# STUDENTS USE OF LEARNING AIDS: LESSONS FROM LEARNING ANALYTICS

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**ABSTRACT**

E-tutorial learning aids as worked examples and hints have been established as effective instructional formats in problem-solving practices. However, less is known about variations in the use of learning aids across individuals at different stages in their learning process in student-centred learning contexts. This study investigates different profiles of students' learning behaviors based on clustering students' use of worked examples and hints in subsequent learning phases in a naturalistic setting. In a blended instructional format, the study was conducted on 1,072 students over an eight-week introductory mathematics course. By explicitly differentiating between learning to prepare a tutorial session, the first phase, learning to prepare a quiz session, the second phase, and learning to prepare the final exam as third phase, this study aims to contribute to the call for more temporality in learning analytics applications. Our study finds three profiles of learning that differ in the intensity and timing of the use of learning aids. Moreover, different profiles come with different learning dispositions, such as epistemic and activity learning emotions.

**KEYWORDS**

Learning Analytics, Dispositional Learning Analytics, Temporal Analysis, E-Tutorials, Learning Aids

## 1. INTRODUCTION

Recent debates in the field of Learning Analytics (LA) focus on the role of time in LA-based models. Traditional LA models by default include time in the role of time on task, often aggregated over longer time spells, but the 'call for more temporality' (Chen et al., 2018; Knight et al., 2017) in applications of learning analytics (LA; Ifenthaler, 2015) is directed at other, time-related aspects of learning processes. Such as timing in the meaning of the order of events in a learning process.

The call for more temporality is often combined with a call for a methodological paradigm shift (Saint et al., 2022): away from the variables-oriented type of models, embracing event-based models using analytic discovery methods as process or sequence mining. This contribution aims to disentangle the two calls: yes, including all facets of time in our LA models is of crucial importance, but no, we do not need to leave variables-based models in order to do so. In fact, staying within the variables-oriented paradigm by applying traditional statistical methods has the great advantage of integrating time-stamped log data with another type of data, such as survey data. Dispositional learning analytics is a field with a long tradition of combining log data with survey data to generate models of learning feedback. The conjecture we entertain in this contribution is that by carefully choosing time windows and granularity levels of the administration of log-data (Molenaar & Wise, 2022), temporal aspects are well integrated into variable-based models based on dispositional LA applications. We aim to showcase by analyzing students' use of learning aids of worked examples and hints types in a blended curriculum, combining problem-based learning with e-tutorials.

# 2. LEARNING AIDS AND THE TEMPORY ASPECT OF LEARNING

## 2.1 Worked Examples and Hints as Learning Aids

A vast body of self-regulated learning (SRL) literature has looked at how learners decide how and when to learn (Winne, 2017). A critical review of six prominent SRL models by Panadero (2017) showed that learners iteratively go through three main phases: the preparatory phase (i.e., planning and goal-setting), the performance phase (i.e., performing the task and monitoring and controlling their own cognition), and the appraisal phase (i.e., reflecting and adapting on their SRL process, as part of self-reflection, by peers, by a computer, or via a teacher). Students' self-regulated choices to use learning aids when learning in technology-enhanced learning environments have been analysed in empirical research, focusing on the use of worked examples (Tempelaar et al., 2020). Previous studies proposed that novice learners would be more likely to benefit from using worked examples prior to problem-solving than vice versa or only using problem-solving (van Merrienboer & Sweller, 2010). The theoretical underpinning behind this is that worked examples are more beneficial to novice learners at the stage of schema acquisition because learners can focus their limited cognition on understanding the principle or concept. However, when learners are given autonomy over their choice of help-seeking, they do not always choose the most optimal learning strategies as proposed in the literature. Furthermore, when looking at how students self-regulated learning over a longer period, we found temporal variances in the use of worked examples over different study phases, which subsequently influenced academic performance (Rienties et al., 2019).

