Analysing the Use of Worked Examples and Tutored and Untutored Problem-Solving in a Dispositional Learning Analytics Context

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Abstract: The identification of students' learning strategies by using multi-modal data that combine trace data with self-report data is the prime aim of this study. Our context is an application of dispositional learning analytics in a large introductory course mathematics and statistics, based on blended learning. Building on previous studies in which we found marked differences in how students use worked examples as a learning strategy, we compare different profiles of learning strategies on learning dispositions and learning outcome. Our results cast a new light on the issue of efficiency of learning by worked examples, tutored and untutored problem-solving: in contexts where students can apply their own preferred learning strategy, we find that learning strategies depend on learning dispositions. As a result, learning dispositions will have a confounding effect when studying the efficiency of worked examples as a learning strategy in an ecologically valid context.

1 INTRODUCTION

For many decades, research into student learning tactics and strategies has primarily relied on self-reports or think-aloud protocols, open to the bias often present in self-reported perceptions, or excluding naturalistic contexts from the analysis (Azevedo et al., 2013; Gašević et al., 2017a; Gašević et al., 2017b). The increasing use of blended learning and other forms of technology-enhanced education gave way to measure revealed learning strategies by collecting traces of students' learning behaviours in the digital learning platforms. This new opportunity of combining trace data with self-report data has boosted empirical research in learning tactics and strategies. Examples of such are Azevedo et al. (2013), and research by Gašević and co-authors (Gašević et al., 2017a; 2017b).

This type of research aims to investigate relationships between learning strategies measured by trace data, learning approaches measured by self-reports, and academic performance as learning outcomes. For instance, Gašević et al. (2017a) finds that learning strategies are related to deep learning approaches, but not to surface learning approaches. In the experimental study Gašević et al. (2017b), the role of instructional conditions and prior experience with technology-enhanced education is investigated. However, most of these studies do not take individual differences into account, as expressed in Gašević et al. (2017b, p. 216): 'Future studies should also account for the effects of individual differences -e.g., motivation to use technology, self-efficacy about the subject matter and/or technology, achievement goal orientation, approaches to learning, and metacognitive awareness'.

Our paper aims to contribute to this lack of empirical work incorporating individual differences, by addressing students' learning strategies within a dispositional learning analytics context. The Dispositional Learning Analytics (DLA) infrastructure, introduced by Buckingham Shum and Crick (2012), combines learning data (generated in learning activities through technology-enhanced systems) with learner data (student dispositions, values, and attitudes measured through self-report

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surveys). Learning dispositions represent individual difference characteristics that impact all learning processes and include affective, behavioural and cognitive facets (Rienties et al., 2017). Student's preferred learning approaches are examples of such dispositions of both cognitive and behavioural type.

The current study builds on our previous DLA-based research (Nguyen et al., 2016; Tempelaar et al., 2013; 2015; 2017a; 2017b; 2017c; 2018). One of our empirical findings in these studies was that traces of student learning in digital platforms show marked differences in the use of worked examples (Nguyen et al., 2016; Tempelaar et al., 2017a; 2017b; 2018). The merits of the worked examples principle Renkl (2014) in the initial acquisition of cognitive skills are well documented. The use of worked 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 examples may be more efficient as it reaches similar learning outcomes in less time and with less learning efforts. The mechanism responsible for this outcome is disclosed in Renkl (2014, p. 400): 'examples relieve learners of problem-solving that – in initial cognitive skill acquisition when learners still lack understanding – is typically slow, error-prone, and driven by superficial strategies. When beginning learners solve problems, the corresponding demands may burden working memory capacities or even overload them, which strengthens learners' surface orientation. … When learning from examples, learners have enough working memory capacity for self-explaining and comparing examples by which abstract principles can be considered, and those principles are then related to concrete exemplars. In this way, learners gain an understanding of how to apply principles in problem-solving and how to relate problem cases to underlying principles'.

However, empirical research based on measured learning behaviour suggests that students may abuse help facilities available in digital learning environments through bypassing more abstract hints and going straightforwardly to concrete solutions (Shih et al., 2008). Analysing log behaviour of students, distinguishing proper use and abuse of help facilities, would allow creating profiles of adaptive and maladaptive learning behaviours (Shih et al., 2008; see also Papamitsiou and Economides, 2014).

