# Computer Assisted, Formative Assessment and Dispositional Learning Analytics in Learning Mathematics and Statistics

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**Abstract.** Learning analytics seeks to enhance the learning process through systematic measurements of learning related data and to provide informative feedback to learners and teachers, so as to support the regulation of the learning. Track data from technology enhanced learning systems constitute the main data source for learning analytics. This empirical contribution provides an application of Buckingham Shum and Deakin Crick's theoretical framework of dispositional learning analytics [1]: an infrastructure that combines learning dispositions data with data extracted from computer assisted, formative assessments. In a large introductory quantitative methods module based on the principles of blended learning, combining face-to-face problem-based learning sessions with e-tutorials, we investigate the predictive power of learning dispositions, outcomes of continuous formative assessments and other system generated data in modeling student performance and their potential to generate informative feedback. Using a dynamic, longitudinal perspective, Computer Assisted Formative Assessments seem to be the best predictor for detecting underperforming students and academic performance, while basic LMS data did not substantially predict learning.

**Keywords:** blended learning, computer assisted assessment, dispositional learning analytics, e-tutorials, formative assessment, learning dispositions, student profiles.

## 1 Introduction

Many learning analytics (LA) applications use data generated by learner activities, such as learner participation in discussion forums, wikis or (continuous) computer assisted formative assessments. This user behavior data is frequently supplemented with background data retrieved from learning management systems (LMS) and other student admission systems, as for example accounts of prior education. In their theoretical contribution to LAK2012 [1] (see also the 2013 LASI Workshop [2]), Buckingham Shum and Deakin Crick propose a dispositional LA infrastructure that

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combines learning activity generated data with learning dispositions, values and attitudes measured through self-report surveys, which are fed back to students and teachers through visual analytics. However, a combination with intentionally collected data, such as self-report data stemming from student responses to surveys, is the exception rather than the rule in LA ([3], [4], and [5]). In our empirical contribution focusing on a large scale module in introductory mathematics and statistics, we aim to provide a practical application of such an infrastructure based on combining learning and learner data. In collecting learner data, we opted to use a wide range of validated self-report surveys firmly rooted in current educational research, including learning styles, learning motivation and engagement, and learning attitudes. This operationalization of learning dispositions closely resembles the specification of cognitive, metacognitive and motivational learning factors relevant for the internal loop of informative tutoring feedback (see [6], [7] for examples). Other data sources used are more common for LA applications, and constitute both data extracted from a learning management system, as well as system track data extracted from the e-tutorials used for practicing and formative assessments. The prime aim of the analysis is to provide a stepping stone for predictive modeling, with a focus on the role each of these data sources can play in generating timely, informative feedback. This paper extends our earlier study [8], which found empirical evidence for the role of dispositional data in LA applications.

## 2 Background

### 2.1 Computer Assisted Formative Assessment

The classic function of assessment 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 assessment is no more than a grade which becomes available only after finishing all learning activities. In recent years, the conception of assessment as a summative function (i.e. assessment of learning) has been broadened toward the conception of assessment as a formative function (i.e. assessment for learning). That is, as a means to provide feedback to both student and teacher about teaching and learning prior to or during the learning process [9, 10]. Examples of formative assessment are diagnostic testing, and test-directed learning approaches that constitutes the basic educational principle of many e-tutorial systems [11]. Because feedback from assessments constitutes a main function for learning, it is crucial that this information is readily available, preferably even directly. At this point digital testing enters the stage: it is unthinkable to get just-in-time feedback from formative assessments without using computers.

### 2.2 Learning Analytics

A broad goal of LA is to apply the outcomes of analyzing data gathered by monitoring and measuring the learning process, whereby feedback plays a crucial part to assist regulating that same learning process. Several alternative operationalizations are possible to support this. In [12], six objectives are distinguished: predicting learner performance and modelling learners, suggesting relevant learning resources, increasing reflection and awareness, enhancing social learning environments, detecting undesirable learner behaviors, and detecting affects of learners. Although the combination of self-report learner data with learning data extracted from e-tutorial systems allows us to contribute to at least five of these objectives of applying learning analytics (as described in [8]), in this contribution we will focus on the first objective: predictive modeling of performance and learning behavior. The ultimate goal of this predictive modeling endeavor is to investigate which components from a rich set of data sources, best serve the role of generating timely, informative feedback and afford signaling the risk of underperformance.