In technology-enhanced learning environments, self-regulated learning is facilitated by the availability of instructional scaffolding. Worked examples, the step-by-step demonstration of the solution to a problem, is only one of them. The facility to request for hints that provide concrete help in proceeding with a problem-solving step when students get stuck shapes another type of scaffold. Salden et al. (2010) define problem-solving with a hint request facility as tutored problem-solving, where untutored problem-solving represents the situation without instructional scaffolds. In comparing tutored problem-solving with and without the support of worked examples, McLaren et al. (2016) conclude that the main difference is the efficiency gain resulting from having access to worked examples.

Having access to multiple instructional scaffolds gives way to another phenomenon: opting for non-optimal forms of scaffolding, also coined as 'help abuse' (Aleven et al., 2004). The most common form of help abuse is bypassing more abstract hints and going straightforwardly to concrete solutions. Analyzing log behaviors of students, and distinguishing 'proper use and abuse' of worked examples, Shih et al. (2010) created profiles of adaptive and maladaptive learning behaviors. Such profiling based on differences in learning behaviors is also the aim of our current study and builds on the authors' previous research (Nguyen, Tempelaar, Rienties, & Giesbers, 2016). However, we do not seek to demonstrate the difference between proper use and abuse of worked examples but rather to find different patterns in the use of worked examples and hints and connect these patterns to antecedents and consequences.

Another difference with Shih et al. (2010) is our study's Dispositional Learning Analytics (DLA) dimension. The DLA infrastructure, introduced by Buckingham Shum and Deakin Crick (2012), combines learning data (trace data generated in logs of learning activities through technology-enhanced systems) with learner data (e.g., student dispositions, values, and attitudes measured through self-report surveys) (Rienties et al., 2019; Tempelaar, Rienties, & Giesbers, 2015). Learning dispositions represent individual differences that affect all learning processes and include affective, behavioral and cognitive facets (Rienties, Cross, & Zdrahal, 2017).

## 2.2 The Role of Time in a Problem-Based Learning Context

The notion that learning is a fundamentally temporal process, that 'learning unfolds over time', is the departure point of Reimann's (2009) call to pay better tribute to the fact that 'time is precious'. In this, time allows different conceptualizations. First, the notion of temporality as the 'passage of time' refers to the duration and frequency of learning activities (Knight et al., 2017; Molenaar, 2014; Molenaar & Wise, 2022). How often do activities take place, and how much is the time-on-task? The second conceptualization relates to the temporal order of learning activities: what comes first, what follows?

To do justice to both notions of time, we need to ground them in the instructional context. Our case study investigates the self-regulated learning by students in a problem-based learning (PBL; Hmelo-Silver, 2004) programme. The learning process is subdivided into three consecutive learning phases in line with PBL principles. The first learning phase is preparing the tutorial session in which small groups of students, the tutorial groups, collaboratively try to solve problem tasks. A second learning phase follows later the same week when students prepare a so-called quiz session in which students demonstrate their mastery of topics learned in the weekly learning cycle. The third and last learning phase refers to the preparation for the final examination at the end of the module, where students demonstrate how well they have integrated the several weekly learning cycles by solving comprehensive problems. Since each learning phase is sharply demarcated by the timing of tutorial sessions, quizzes, and final exam, an operationalization of log file data that distinguishes student engagement in subsequent learning phases can be implemented. This operationalization enables to include both passage of time measures (Knight et al. 2017), the intensity of engagement in each learning phase, and order of time measures: the relative allocation of engagement over three learning phases.

The second component of grounding measures on relevant theoretical principles stems from the social-cognitive nature of PBL (Hmelo-Silver, 2004). In such instructional philosophy of student-centred learning, a crucial consideration is: what learning skills do students need to be successful learners in a programme applying problem-based learning? The skill of being a self-regulated learner is generally regarded as a key disposition for problem-based learning (Loyens et al., 2013). This is in line with the Reimann et al. (2014) recommendation to include aptitudes as 'other levels' in the form of dispositional accounts to complement event-based data, as candidates for explanation in self-regulated learning research. Reimann et al. (2014) introduced learning styles, epistemic beliefs, and attitudes as crucial for self-regulated learning. Our perspective is largely overlapping but slightly broader: to pay tribute to all facets of social constructivism, aptitudes were included that cover the full range of affective measures. Following Reimann et al. (2014), we regard these aptitudes as sufficiently static to assume stationarity over the entire module period. That supposition allows to measure aptitudes at the very start of the module and regard these as students' entry characteristics.