Following research by McLaren and co-authors (McLaren et al., 2014; 2016), we extend the range of preferred learning strategies taken into account to include, beyond worked-examples, the tutored and untutored problem-solving strategies. In the tutored problem-solving strategy, students receive feedback in the form of hints and an evaluation of provided answers, both during and at the end of the problem-solving steps. In untutored problem-solving, feedback is restricted to the evaluation of provided answers at the end of the problem-solving steps (McLaren et al., 2014; 2016).

Evidence for the worked examples principle is typically based on laboratory-based experimental studies, in which the effectiveness of different instructional designs is compared (Renkl, 2014). McLaren and co-authors take the research into the effectiveness of several learning strategies a step into the direction of ecological validity, by choosing for an experimental design in a classroom context, assigning the alternative learning approaches worked-examples, tutored and untutored problem-solving, and erroneous examples as the conditions of the experiment (McLaren et al., 2014; 2016). In our research, we increase ecological validity one more step by offering a digital learning environment that encompasses all learning strategies of worked-examples, tutored and untutored problem-solving, and observing the revealed preference of the students in terms of learning strategy they apply. In this naturalistic context, the potential contribution of LA-based investigations is that we can observe students' revealed preferences for a specific learning strategy, how these preferences depend on the learning task at hand, and how these preferences link to other observations, such an individual difference characteristics. By doing so, we aim to derive a characterization of students who actively apply worked examples or tutored problem-solving, and those not doing so. In line with contemporary research into learning strategies applying trace data (Gašević et al., 2017a; 2017b), we adopt two research questions: 1) how does the choice for learning strategy relate to learning dispositions? and 2) how does the learning strategy of using worked examples or tutored problem-solving relate to learning outcomes?

2 METHODS

2.1 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 programme 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 content expert tutors (in 78 parallel tutorial groups). Participation in tutorial groups is required. Optional is the online component of the blend: the use of the two e-tutorials SOWISO (https://sowiso.nl/) and MyStatLab (MSL) (Nguyen et al., 2016; Tempelaar et al., 2013; 2015; 2017a; 2017c). This design 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 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 shares most characteristics of the flipped-classroom design. Using and achieving good scores in the e-tutorial practice modes is incentivized by providing bonus points for good performance in quizzes that are taken every two weeks and consist of items that are drawn from the same item pools applied in the practising mode. This approach was chosen to encourage students with limited prior knowledge to make intensive use of the e-tutorials.

The subject of this study is the full 2016/2017 cohort of students (1093 students). A large diversity of the student population was present: only 19% were educated in the Dutch high school system, against 81% being international students, with 50 nationalities 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. Therefore, it is crucial that this introductory module is flexible and allows for individual learning paths. 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 both topics.

2.2 Instruments and Procedure

Both e-tutorial systems SOWISO and MSL follow a test-directed learning and practising 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. After receiving feedback, a new version of the problem loads (parameter based) to allow the student to demonstrate his/her newly acquired mastery. Students' revealed preferences for learning strategies are related to their learning dispositions, as we demonstrated in previous research (Nguyen et al., 2016; Tempelaar et al., 2017a; 2017c) for the use of worked-examples in SOWISO), and the use of worked-examples in MSL (Tempelaar, 2017b). This study extends Nguyen et al. (2016) and Tempelaar et al. (2017a; 2017c) by investigating three learning strategies in the SOWISO tool: worked examples, and supported and tutored problem-solving.

Figure 1 demonstrates the implementation of the alternative learning strategies students can opt for a sample exercise:

- Check: the untutored problem-solving approach, offering only correctness feedback after problem-solving;
- Hint: the tutored problem-solving approach, offering feedback and hints to assist the student in the several problem-solving steps;
- Solution: the worked-examples approach;
- Theory: asking for a short explanation of the mathematical principle.

Our study combines trace data of the SOWISO e-tutorial with self-report survey data measuring learning dispositions. Clicks in the two e-tutorial systems represent an important part of that trace data, and in that respect, our research design is aligned with the research by Amo-Filvà and co-authors (Amo et al., 2018; Amo-Filvà et al., 2019) who use a tool called Clickstream to describe click behaviour in the digital learning environment. But trace data can include more than click data only. Azevedo (Azevedo et al., 2013) distinguishes between trace data of product and process type, where click data is part of the category of process data. In this study, we will combine both process data, as, e.g. the clicks to initiate the above-mentioned learning supports of Check, Hint, Solution and Theory, but also product data, as, e.g. mastery in the tool, as discussed below. 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 learning strategies.