### 2.3 Related Work

Previous research by Wolff, Zdrahal, Nikolov, and Pantucek [13] found that a combination of LMS data with data from continuous summative assessments were the best predictor for performance drops amongst 7,701 students. In particular, the number of clicks in a LMS just before the next assessment significantly predicted continuation of studies [13]. As is evident from our own previous research [8], formative assessment data, supplemented with learning disposition data, also had a substantial impact on student performance in a blended course of 1,832 students.

## 3 Case Study: Mathematics and Statistics

### 3.1 Internationalization of Higher Education

Our empirical contribution focuses on freshmen students in quantitative methods (mathematics and statistics) course of the Maastricht University School of Business & Economics. The course is the first module for students entering the program. It is directed at a large and diverse group of students, which benefits the research design. The population consists of 1,840 freshmen students, in two cohorts: 2012/2013 and 2013/2014, who in some way participated in learning activities (i.e., have been active in the learning management system BlackBoard). Besides BlackBoard, two different e-tutorial systems for technology-enhanced learning and practicing were utilized: MyStatLab and MyMathLab.

The diversity of the student population mainly lies in its international composition: only 23% received their prior (secondary) education from the Dutch high school system. The largest group, 45% of the freshmen, was educated according to the German Abitur system. The remaining 32% are mainly from central-European and south-European countries. High school systems in Europe differ strongly, most particularly in the teaching of mathematics and statistics. Therefore it is crucial that the first module offered to these students is flexible and allows for individual learning paths.

### 3.2 Test-Directed E-tutorials

The two e-tutorial systems MyStatLab (MSL) and MyMathLab (MML) are generic digital learning environments for learning statistics and mathematics developed by the publisher Pearson. Although MyLabs 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 and practicing. Each step in the learning process is initiated by submitting a question. Students are encouraged to (try to) answer each question (see Fig. 1 for an example). If they do not master a question (completely), the student can either ask for help to solve the problem step-by-step (Help Me Solve This), or ask for a fully worked example (View an Example). These two functionalities are examples of Knowledge of Result/response (KR) and Knowledge of the Correct Response (KCR) types of feedback; see Narciss [6], [7].

After receiving this type of feedback, a new version of the problem loads (parameter based) to allow the student to demonstrate his/her newly acquired mastery. When a student provides an answer and opts for ‘Check Answer’, Multiple-Try Feedback (MTF, [6]) is provided, whereby the number of times feedback is provided for the same task depends on the format of the task (only two for a multiple choice type of task as in Fig.1, more for open type of tasks requiring numerical answers).

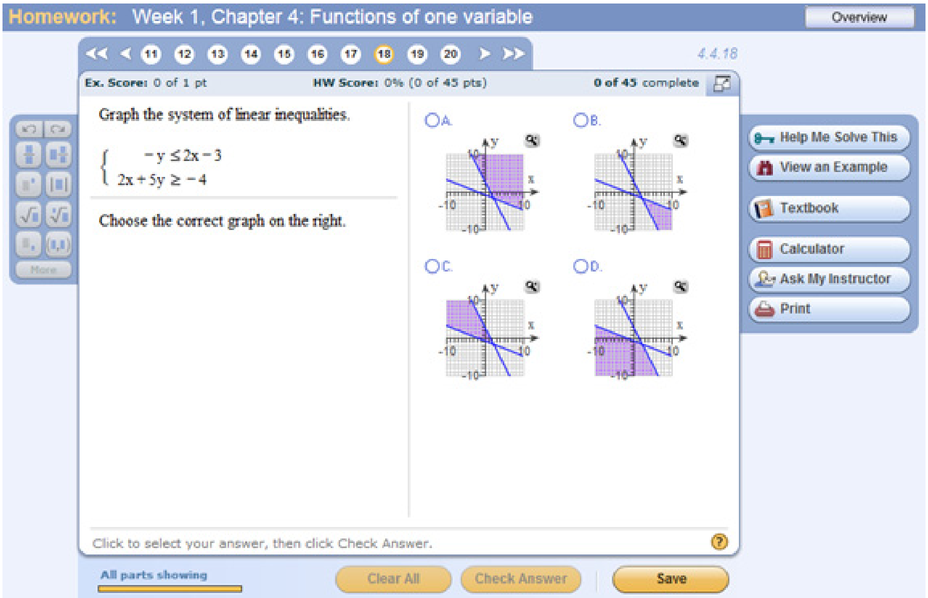


**Fig. 1.** MyMathLab task and feedback options

In the investigated course, students on average work 35.7 hours in MML and 23.6 hours in MSL, which is 30% to 40% of the available time of 80 hours for learning in both topics. In the present study, we use two different indicators for the intensity of the MyLabs usage: MMLHours and MSLHours indicate the time a student spends practicing in each respective MyLab environment per week; MMLMastery and MSLMastery indicate the average final score achieved for the practice questions in any week.