Within this context, our study aims to demonstrate that ‘traditional’, variables-oriented LA models that combine dispositions with well-operationalized log data are fully capable of giving time the preciousness it deserves in the study of which students use what learning aids in their self-regulated learning.

# 3. METHODS

## 3.1 Context and Setting

This study took place in a large-scale introductory mathematics and statistics module for first-year undergraduate students in a business and economics programme in the Netherlands, with a study load of 20 hours per week, for eight weeks. This module was a compulsory first module for all first-year students and often a stumbling block for students with limited mathematics affinity. The educational system is best described as ‘blended’ or ‘hybrid’ according to the principle of flipped class design. The main component was face-to-face: Problem-Based Learning (PBL), in small groups (14 students), coached by a content expert tutor. Participation in tutorial groups was required and constituted around 2 x 2 hours per week. In addition, weekly lectures introduce the key concepts in that week. The remaining hours were self-study, which was supported by printed materials (i.e., textbooks) and two interactive e-tutorials: Sowiso (https://sowiso.nl/) and MyStatLab (Nguyen et al., 2016; Rienties et al., 2019; Tempelaar et al., 2015, 2020). This design was based on the philosophy of student-centred education, placing the responsibility for making educational choices primarily on the student.

In terms of the timing of the learning, this study distinguished three learning phases introduced before. In phase 1, students prepare for the first tutorial session of the week. The face-to-face time of tutorial sessions was used to discuss solving "advanced" mathematical and statistical problems and required preceding self-study by students to enable participation in discussion. Phase 1 was not formally assessed, other than that such preparation allowed students to actively participate in the discussion of the problem tasks in the tutorial session. Phase 2 was preparing the quiz session at the end of every second week of the module. Those quizzes were primarily formative, providing students at the end of the weekly learning cycle feedback on their mastery of the mathematical and statistical topics covered that week. However, they also contained a small, summative component to stimulate students to participate in the quizzes. Finally, phase 3 consisted of preparing for the final exam in the eighth week of the module. In addition, phase 3 included formal, graded assessments. Therefore, students' timing decisions are related to the amount of preparation in each of the three phases.

## 3.2 Participants

We included 1072 first-year students from academic years 2019/2020 in this study who had been active in at least one digital platform. Of these students, 39% were female, 61% male, 21% had a Dutch high school diploma, and 79% were international students. Amongst the international students, neighbouring countries of Germany (31.5%) and Belgium (13.3%) were well presented, as well as other European countries. In addition, 5.1% of students were from outside Europe. High school systems in Europe differ strongly, most notably in the teaching of mathematics and statistics (i.e., the Dutch high school system has a strong focus on statistics, whereas this topic is completely missing in high school programs of many other countries). Next, all countries distinguish between several levels of math education in high school: preparing for sciences, social sciences, or humanities. To enter this international business programme, prior mathematics education preparing social sciences is required. At the same time, 35.7% of the students followed the highest track in high school, adding to the diversity in prior knowledge in the current sample. Therefore, it was crucial that the first module offered to these students was flexible and allowed for individual learning paths with frequent, interactive feedback on students' learning strategies and tasks.

Beyond a final written exam, student assessment included a student project in which students performed a statistical analysis of personal learning disposition data. To this end, students administered several questionnaires addressing affective, behavioral and cognitive aspects of aptitudes at the start of the module and received personal data sets for their project work some weeks later.