In total, five trace variables were selected:

- Mastery in the tool, the proportion of exercises successfully solved as product indicator;
- #Attempts: the total number of attempts of individual exercises;

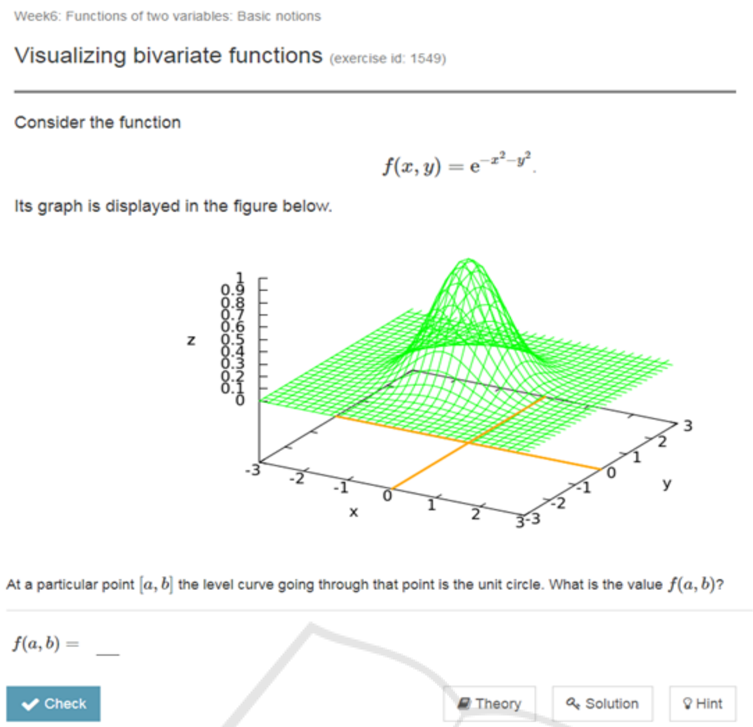

Figure 1: sample of SOWISO exercise with the options Check, Theory, Solution, and Hint.

- #Hints: the total number of Hints called for.
- #Examples: the total number of worked-out examples called.

To disentangle the effects of learning intensity from learning strategy, we restricted the sample to those students who have been very active in the e-tutorial and achieved at least a 70% mastery level (that is, successfully solved at least 162 of the 231 exercises): 860 of the 1080 students. The next step in the analysis is to create profiles of learning behaviours by distinguishing different patterns of student learning in the e-tutorials, as in Amo et al. (2018) or Amo-Filvà et al. (2019). Rather than applying advanced statistical techniques to create different profiles of using worked examples, as in Gašević and co-authors (Gašević et al., 2017a; 2017b) or our previous research (Nguyen et al., 2016; Tempelaar, et al., 2017a; 2017c), we applied quartile splits: the selected students were split into four equal-sized groups according to intensity of using worked examples, as well the intensity of using hints. Table 1 provides descriptive statistics of these four times four sub-samples.

The operationalization of revealed preferences for learning strategies follow these quartile splits. The revealed preference for the worked-examples strategy is operationalized as students calling for many examples, ending up in the higher quarters of the quartile-split for examples. The revealed preference for the tutored problem-solving strategy is operationalized as calling for a large number of hints, thus ending in the higher quarters of the quartile-split for hints. As is clear from Table 1, revealed preferences for learning strategies are not disjunct. A student can combine the strategies of worked-examples and tutored problem-solving, calling for an above-average number of hints as well as above average number of examples.

The strategy of untutored problem-solving is a necessary component of any of the revealed preferences, since students can only build mastery through untutored problem-solving, and the students included in this analysis all obtained high mastery levels.

Mastery level is indeed invariant over groups, and never below 96%: there is a large majority of students in all sub-samples that reached full mastery. There is considerable variation in the use of hints, and the use of examples. The use of hints and examples seems only weakly associated, except for the quarter of students using most hints: HintsQ4. In that quarter, the use of hints and examples is positively correlated (in HintsQ4, the correlation of hints and examples equals 0.23, against 0.07 in all four quarters).

