

## FORMATIVE ASSESSMENT AND LEARNING ANALYTICS IN STATISTICS EDUCATION

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*Learning analytics seeks to enhance the learning process through systematic measurements of learning related data, and informing learners and teachers of the results of these measurements, so as to support the control of the learning process. Learning analytics has various sources of information, two main types being intentional and learner activity related metadata. This contribution discusses the potential to apply Buckingham and Deakin's theoretical framework of a learning analytics infrastructure that combines learning dispositions data with data extracted from computer based, formative assessments. In a large introductory statistics course based on the principles of blended learning, combining face-to-face problem-based learning sessions with technology enhanced education, we demonstrate that students learning choices can profit from providing students with feedback based on learning analytics, as to optimize individual learning.*

### INTRODUCTION

The prime data source for most learning analytic applications is data generated by learner activities, such as learner participation in continuous, formative assessments. That information is frequently supplemented by background data retrieved from learning management systems and other concern systems, as for example accounts of prior education. A combination with intentionally collected data, such as self-report data stemming from student responses to surveys, is however the exception rather than the rule. In their theoretical contribution to LAK2012, Buckingham and Deakin (2012) propose a learning analytics infrastructure that combines learning activity generated data with learning dispositions, values and attitudes measured through self-report surveys and fed back to students and teachers through visual analytics. In our conceptual contribution of the application of learning analytics in statistics education, we aim to describe several capabilities of such an infrastructure based on combining learning and learner data. In collecting learner data, we opted to use a wide range of well validated self-report surveys firmly rooted in current educational research, including learning styles, learning motivation and engagement, and learning emotions. Learner data were reported to both students and teachers. Our second data source is rooted in the instructional method of formative testing, and brings about the second focus of this empirical study: to demonstrate the crucial role of data derived from computer-based formative assessments in designing effective learning analytic infrastructures.

### FORMATIVE ASSESSMENT

The classic function of testing is that of taking an aptitude test. After completion of the learning process, we expect students to demonstrate mastery of the subject. According to test tradition, feedback resulting from such classic tests is no more than a grade, and that feedback becomes available only after finishing all learning. The alternative form of assessment, formative assessment, has an entirely different function: that of informing student and teacher. The information should help better shape the teaching and learning and is especially useful when it becomes available during or prior to the learning. Diagnostic testing is an example of this, just as is practice testing. Because here the feedback that tests yield for learning constitutes the main function, it is crucial that this information is readily available, preferably even directly.

### LEARNING ANALYTICS

The broad goal of learning analytics is to apply the outcomes of analyzing data gathered by monitoring and measuring the learning process, as feedback to assist directing that same learning process. Several alternative operationalizations are possible to support this. In Verbert, Manouselis, Drachler, and Duval (2012), six objectives are distinguished: predicting learner performance and modeling learners, suggesting relevant learning resources, increasing reflection and awareness, enhancing social learning environments, detecting undesirable learner behaviors, and detecting

affects of learners. In the following sections describing our approach, we will argue that the combination of self-report learner data with learning data from test-directed instruction allows to contribute to at least five of these objectives of applying learning analytics. Only social interaction is restricted to learners being able to assess their individual learning profiles in terms of a comparison of their own strong and weak characteristics relative to the position of other students. These profiles are based on both learner behavior, including all undesirable aspects of it, and learner characteristics: the dispositions, attitudes and values. Learner profiles are used to model different types of learners, and to predict learner performance for each individual student. Since our instructional format is of student-centered type, with the student, and not the teacher, steering the learning process, it is crucial to feedback all this information to learners themselves as to make them fully aware of how to optimize their individual learning trajectories. Feedback that for a major part was shaped in a student project with students analyzing their own learning characteristics, relative to the scores achieved by other students.

#### CASE STUDY: STATISTICS EDUCATION

The empirical component of our contribution focuses on freshmen education in quantitative methods (mathematics and statistics) of the business & economics school at Maastricht University. The population of students studied here consists of two cohorts of freshmen: 2011/2012 and 2012/2013, containing 1,832 students who in some way participated in school activities (have been active in the digital learning environment Blackboard). Besides BlackBoard, a digital learning environment for formative assessment was utilized: MyStatLab, by a large majority of students.