## 3.3 E-tutorial Log Data

Log data were collected from both e-tutorial systems (Sowiso, mathematics or math in short, and MyStatLab, statistics), as well as Canvas, which was used as the university-wide generic learning management system to provide general information and links to Sowiso and MyStatLab. Both Sowiso and MyStatLab are e-tutorials based on the instructional method of mastery learning (Nguyen et al., 2016; Rienties et al., 2019; Tempelaar et al., 2015, 2020). However, only one of the systems, the e-tutorial for math learning, makes time-stamped log data for students' use of learning aids available, so this data is the basis of our analysis. The module counts seven educational weeks with every week a new learning cycle; each learning cycle distinguishes three learning phases; in each learning phase, students take decisions upon the use of worked examples and hints as learning aids, resulting in 40 measurements per student:

- SolTopic1TG … SolTopic7TG: number of worked examples consulted in learning phase 1, tutorial session preparation, for seven weekly topics;
- HintsTopic1TG … HintsTopic7TG: same for hints;
- SolTopic1QZ … SolTopic6QZ: number of worked examples consulted in learning phase 2, quiz session preparation, for six weekly topics (no quiz for last topic);
- HintsTopic1QZ … HintsTopic6QZ: same for hints;
- SolTopic1EX … SolTopic7EX: number of worked examples consulted in learning phase 3, exam preparation, for seven weekly topics;
- HintsTopic1EX … HintsTopic7EX: same for hints.

## 3.4 Disposition Data

*Epistemic learning emotions.* Epistemic emotions are related to cognitive aspects of the tasks undertaken by students. Prototypical epistemic emotions are curiosity and confusion. This study measured epistemic emotions with the Epistemic Emotion Scales (EES: Pekrun et al., 2017). Scales in that instrument can be classified according to valence (positive or negative emotion) and activation component: activating or deactivating.

Positive, activating emotions are Curiosity and Enjoyment; negative, deactivating emotions are Confusion, Frustration and Boredom; Anxiety is a negative, activating emotion and Surprise is a neutral emotion.

*Learning Activity Emotions*. The Control-Value Theory of Achievement Emotions (CVTAE, Pekrun, 2000) postulates that emotions in learning activities differ in valence, focus, and activation. Emotional valence can be positive (enjoyment) or negative (anxiety, hopelessness, boredom). CVTAE describes the emotions experienced about an achievement activity (e.g. boredom experienced while preparing homework) or outcome (e.g. anxiety towards performing at an exam). The activation component describes emotions as activating (i.e. anxiety leading to action) versus deactivating (i.e. hopelessness leading to disengagement). From the Achievement Emotions Questionnaire (AEQ, Pekrun, et al., 2011) measuring learning emotions, we selected four scales: Enjoyment as positive activating emotion, Anxiety as negative activating emotion, Boredom and Hopelessness as negative deactivating emotions. Next, Academic Control, students' self-efficacy in learning math, served the role of the proximal antecedent of all activity emotions.

# 4. RESULTS

## 4.1 Students Use of Learning Aids by Clustering Log Data

A four-cluster solution provides four profiles that allow a straightforward interpretation. One cluster is composed of one single student, who, over the several weeks, consulted 3235 worked examples. Such learning behavior appeared to be so extreme that this student came out as a separate cluster for every choice of a number of clusters. Omitting this case, the other three profiles were labelled as *Tutorial & quiz oriented*, *Quiz oriented* and *Low use of learning aids*, where these labels provide a first characterization of the profiles. See Figure 1 for graphical interpretations, and Table 1 for descriptive statistics.