Table 1: Descriptive statistics of four times four sub-samples of students achieving at least 70% mastery level.

Group	N	Mastery	#Attempts	#Hints	#Examples
HintsQ1&ExamplesQ1	72	96.2%	340	4.3	38.7
HintsQ1&ExamplesQ2	41	97.8%	418	4.8	88.7
HintsQ1&ExamplesQ3	59	98.2%	534	4.2	139.9
HintsQ1&ExamplesQ4	59	97.7%	729	4.5	157.7
HintsQ2&ExamplesQ1	64	97.5%	367	20.8	41.9
HintsQ2&ExamplesQ2	55	99.2%	432	21.8	85.3
HintsQ2&ExamplesQ3	39	99.7%	520	21.0	134.5
HintsQ2&ExamplesQ4	45	98.8%	758	20.3	269.9
HintsQ3&ExamplesQ1	53	97.0%	370	57.4	48.5
HintsQ3&ExamplesQ2	53	98.8%	433	53.8	88.6
HintsQ3&ExamplesQ3	56	99.3%	528	56.7	136.1
HintsQ3&ExamplesQ4	52	99.5%	786	59.5	275.4
HintsQ4&ExamplesQ1	33	99.2%	486	135.8	49.1
HintsQ4&ExamplesQ2	60	98.4%	476	137.9	89.7
HintsQ4&ExamplesQ3	61	99.3%	587	157.2	140.8
HintsQ4&ExamplesQ4	58	99.4%	764	174.9	249.1
Total	860	98.4%	530	58.1	135.5

In this study, we will focus on a selection of the self-report surveys measuring student learning dispositions. More than a dozen were administered, ranging from affective learning emotions to cognitive learning processing strategies:

- Epistemological self-theories of intelligence;
- Epistemological views on role effort in learning;
- Epistemic learning emotions;
- Cognitive learning processing strategies;
- Metacognitive learning regulation strategies;
- Subject-specific (math & stats) learning attitudes;
- Academic motivations;
- Achievement goals;
- Achievement orientations;
- Learning activity emotions;
- Motivation & Engagement wheel;
- Cultural intelligence;
- National cultural values; and
- Help-seeking behaviour

Main self-report instruments measuring learning dispositions used in this study are shortly described in the following subsections. For more extensive coverage, please see previous studies by the authors (Nguyen et al., 2016; Tempelaar et al., 2015; 2017a, 2017c; 2018). The description of the research outcomes will focus on specific aspects of learning dispositions: learning approaches, anxiety and uncertainty as aspects of students' attitudes and learning emotions.

Course performance data is based on the final written exam, as well as the three intermediate quizzes. Quiz scores are averaged, and both exam and quiz are decomposed into two topic scores, resulting in MathExam, StatsExam, MathQuiz and StatsQuiz.

2.2.1 Learning Approaches

Students' learning approaches are based on Vermunt's Inventory of Learning Styles (ILS) instrument (Vermunt, 1996). Our study focused on two of four domains of the ILS: cognitive processing strategies and metacognitive regulation strategies. The instrument distinguishes three different processing strategies: deep approaches to learning, stepwise or surface approaches to learning and concrete or strategic approaches to learning, as well as three regulations strategies: self-regulation, external regulation and lack of regulation.

2.2.2 Dispositional Attitudes Data

Attitudes towards learning of mathematics and statistics were assessed with the SATS instrument (Tempelaar et al., 2007). The instrument contains six quantitative methods-related learning 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.

2.2.3 Dispositional Epistemic Emotions Data

Epistemic emotions are related to the cognitive aspects of a learning task. Prototypical epistemic emotions are curiosity and confusion. In this study, epistemic emotions were measured with the Epistemic Emotion Scales (EES; Pekrun et al., 2017). 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 RESULTS