### 3.3 Educational Practice

The educational system in which students learn mathematics and statistics is best described as a ‘blended’ or ‘hybrid’ system. The main component is 'face-to-face':

problem-based learning (PBL, see [14] for an elaborate overview), 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. The online component of the blend, that is, the use of the two e-tutorials, is optional. The reason for making the online component optional is that this best fits the Maastricht educational model, which is student-centered and places the responsibility for making educational choices primarily with the student. At the same time, due to the diversity in prior knowledge, not all students will benefit equally from using these environments; in particular for those at the high performance end, extensive practicing will not be the most effective allocation of learning time. However, the use of e-tutorials is stimulated by making bonus credits available for good performance in the quizzes, and for achieving good scores in the practicing modes of the MyLab environments. 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 for this particular constellation, since it stimulates students with little prior knowledge to make intensive use of the MyLab platforms. They realize that they may fall behind other students in writing the exam, and therefore need to achieve a good bonus score both to compensate, and to support their learning. The most direct way to do so is to frequently practice in the MML and MSL environments. The bonus is maximized to 20% of what one can score in the exam.

The student-centered characteristic of the instructional model first and foremost requires adequate informative feedback to students so that they are able to monitor their study progress and their topic mastery in absolute and relative sense. The provision of relevant feedback starts on the first day of the course when students take two diagnostic entry tests for mathematics and statistics. Feedback from these entry tests provide the first signals to students of the importance of using the MyLab platforms. Next, the MML and MSL-environments contain a monitoring function: at any time students can see their progress in preparing the next quiz, and can get feedback on the performance in completed quizzes and on their performance in the practice sessions. The same information is also available to the tutors. Although the primary responsibility for directing the learning process lies with the student, the tutor can act complementary to that self-steering, especially in situations where the tutor considers that a more intense use of e-tutorials is desirable, given the position of the student concerned. In this way, the application of LA shapes the instructional situation.

## 4 The Array of Learning Analytics Data Sources

In order to explore the potential of feedback based on the several components of the learning blend, we investigate the relationship between an array of LA data sources, and academic performance in the Quantitative Methods module. Academic performance consists of the individual scores in both topic components of the final written exam (MathExam and StatsExam), and the overall grade in the module (QMGrade). Both are subject to a weight factor, weighting the final exam with factor 5, and the bonus score from quizzes and homework with factor 1. In designing models covering two class years, performance scores have been standardized by calculating Z-scores in order to compare performance across the two cohorts. Prediction models for these three learning performance measures are based on the following data sources:

- Formative assessment data consisting of:
  - Week0: diagnostics entry tests for mathematics and statistics, with a strong focus on basic algebraic skills, a well-known topic for high school deficiencies.
  - Week1: mastery scores and practice time in MyMathLab and MyStatLab.
  - Week2: mastery scores and practice time in MyMathLab and MyStatLab.
  - Week3: mastery scores and practice time in MyMathLab and MyStatLab, and Quiz1 scores for mathematics and statistics.
  - Week4: mastery score and practice time in MyMathLab and MyStatLab.
  - Week5: mastery scores and practice time in MyMathLab and MyStatLab, and Quiz2 scores for mathematics and statistics.
  - Week6: mastery score and practice time in MyMathLab and MyStatLab.
  - Week7: mastery scores and practice time in MyMathLab and MyStatLab, and Quiz3 scores for mathematics and statistics.
- BlackBoard use intensity data, in terms of number of clicks, again decomposed into weekly figures (BB time on task data was initially included in the study, but appeared to be dominated by click data with regard to predictive power, and was therefore excluded in the final analyses).
- Learning dispositions and demographic data from several concern systems. These data are, in terms of designing longitudinal models, assigned to Week0.