The diversity of the student population derives mainly from its very international composition: only 34.8% took Dutch high school, whereas all others were educated in international high school systems. The largest group, 41.9% of the freshmen, were educated according to the German Abitur system. High school systems in Europe differ strongly, most particularly in the teaching of mathematics and statistics. In that European palette the Netherlands occupies a rather unique position, both in choice of subjects (one of the few European systems with substantial focus on statistics) and the chosen pedagogical approach. But even beyond the Dutch position, there exist large differences, such as between the Anglo-Saxon and German-oriented high school systems. Therefore it is crucial that the first course offered to these students is flexible and allows for individual learning paths. To some extent, this is realized in offering optional, developmental summer courses, but for the main part, this diversity issue needs to be solved in the program itself. The digital environments for test-directed learning play an important role in this.

#### EDUCATIONAL PRACTICE

The educational system in which students learn mathematics and statistics is best described as a 'blended system'. The main component is 'face-to-face': problem-based learning (PBL), in small groups (14 students), coached by a content expert tutor. Participation in these tutor groups is required, as for all courses based on the Maastricht PBL system. Optional is the online component of the blend: the use of technology enhanced education MyStatLab (MSL) environment. MSL is a generic digital learning environment, developed by the publisher Pearson, for learning statistics. It adapts to the specific choice of a textbook from Pearson. Although MSL can be used as a learning environment in the broad sense of the word (it contains, among others, a digital version of the textbook), it is primarily an environment for test-directed learning. Each step in the learning process is initiated by submitting a question. Students are encouraged to (try to) answer the question. If they do not master (completely), the student can either ask for help to step by step solve the problem (Help Me Solve This), or ask for a fully worked example to show (View an Example). Next, a new version of the problem loads (parameter based) to allow the student to demonstrate their newly acquired mastery. In the investigated courses, students work an average 19.2 hours in MSL, about a quarter of the available time of 80 hours for learning statistics. In this study, we use two different indicators for the intensity of use of MSL: Stats#hours, the number of hours a student spent practicing in the MSL environment, and StatsTestScore, the average score for the practice questions, all chapters aggregated.

## DISPOSITIONAL VARIABLES FOR LEARNING ANALYTICS

As a first step, data from the regular student administration such as whether or not Dutch high school, whether or not advanced prior math schooling, gender, nationality and entry test score is applied. Students with advanced prior schooling are better at math, without incurring more need to practice, but they are not better at statistics, which corresponds to the fact that in programs at advanced level, the focus is not on statistics but abstract math. Dutch students make considerably less use of both test environments and hence achieve a slightly lower score, benefiting from a smoother transition than international students, but relying just somewhat too much on that. Students with a high entry test score do better in mathematics and a little better in statistics in the test environments, without the need to exercise more. Finally, there are modest gender effects, the strongest in the intensity of exercising: female students are more active than male students.

The remaining data from the student records of administrative systems regard the nationality of students. Because cultural differences in education has been given an increasingly important role, and because the Maastricht student population makes it very suitable through its strong international composition, the nationality data are converted into so-called national culture dimensions, based on the framework of Hofstede (Hofstede, Hofstede, & Minkov, 2010). In that framework, there are a number of cultural dimensions that refer to values that are strongly nationally determined. In this study we use six of these dimensions: Power Distance, Individualism versus Collectivism, Masculinity versus Femininity, Uncertainty Avoidance, Long-Term vs. Short-Term Orientation and Indulgence vs. Restraint. Scores for each of these national dimensions are assigned to the individual students. Correlating these scores with the four indicators of practice tests intensity result in several significant effects, all in line with Hofstede's framework. The most significant effects are for students from a masculine culture, where mutual competition is an important driver in education, for students from a culture that value long-term over short-term and, somewhat in relation thereto, cultures that value sobriety rather than enjoyment. In this, masculinity and hedonism have a stronger impact on the intensity of exercising, than on the proceeds of exercising, in contrast to long-term orientation that has about equal impact on both aspects. Uncertainty avoidance contributes, as expected, to practicing, albeit to a lesser extent and again primarily toward intensity of exercising rather than its outcome. The roles of power distance and individualism play a less salient role in learning, as expected.

Although the effects are smaller in size, learning data based on the learning style model of Vermunt (1996) exhibit a characteristic role. Vermunt's model distinguishes learning strategies (deep, stepwise, and concrete ways of processing learning topics), and regulation strategies (self, external, and lack of regulation of learning). Deep-learning students demonstrate no strong relationship with test directed learning: they exercise slightly less, but achieve a slightly better score. That is certainly not true for the stepwise learning students. Especially for these students the availability of practice tests seems to be meaningful: they practice more often and longer than other students and achieve, especially for statistics, a better score than the other students.