3.1 Previous Research

In previous research (Nguyen, 2016; Tempelaar et al., 2015; 2017a; 2017c; 2018), we investigated the role of worked examples in LA applications and found that a range of dispositions predict the use of worked examples as a learning strategy. Demographic variables, student-learning approaches, learning attitudes and learning emotions influenced the use of worked examples, with effect sizes up to 7% for individual dispositions. In our profiling study (Tempelaar et al., 2017a) we found that the use of worked examples and the total number of attempts to be the two variables shaping most of the characteristic differences between different profiles in the use of the e-tutorial. The use of hints did not strongly contribute to the creation of the student use profiles. As a consequence, we expect dispositions to play a less strong role in the explanation of the use of hints as a learning strategy than it has in the explanation of the use of worked examples. This expectation does indeed come true, and in the reporting of the empirical outcomes in the next sections, we will focus on the cases where dispositions matter in the explanation of both learning strategies, leaving out the cases where the impact is primarily on the use of worked examples, that are described in previous research (Nguyen et al., 2016; Tempelaar et al., 2015; 2017a; 2017c; 2018).

3.2 Demographics

Demographic variables have no practical significance in the explanation of the use of hints: gender and international status have statistically non-significant relationships with the intensity of use of hints. Math prior education has a marginally significant effect with limited size (p-value=.04, eta squared=1.2%). Differences in national cultural values follow this pattern, with the single exception that students from cultures that assign greater value to long-term orientation tend to apply the learning strategy of using hints more often than students from other cultures (p-value=.004, eta squared=1.2%).

3.3 Learning Approaches

Although the use of learning strategies is the explicit focus of learning approaches frameworks, the learning strategy of supported problem solving by using hints was not adequately captured in our learning approaches instrument. Hence, we found no differences in learning approaches for the use of hints. In the use of worked examples, there were significant differences for both the deep and stepwise processing strategies and self-regulation of learning.

3.4 Prior Knowledge

Differences induced by different levels of prior math schooling are enlarged in the first measurement of cognitive type: the math entry test, administered at the very start of the course. The score of diagnostic test was strongly associated with the intensity of using hints, and the use of worked examples. Significance levels are .006, <.001 and .018 for the hints effect, the examples effect, and the interaction effect, respectively, with a total effect size of eta squared=11.9%. Figure 2 provides a graphical illustration of the effects in the several quarters, where we applied reversed scaling to the several quarters to facilitate readability. Students with the highest prior knowledge levels tend to use fewer hints and fewer examples than the other students. However, there was more consistency in the pattern for the use of examples than that for the use of hints: in the quarter of students with the highest intensity of using examples, both the Q1 and Q4 quarters of hint use demonstrate low levels of prior knowledge.

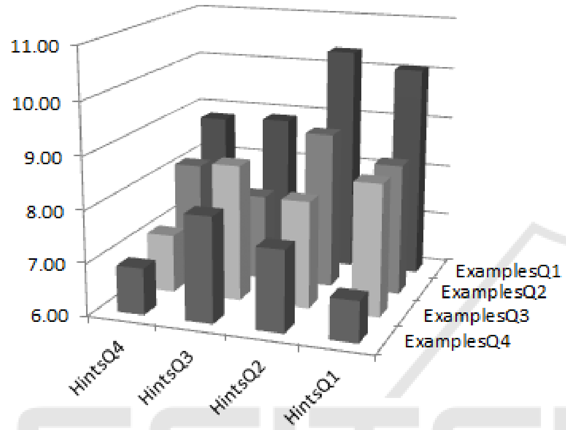

Figure 2: Quarter differences for prior math knowledge, as measured by a diagnostic test (reversed scaling).

3.5 Learning Attitudes

Since learning attitudes as Affect and Cognitive Competence are associated with levels of prior knowledge, it is to be expected that the intensity of use of both learning strategies is associated with learning attitudes. That was indeed the case: Affect (p-value hints<.001, p-value examples<.001, total eta squared=8.9%), Cognitive competence (p-value hints<.001, p-value examples<.001, total eta squared=8.8%) demonstrated clear linear effects in the absence of interaction effects. Value and Interest had no role in explaining difference in strategy use, whereas the NoDifficulty variable was only weakly associated with both strategies (p-value hints=.034, p-value examples=.008, total eta squared=2.9%), and the Effort variable is associated with only the examples strategy (p-value hints=.461, p-value examples=.002, total eta squared=3.5%). Figure 3 provides a graphical presentation for the case of Affect. As in the previous figure, we see that the highest levels of Affect are to be found in the group of students who use both hints and examples least frequently and that intensive use of both strategies is associated with low levels of Affect.