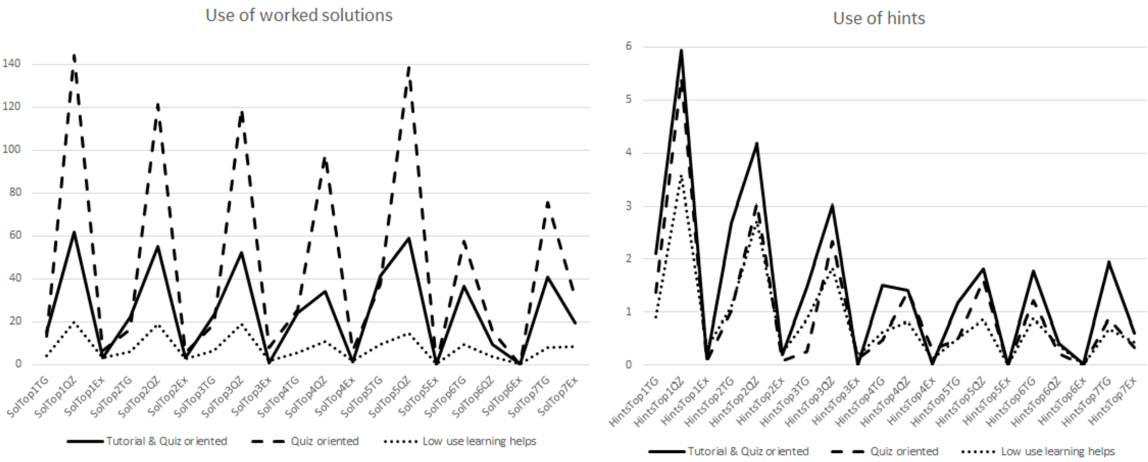


Figure 1. Three profiles of students based on clustering weekly use of worked examples and hints

Table 1. Descriptive statistics of the three profiles of students' use of learning aids

| Profile | *Tutorial & quiz oriented* | *Quiz oriented* | *Low use of learning aids* |
|---|---|---|---|
| Number of students | 442 | 122 | 712 |
| Number worked examples | 504 | 940 | 155 |
| Number hints | 30.5 | 20.7 | 17.2 |
| Advanced math % | 33% | 21% | 45% |
| Math entry test score | 52.1 | 45.7 | 58.2 |
| Math exam score | 11.45 | 9.36 | 12.08 |
| Math quiz score | 2.04 | 1.80 | 1.64 |
| Risk taking | 5.80 | 5.83 | 6.19 |
| Postpone | 4.95 | 4.92 | 5.53 |

Figure 1 provides the use of learning aids for the seven weekly topics in each of the three learning phases. The saw tooth gradient in both the left panel, use of worked examples, and the right panel, use of hints, demonstrate that the use is most intensive in the second learning phase: the preparation of the quiz session. The intensity in the first and third learning phases is at lower levels. With some differences between the profiles: students in the profile *Tutorial & quiz oriented* use less worked examples than students in the profile *Quiz oriented*, and have a better balance over the first and second learning phase, whereas students in the *Quiz oriented* profile concentrate fully on the preparation of their quiz sessions. Another remarkable difference is that students in the *Quiz oriented* profile champion the use of worked examples, while students in the *Tutorial & quiz oriented* profile use more hints than any other student.

Turning to Table 1: we observe that prior education and prior math mastery resulting from that education are important predictors of profile membership. In the *Low use of learning aids* profile, students educated at advanced level make up 45% of all students, a much higher percentage than in other profiles. That difference in prior education shows up in the mastery they demonstrate in writing the Math entry test the first day of the module. However, it is not only prior math mastery that determines the profiles. Differences in average scores for the two personality characteristics of willingness to take risk and the tendency to postpone work make clear that students who score high for both of these maladaptive personal attributes are overrepresented in the large profile of *Low use of learning aids*.

In terms of course performance, students in the low use profile still profit from their prior education when writing their final exam. However, in writing the quizzes, they are outperformed by students of the other two profiles, who prepare more intensively for tutorial and quiz sessions.

## 4.2 Profiles and Epistemic and Activity Learning Emotions

Profile differences are visible in several of the disposition data collected in the framework of the dispositional learning analytics application. Motivation and engagement measures demonstrate profile differences, most outspoken in the category of engagement. Students' approaches to learning have profile differences for the cognitive processing strategy of stepwise learning and the metacognitive regulation strategy of external learning regulation. In this study, for reasons of space and the importance of learning emotions, we will focus on profile differences in dispositions of affective type: the epistemic learning emotions that are measured at the start of the module and are grounded on learning experiences with math in senior high school, and the achievement emotions that are measured amid the module, based on how students experience performing mathematical activities. Figure 2 provides an impression of profile differences for these dispositions.