Recent Anglo-Saxon literature on academic achievement and dropout assigns an increasingly dominant role to the theoretical model of Andrew Martin: the 'Motivation and Engagement Wheel' (Martin, 2007). That model includes both behaviors and thoughts or cognitions that play a role in learning. Both are then divided into adaptive and mal-adaptive or obstructive forms. As a result, the four quadrants are: adaptive behavior and adaptive thoughts, mal-adaptive behavior and obstructive thoughts. All adaptive thoughts and all adaptive behaviors have a positive impact on the willingness of students to use the test environments, where the effect of the adaptive behavior dominates that of cognitions. The mal-adaptive variables show a less uniform picture. Mal-adaptivity manifests itself differently in female and male students: for female students primarily in the form of limiting thoughts, especially fear and uncertainty, in male students primarily as mal-adaptive behaviors: self-handicapping and disengagement. That difference has a significant impact on learning. Mal-adaptive behaviors negatively impact the use of the test environments: all the correlations, both for use intensity and performance, are negative. The effect of inhibiting mind, however, is different: uncertainty and anxiety have a stimulating effect on the use of the test environments rather than an inhibitory effect. Combination of both effects provides a partial explanation for the observed gender effects in the use of the test environments.

## CONCLUSIONS

Our experiment tells that both data generated by formative assessments, and individual learner characteristics, have a strong impact on academic performance, suggesting that the learning process will profit from systematic feedback based on these sources. But in a student-centered curriculum it is not sufficient when teachers are convinced of the benefits that formative assessment in digital learning environments entails. Students regulate their own learning process, making themselves choices on how intensively they will exercise and therefore, are the ones who need to become convinced of the usefulness of these digital tools. In this, learning analytics can play an important role: it provides a multitude of information that the student can use to adapt the personal learning environment as much as possible to the own strengths and weaknesses. For example, in our experiment the students were informed about their personal learning dispositions, attitudes and values, together with information on how learning in general interferes with choices they can make in composing their learning blend. At the same time: the multitude of information available from learning analytics is also the problem: that information requires individual processing. Some information is more important for one student than the other, requiring a personal selection of information to take place. Learning analytics deployed within a system of student-centered education thus has its own challenges.

The aim of this contribution extends beyond reasoning the practical importance of Buckingham and Deakin's learning analytics infrastructure. Additionally, this research suggests many clues as to what individualized feedback could look alike. In the learning blend described in this study, the face-to-face component PBL constitutes the main instructional method. The digital component is intended as a supplementary learning tool, primarily for students for whom the transition from secondary to university education entails above average hurdles. Part of these problems are of cognitive type: e.g. international students who never received statistics education as part of their high school mathematics program, or other freshmen who might have been educated in certain topics, without achieving required proficiency levels. For these kind of cognitive deficiencies, the digital test-directed environments suggest to be an effective tool to supplement PBL. But this applies not only to adjustment problems resulting from knowledge backlogs.

Students encounter several types of adjustment problems where the digital tools appear to be functional. The above addressed learning dispositions are a good example: student-centered education presupposes in fact deep, self-regulated learning, where many students have little experience in this, and feel on more familiar ground with step-wise, externally regulated learning. As the analyses suggest: the digital test environments help in this transformation. It also makes clear that the test environments are instrumental for students with non-adaptive cognitions about learning mathematics and statistics, such as anxiety. An outcome that is intuitive: the individual practice sessions with computerized feedback will for some students be a safer learning environment than the PBL tutorial group sessions.

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## REFERENCES

- Buckingham, S. S., & Deakin, C. R. (2012). Learning dispositions and transferable competencies: Pedagogy, modelling and learning analytics. *Proceedings LAK2012: 2nd International Conference on Learning Analytics & Knowledge* (pp. 92-101). ACM Press: New York
- Hofstede, G., Hofstede, G. J., & Minkov, M. (2010). *Cultures and organizations: Software of the mind. (Revised and expanded 3<sup>rd</sup> ed.)*. 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, 413-440.
- Verbert, K., Manouselis, N., Drachsler, H., & Duval, E. (2012). Dataset-driven research to support learning and knowledge analytics. *Educational Technology & Society*, 15(3), 133-148.
- Vermunt, J. D. (1996). *Leerstijlen en sturen van leerprocessen in het Hoger Onderwijs*. Amsterdam/Lisse: Swets & Zeitlinger.