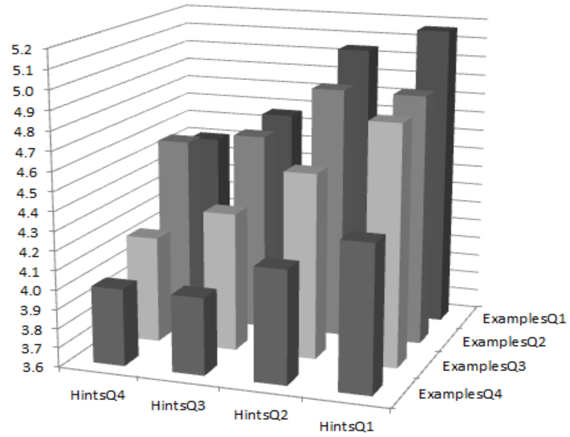

Figure 3: Quarter differences for learning attitude Affect (reversed scaling).

3.6 Epistemic Emotions

Epistemic emotions demonstrated group differences for the negative emotions Confusion (p-value hints=.004, p-value examples<.001, total eta squared=7.0%) and Frustration (p-value hints<.001, p-value examples<.001, total eta squared=6.4%). Frustration was one of the few disposition variables that was associated with the use of hints (partial eta-squared=2.7%) more than with the use of examples (partial eta-squared=2.4%). Epistemic Enjoyment makes an even stronger case: here the only significant relationship is with the use of hints (p-value hints=.001, p-value examples=.083, total eta squared=4.8%). Figure 4 demonstrates the association for Epistemic Frustration, Figure 5 that for Epistemic Enjoyment.

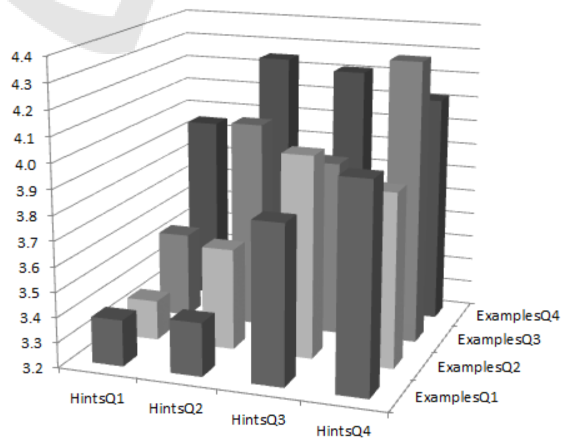

Figure 4: Quarter differences for Epistemic Frustration (non-reversed scaling).

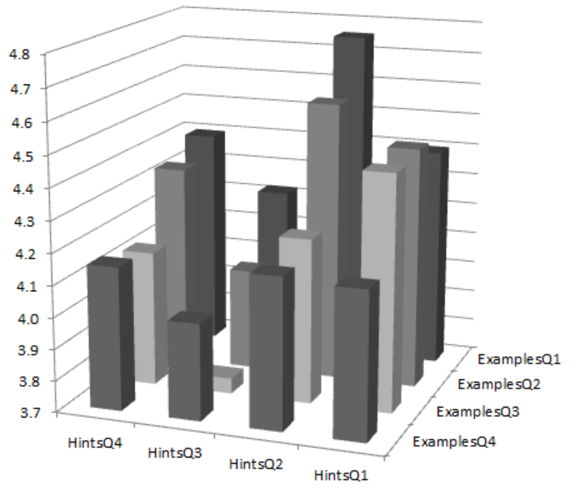

Figure 5: Quarter differences for Epistemic Enjoyment (reversed scaling).

3.7 Learning Outcomes

In the main outcome variable of the learning process, Math Exam or the achievement in the math section of the final written exam, only associations with the learning strategy of using examples can be found, be it that the interaction term is significant (p-value hints=.106, p-value examples<.001, p-value interaction=.013, total eta squared=10.9%). Figure 6 provides a graphical description: math exam score is generally increasing for less intensive use of examples, but the pattern is not identical for all quarters of hint use intensity. Specifically, in students in the third quarter of hint use intensity, the use of examples and performance seem fairly unrelated.