Demographic data were obtained from the regular student administration. An important part of demographic data is prior education. High school educational systems generally distinguish between a basic level of mathematics education preparing for the social sciences, and an advanced level preparing for sciences. An indicator variable is used for mathematics at advanced level (about one third of the students), with basic level of mathematics prior schooling being the reference group. Students with advanced prior schooling are generally better in mathematics, but not in statistics, which corresponds to the fact that in programs at advanced level, the focus is abstract mathematics (calculus) rather than statistics. Other demographic data refer to gender, nationality and age.

Learning style data based on the learning style model of Vermunt [15] constitute the first component of measured learning dispositions (see also: Vermunt & Vermetten, [16]). Vermunt distinguishes four domains or components of learning in his model: cognitive processing strategies, metacognitive regulation strategies, learning conceptions or mental models of learning, and learning orientations. In each domain, five different scales describe different aspects of the learning component. In this study, we applied the two domains of processing and regulation strategies, since these facets of learning styles are most open to interventions based upon learning feedback. In Vermunt's model, three types of learning strategies are distinguished: deep learning, step-wise (or surface) learning, and concrete ways of processing learning topics. In a similar way, three types of regulation strategies are distinguished: self-regulation of learning, external regulation of learning, and lack of regulation. Combining scores on processing and regulation strategies, we can find alternative profiles of learning approaches often seen in students in higher education. For instance, the meaning directed learning approach combines high levels for deep learning, with students critically processing the learning materials, with high levels for self-regulation, both with regard to learning process and learning content. These students are the 'ideal' higher education students: being self-directed, independent learners. The typical learning approach of students with high scores on step-wise learning, who depend a lot on memorization and rehearsing processes, and at the same time score high on external regulation of learning, does carry a lot more risks with regard to academic success. These learning approaches are very often guarantees for success in high school, but start to fail in university. Students with high scores for lack of regulation of any type run the highest risk; drop-out for these profiles is higher than for any other profile.

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' [17]: see Fig. 2.

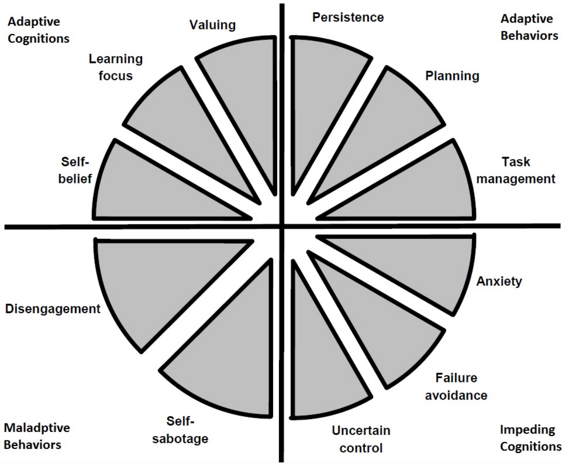


**Fig. 2.** Motivation and Engagement Wheel (Source: [17])

This model includes both behaviors and thoughts, or cognitions, that play a role in learning. Both are subdivided into adaptive and mal-adaptive or impeding forms. As a result, the four quadrants are: adaptive behavior and adaptive thoughts (the 'boosters'), mal-adaptive behavior (the 'guzzlers') and impeding thoughts (the 'mufflers'). Adaptive thoughts consist of Self-belief, Learning focus, and Value of school, whereas adaptive behaviors consist of Persistence, Planning, and Task management. Maladaptive or impeding thoughts include Anxiety, Failure avoidance, and Uncertain control, and lastly, maladaptive behaviors include Self-sabotage and Disengagement. Further components of learning dispositions are learning attitudes, and intrinsic versus extrinsic motivation to learn. All learning dispositions are administered through self-report surveys. From 1,794 out of 1,840 students (97.5%), complete information was obtained on the various instruments.

Similar to the feedback based on student activity in the two MML and MSL platforms, also learning dispositions data was used to provide feedback during the course. Students were given access to visualizations of their characteristic learning approaches, relative to the profile of the average students. Next to that, all students received individual data on personal dispositions, in order to analyze these data as a required statistical project. The only retrospective part of this study is the investigation of the predictive power of the several data sources with regard to course performance, as discussed in the next section.

## 5 Predicting Performance

Before turning to longitudinal models predicting performance using week by week data, the first step is to determine the maximum predictive power for each of the data sources, using aggregated data for all weeks. For one category of data, the outcome appears to be simple: BlackBoard track data can predict no more than 1% of variation in the three performance measures. In other words, the (multiple) correlation of BlackBoard user track data and the performance variables is not above 0.1. From a substantial perspective, that excludes the category of BlackBoard data for developing prediction models as being practically insignificant.