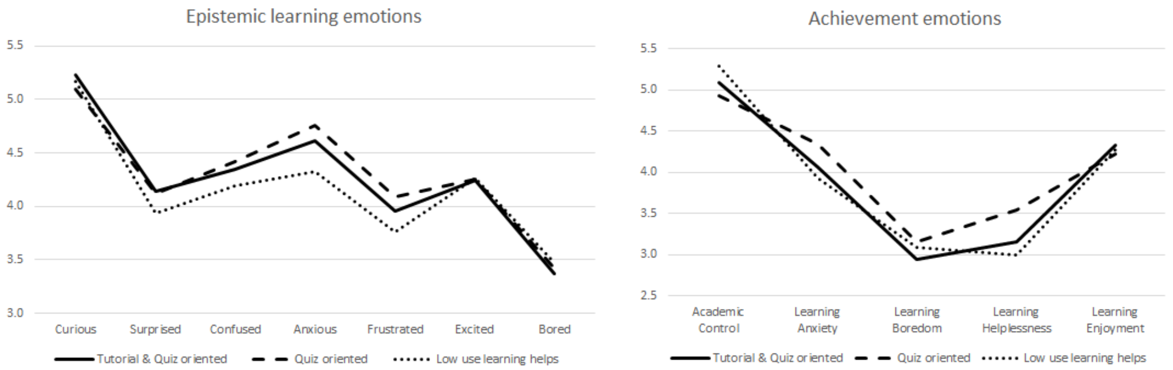


Figure 2. Epistemic learning emotions, left panel, and Activity learning emotions, right panel, of the three profiles

Epistemic emotions generate statistically significant profile differences for the negative emotions *Confused*, *Anxious* and *Frustrated*, and the neutral emotion *Surprised*. For these negative emotions, the pattern visible in the profiles is consistent: the *Quiz oriented* profile scores highest on negative emotions, the *Low use* profile scores lowest on negative epistemic emotions.

Four weeks later, halfway through the module, that pattern is repeated in the activity emotions scores: see the right panel of Figure 2. Unlike the epistemic emotions that signal what learning emotions students developed in high school education, due to the timing of the survey administration, activity emotions refer to affect coming with learning and practicing math in our module. We find statistically significant differences in *Academic Control*, *Learning Anxiety* and *Learning Helplessness*. Again, the highest negative emotion scores are seen in the *Quiz oriented* profile, the lowest in the *Low use* profile.

## 5. DISCUSSION AND CONCLUSIONS

Prior education and its knowledge play a crucial role in any new learning. In this case study, differences in learning behaviors due to differences in prior knowledge are of extreme dimensions: one-third of our students just finished six years of math education preparing for the sciences and would have been able to write the final exam on day one of the module. (If regulations allowed for streaming, this would have been the ideal situation, but regulations prevent doing so.) For the remaining two-thirds of students, this module is among the most challenging. These large differences are not only visible in prior education data but also in the entry test scores taken on day one and transform into the epistemic emotions towards math.

Superior prior knowledge affords superior learning approaches. Well-prepared students do not need that many worked examples, and when they use them, it is in the initial learning process. Compared to using worked examples, these students use relatively more hints: the learning aid that supports them in one specific learning step without giving away the full solution procedure. In contrast, the less well-prepared students use the worked examples intensively, but often 'too late' for the optimal learning process: when the quiz or exam is nearing, the initial learning phase should already be finished.

The educational implications of these findings are that in large-scale education with heterogeneous classes, the systematic collection of learning and learner data is of crucial importance for timely interventions. At the end of the second week of the module already, data analysis of the use of learning aids would have brought essential clues. For example, which students use worked examples optimally: as part of their initial learning of new concepts and solution strategies? Which students use worked examples in a suboptimal way: generating many solved problems as part of a just-in-time preparation of the first quiz. Knowing these different profiles based on learning data is the first step toward intervention. Connecting these profiles with differences in learner data is the crucial second step in successfully addressing learning obstacles.

These observations are not very startling in themselves. What is, however, striking is that all data sources provide complementary and mutually reinforcing facets of the learning challenges in this authentic learning context. For example, the application of analytic discovery methods to event-based log data, as suggested in contemporary writings addressing temporality in LA models, might have discovered differences in timing and intensity in the log-based event data, but never the connection to prior knowledge, epistemic emotions and activity emotions. So better, not throw away our old shoes before we have new ones that do as well.

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