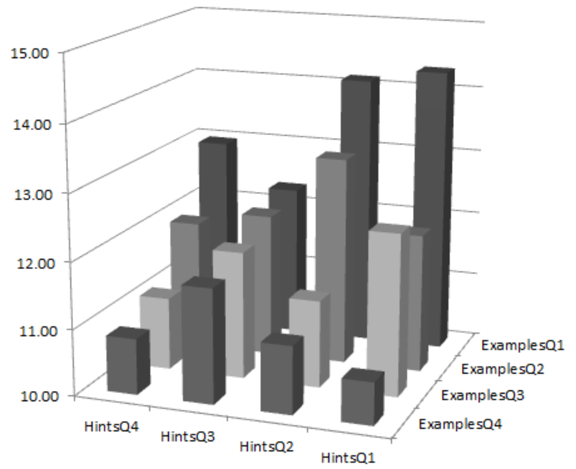

Figure 6: Quarter differences for Math Exam score (reversed scaling).

4 DISCUSSION AND CONCLUSIONS

Existing studies into the efficiency of alternative learning strategies, both in lab settings (Renkl, 2014) and in classroom settings (McLaren et al., 2014; 2016), point in the direction of worked-examples being superior to tutored and untutored problem-solving. These are generic conclusions, which do not differentiate between types of academic tasks or types of students. The main contribution of this study was the emphasis on the individual differences: learning dispositions make a difference, academic tasks make a difference. Allowing for individual differences and task differences also changes the first order conclusions.

Regarding the first research question, we found that students who had less prior knowledge sought more support from both worked-examples and hints. Similarly: students who experienced more negative epistemic emotions such as confusion and frustration, examples of mal-adaptive dispositions, sought more support from both worked-examples and hints. Students who scored higher in the prior knowledge test usually took on the task by themselves without seeking help from hints or examples. At the same time, students who used fewer hints and worked examples scored higher on the math exam (second research question). This implies that worked-examples are only superior to tutored and untutored problem-solving when the latter two learning strategies are not sufficient to achieve proficiency. The initial acquisition of complex knowledge is an example of such a context. In cases the cognitive challenges of the learning tasks are less, this superiority may break down, and worked-examples may be less efficient learning strategies than problem-solving approaches.

Transferring the findings of the Renkl (2014) and the McLaren et al. (2014; 2016) studies to our context, suggests that the superiority of the worked-examples strategy may be the result of the tasks offered to the participants of these studies to be of such type that students in their studies had little or no prior knowledge. Our context has been different: given the wide variety of the tasks and the large diversity in prior knowledge of students, there exists a wide range of relevant prior knowledge levels for any task at hand. In such a context, where students are expected to demonstrate mastery, a mastery that can only be acquired in the untutored problem-solving mode, the use of examples and hints is inevitably a roundabout route, adding inefficiency to the most direct way to mastery. That route of using tutored problem-solving and worked-examples is taken by students who assessed the direct way of untutored problem-solving to be -still- impassable, explaining the relationship with prior knowledge.

Our study is based on creating a taxonomy of learning behaviours by measuring trace data generated by student activity in e-tutorials. That taxonomy corroborates the concept of ‘help abuse’ developed by Shih et al. (2008). Rather than trying to solve problems by asking for hints, some students bypass these hints and directly call for complete solutions. Table 1 makes clear that there exist huge differences in the ratio of hints called for and solutions called for between the several categories generated on the quartile splits. That finding is in line with the hypothesis of help abuse. However, we cannot easily characterize the extreme categories of few hints and many solutions versus many hints and few solutions in terms of the learning dispositions included in this study. That is: although we find categories that might represent help abuse, they are not easily connected with the notions of good and bad student use as introduced in Shih et al. (2008).

We also corroborate the findings of, e.g. Amo et al. (2018) and Amo-Filvà et al. (2019) that traces of learning processes represent useful sources of data for profiling learning behaviour. At the same time: these data do capture only part of the learning process. That is: the main limitation of this research approach is that all learning that takes place outside the traced e-tutorials remains unobserved.

The current study has focussed on individual differences between students in their preference for learning strategies, and the relationship with learning dispositions. In future research, we intend to additionally include the task dimension, by investigating student preference for learning strategies as a function of both individual differences in learning dispositions and task characteristics.

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