With regard to the MyLab data, both overall mastery in MML and MSL correlate strongly with all performance measures (correlations in the range of 0.35 to 0.55), whereas correlations between time in the system and performance measures are weaker, but still substantial (in the range 0.1 to 0.2). Composing regression models that predict performance measures from multiple regressions containing both mastery and time in MyLab systems variables, generates the following prediction equations (in normalized performance measures, using Z-scores, and standardized beta's):

$$\text{ZMathExam} = 0.562 * \text{MMLMastery} - 0.277 * \text{MMLHours}, \text{R} = 0.47$$

$$\text{ZStatsExam} = 0.506 * \text{MSLMastery} - 0.251 * \text{MSLHours}, \text{R} = 0.40$$

$$\text{ZQMGrade} = 0.36 * \text{MMLMastery} - 0.196 * \text{MMLHours}$$

$$+0.341 * \text{MSLMastery} - 0.092 * \text{MSLHours}, \text{R} = 0.58$$

All prediction equations have substantial multiple correlations, which suggests that feedback based on overall mastery and time for both MyLab systems has good prospects. A remarkable and very consistent feature of all three prediction equations is that the beta of mastery is always positive, and the beta of time in system is always negative, although all bivariate correlations between time in system variables and performance measures are positive. There is however a simple explanation for this sign reversal: mastery and time in system variables are strongly collinear, with a 0.59 correlation for the MML platform, and a .66 correlation for the MSL platform. Practicing longer in the two MyLab systems increases expected performance, since students who practice more, achieve higher mastery levels. In a multiple regression model, one however corrects for mastery level, and now time has a negative impact: for a given mastery level, students who need more time to reach that level, have lower expected performance, which is quite intuitive.

After the potential of building prediction models for performance based on data from the two MyLab systems has been established, the next step is to design these prediction models using incremental data sets of system data. Starting with the Week0 data set, containing data that are available at the very start of the module (in our example: data from the diagnostic entry tests), we extend the data set in weekly steps, arriving at the final set of predictor variables after seven weeks. Thus, the incremental system data contains entry test data, mastery and time in system data of seven consecutive weeks, and MyLab quiz data administered in weeks 3, 5, and 7. Instead of providing regressions for all seven weeks and all three performance measures, Fig. 3 describes the development of the multiple correlation coefficient R in time, that is, over incremental weekly data sets.

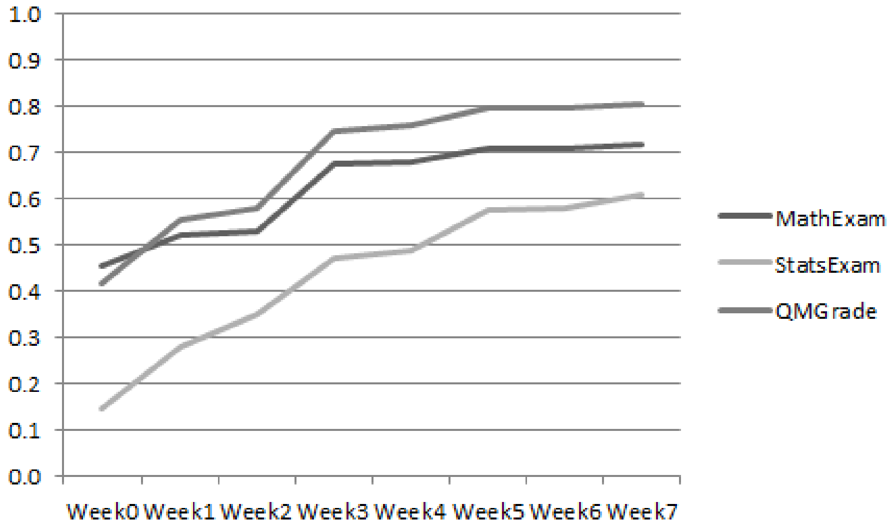


**Fig. 3.** Longitudinal Performance Predictions based on Formative Assessments: Multiple Correlation R

Since the predictor data sets are incremental, the values of multiple correlation increase over weeks. Those for performance in the mathematics exam, and the overall grade, start at values around 0.45 in Week0, and increase to values between 0.7 and 0.8 in the last week. In contrast, there is less power in predicting performance in statistics, the difference caused by the statistics entry test being less informative for later statistics performance, than the mathematics entry exam is for later mathematics performance. The circumstance that many of the students have not been educated before in statistics is crucial for understanding the entry test being not very informative.

