions that correlated most strongly to delayed use of worked-out examples.

Marked differences were also visible in the trace data between students disposed to use superficial cognitive processing strategies, Analysing and especially Memorising, and all other processing strategies. Stepwise learners, VERMUNT's (1996) term for learners focussing on Analysing and Memorising, were stronger facilitated by the SOWISO tool than Deep learners: they were a lot more active in the e-tutorial, and reach this way higher mastery levels, without falling into the inefficient learning behaviour of the late calling of work-out examples. In contrast, Deep learners did not need intensive practicing, could rely on the face-to-face component as the main mode of learning, and when calling for examples from the digital tool, did it mostly in an optimal way, which is at the start of the learning cycle.

Metacognitive learning regulation, both with regard learning content and learning processes, made a similar difference visible. Self-regulated learners, like deep learners, did not depend on SOWISO, and when they did use the e-tutorials they tended to use examples in an optimal way. In contrast, External-regulated learners depend on their learning environment, their tutors and SOWISO. They made more frequent use of these tools but were applying worked-out examples in the same way, mostly at the start of the learning cycle. It is the learner that Lacks any regulation, either of self or external type, who stands out: low in activity, and when using worked-out examples, at the end of the learning cycle.

Help-seeking behaviour was one of the metacognitive dispositions of strong relevance to learning in e-tutorial systems (PAJARES et al., 2004). Instrumental help seeking as the single adaptive version of help seeking resembled deep learning and self-regulated learning in its correlational pattern: lack of relationship with activity levels, a tendency to use worked-out examples early in the learning cycle. Again, this was mirrored in both Executive help seeking and Avoidance of help seeking: the mal-adaptive versions. Both correlate negatively with activity in SOWISO, and positively with the delayed use of worked-out examples.

Finally, dispositions of learning emotions also distinguished adaptive and mal-adaptive types (PEKRUN & MEIER, 2011). Enjoyment and Curiosity were strong examples of the first type, whereby students scoring high on these two positive and activating emotions indeed showed higher activity levels and optimal use of worked-out examples. In contrast, negative, de-activating emotions, here represented by Frustration, Confusion, and Boredom, blocked students from using the e-tutorials and acted as stimuli to postpone the use of worked-out examples till later in the learning cycle. Surprise and Anxiety took a special position in the continuum of epistemic emotions: they lack an unequivocal position on the valence and activation dimensions. Anxiety is a negative emotion that can be activating or deactivating, depending on the context. Relationships between Anxiety and activity measures were weak but tended to be negative. The impact of Anxiety on the position of worked-out examples in the learning cycle is, however, clear: Anxiety pushes the use of examples backward in time. Surprise has no straightforward valence, nor activation dimension. In our context, this translates in the complete absence of any impact of the epistemic emotion Surprise.

In our context, trace and disposition data were fed back to students and their tutors, in problem-based learning the two main actors responsible for taking initiatives to improve student learning. From a researchers' perspective, the disadvantage of our student-centred context is that actions taken by students and tutors to address learning issues are not easily observable. In other, more teaching-centred contexts, one would come up with campaigns informing students about which learning strategies have proven to be effective, and which ones are suboptimal.

Another uncommon aspect of our context is the availability of a rich data set of learning dispositions, gathered by taking self-report surveys. That richness includes two dimensions: a wide range of different instruments relevant to learning, and full response of all students. Of these two dimensions, the second is crucial. Survey data is often 'hard to get', and in many situations, the most difficult to get data is the most informative data (such as from students at risk of drop-out). Having data from so many different instruments helped us built this show-case, but is not crucial for applying DLA: most of the instruments share substantial common variation, and the explained variation of multivariate models is of the same order of size as the univariate models reported here (see TEMPELAAR et al., 2015). Using a single instrument, as in BUCKINGHAM SHUM & DEAKIN CRICK (2012) will primarily impact the diversity of actions it facilitates, rather than explained variation.

In summary: the disposition dimension of DLA brings about gathering data that is not only predictive but also actionable (GASEVIC et al., 2015). Knowing that students who in their learning of new academic topics depend strongly on the most step-wise processing strategy, the strategy of Memorising, tend to postpone the use of worked-out examples, opens a way to act: not by just persuading students to use the worked-out examples earlier, but by focussing on more effective learning strategies. A similar argument can be made for epistemic emotions: pressing one to become more active in practicing will have low success rates when that low activity level is caused by learning boredom. In such a case, any measure to stimulate learning activity is likely to have adverse effects. From this perspective, the introduction of DLA does even more than providing actionable data: it allows educators to direct the interventions at the true causes of the underperforming, rather than its symptoms.

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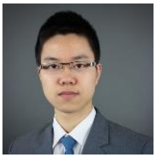

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