Predictor sets used for the generation of Fig. 3 include only MyLab data, together with entry tests data; no learning dispositions data have been used yet. When we add these data, assuming that these data are available at the start of the course so that they are part of the new Week0 data set, we arrive at Fig. 4 describing the development of the multiple correlation coefficients R over all weeks. The main impact of the availability of learning disposition data is the strong increase in predictive power in the first weeks. From the third week onwards, when data from the first quiz becomes available, the difference in predictive power between models including and those excluding learning dispositions, is minimal. Apparently, collinearity between scores in the first quiz and the set of learning dispositions imply that dispositions have hardly any additional predictive power beyond that of quiz performance; most of their impact is also captured in quiz performance scores.

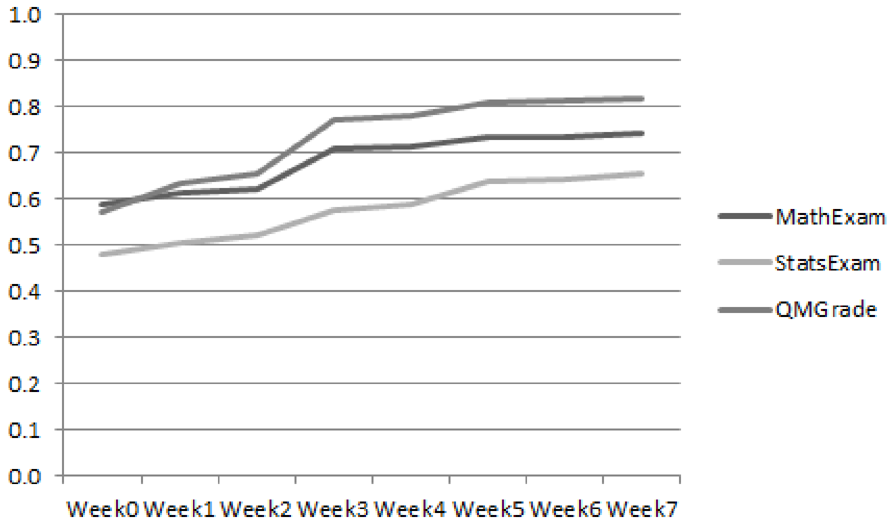


**Fig. 4.** Longitudinal Performance Predictions based on Formative Assessments and Learning Dispositions: Multiple Correlation R

## 6 Conclusions

In this empirical study into predictive modeling of student performance, we investigated three different data sources to explore the potential of generating informative feedback using LA: BlackBoard tracking data, students' learning dispositions, and data from systems for formative, computer assisted assessments. The last data source allows further classification into data generated in the practice mode (both mastery and system time data), and data generated by formative assessments (performance data). It appears that the combination of dispositions data and assessment system data dominate the role of BlackBoard track data in predicting student performance, implying that in applications with such rich data available, BlackBoard data have no added value in predicting performance and signaling underperforming students. This seems to confirm initial findings by Macfayden and Dawson [5], who found that simple clicking behavior in a LMS is at best a poor proxy for actual user-behavior of students.

Data extracted from the testing mode of the MyLab systems dominate in a similar respect data generated by the practicing mode of MyLabs, indicating the predictive power of true assessment data, even if it comes from assessments that are primarily formative in nature. However, assessment data is typically delayed data, not available before midterm, or as in our case, the third week of the course. Up to the moment this richest data component becomes available, mastery data and use intensity data generated by the e-tutorial systems are a second best alternative for true assessment data. This links well with Wolff et al. [13], who found that performance on initial assessments during the first parts of an online module were substantial predictors for final exam performance.

A similar conclusion can be drawn with regard to the learning disposition data: up to the moment that assessment data become available, they serve a unique role in predicting student performance and signaling underperformance beyond system track data of the e-tutorials. From the moment that computer assisted, formative assessment data become available, their predictive power is dominated by that of performance in those formative assessments. Dispositions data are not as easily collected as system tracking data from learning management systems or e-tutorial systems. The answer to the question if the effort to collect dispositional data is worthwhile (or not), is therefore strongly dependent on when richer (assessment) data becomes available, and the need for timely signaling of underperformance. If timely feedback is required, the combination of data extracted from e-tutorials, both in practicing and test modes, and learning disposition data suggests being the best mix to serve LA applications.

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