Learning analytics should not promote one size fits all: The effects of instructional conditions in predicting academic success

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Abstract

This study examined the extent to which instructional conditions influence the prediction of academic success in nine undergraduate courses offered in a blended learning model (n = 4134). The study illustrates the differences in predictive power and significant predictors between course-specific models and generalized predictive models. The results suggest it is imperative for learning analytics research to account for the diverse ways technology is adopted and applied in course-specific contexts. The differences in technology use, especially those related to whether and how learners use the learning management system, require consideration before the log-data can be merged to create a generalized model for predicting academic success. A lack of attention to instructional conditions can lead to an over or under estimation of the effects of LMS features on students' academic success. These findings have broader implications for institutions seeking generalized and portable models for identifying students at risk of academic failure.

1 Introduction

The field of learning analytics has received much attention as a means for addressing institutional teaching and learning problems linked to the early identification of students at-risk of attrition or academic failure (Dawson, Gašević, Siemens, & Joksimovic, 2014). Despite the broad interest and implementation of learning analytics there remain numerous questions regarding the portability of any developed predictive models across student sub-populations and pedagogical contexts within an institution (Jayaprakash, Moody, Lauría, Regan, & Baron, 2014). This paper responds to this issue by investigating the impact of instructional conditions on a predictive model of learner success. In so doing, the paper aims to empirically demonstrate the importance for understanding the course and disciplinary context as an essential step when developing and interpreting predictive models of academic success and attrition (Lockyer, Heathcote, & Dawson, 2013).

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1.1 Learning Analytics and Predictive Modelling

The analysis of data collected by institutional student information systems (SIS), and from student interactions with their Learning Management System (LMS) (e.g. Moodle, Sakai, or Desire2Learn) has attracted much attention among researchers, teachers and managers for its potential to address some of the major challenges confronting the education sector (Baer & Campbell, 2012; Macfadyen & Dawson, 2010; Siemens & Long, 2011). Learning analytics approaches typically rely on data emanating from a user's interactions with Information and Communication Technologies (ICTs), such as LMS, SIS and social media. For example, the trace data (also known as log data) recorded by LMS contains time-stamped events about views of specific resources, attempts and completion of quizzes, or discussion messages viewed or posted. Data mining techniques are commonly applied to identify patterns in these trace data (Baker & Yacef, 2009). The interpretation of these patterns can be used to improve our understanding of learning and teaching processes, predict the achievement of learning outcomes, inform support interventions and aid decisions on resource allocation. This process has been described as *learning analytics* (Siemens & Gašević, 2012).

Research in learning analytics and its closely related field of educational data mining, has demonstrated much potential for understanding and optimizing the learning process (Baker & Siemens, 2014). To date, much of this research has focused on developing predictive models of academic success and retention (Siemens, Dawson, & Lynch, 2014). Specifically, the prediction of students at risk of failing a course (i.e., the dependent variable is binary with two categories – fail and pass) and the prediction of students' grades (i.e., the dependent variable is continuous representing a final percent mark) have been two commonly reported tasks in the learning analytics and educational data mining literature (Dawson et al., 2014). These two types of success predictions have been based on the following sources of data:

I. data stored in institutional student information systems, e.g., high school grades, socio-economic status, citizenship and immigration status, parents' education, and language skills (Araque, Roldán, & Salguero, 2009; Kovacic, 2012);
II. trace data recorded by LMSs and other online learning environments (Agudo-Peregrina, Iglesias-Pradas, Conde-González, & Hernández-García, 2014; Romero, López, Luna, & Ventura, 2013; Romero, Ventura, & García, 2008; Zafra, Romero, & Ventura, 2011); and
III. combinations of data sources described under i) and ii) (Alstete & Beutell, 2004; Barber & Sharkey, 2012; Jayaprakash et al., 2014).

Regardless of the data source, the prediction of student grades is generally determined by applying logistic regression (Barber & Sharkey, 2012; Campbell, DeBlois, & Oblinger, 2007; Lauría, Baron, Devireddy, Sundararaju, & Jayaprakash, 2012; Palmer, 2013). However, many authors, especially those from educational data mining backgrounds, have also reported highly accurate predictions using different classification algorithms such as C4.5, EM, Naïve Bayes, and Support Vector Machines (SVM).

The underlying rationale of these studies is to uncover variables that are common in the undergraduate environment that will either individually or in concert inform a generalized model of predictive risk that acts independently of contextual factors such as institution, discipline, or learning design. These omissions of contextual variables are also occasionally expressed as an overt objective. For example, the large scale Open Academic Analytics Initiative (OAAI) (Jayaprakash, et al., 2014) had the explicit aim of testing an open source risk identification solution that was applicable to most forms of US tertiary education—from community colleges to private liberal arts universities—was impervious to institutional variances, and thereby could prove suitable for "scaling…across all of higher education" (Jayaprakash, et al., 2014, p. 7).

While this rationale suggests that pooling data across contexts to increase the sample size and predictive utility is ideal, studies that employ this approach are the exception rather than the rule. Most of the reported studies investigating the prediction of academic success have been based on trace data extracted from a single, or small number, of courses within a particular discipline (Macfadyen & Dawson, 2010; Romero, López, Luna, & Ventura, 2013). The small sample sizes and disciplinary homogeneity adds further complexity in interpreting the research findings, leaving open the possibility that disciplinary context and course specific effects may be contributing factors.

Research in predictive analytics has an obvious and significant level of importance for contemporary higher education institutions. The capacity for early identification of students at-risk of academic failure or attrition allows for a proactive approach to implementing learning interventions and strategies that target teaching quality and student retention. Thus, it is not surprising that the insights gleaned from research on student academic risk are being so readily and eagerly adopted across the sector (Siemens et al., 2014). Despite the encouraging progress in this research, a significant challenge remains. That is, how best to interpret such findings in order to ascertain generalizability.

1.2 Need for Educational Theory Underpinning in Learning Analytics

Despite the titular reference to 'learning', learning analytics has only recently begun to draw on learning theory, and there remains a significant absence of theory in the research literature that focuses on LMS variables as key indicators of interaction and success (Lust, Juarez Collazo, Elen, & Clarebout, 2012).

Expectations of academic risk drawn from the learning theory literature are largely antithetical to the universalist assumptions underpinning the practice of identifying student risk from pooled LMS data. Most post-behaviourist learning theories would suggest the importance of elements of the specific learning situation and student and teacher intentions. For example, contemporary process theories would emphasise the dialectic between instruction and learning (Engeström, 2014), while motivational approaches focus (in part) on the beliefs that students hold regarding their capabilities with respect to specific content (Zimmerman & Schunk, 2011), and constructivist theories investigate the interplay of instructional design and student internal conditions (Winne, 2006; Winne & Hadwin, 1998). All therefore acknowledge the contextual conditions that shape student learning, and so posit that learning is fundamentally situated (Lave & Wenger, 1991), suggesting there are potentially important differences between disciplines and courses. Furthermore, there is a long history of research on the particular characteristics of students within disciplines and courses suggesting that, for example, self-regulation of learning may be course specific (Black & Deci, 2000), and that self-efficacy (Chung, Schwager, & Turner, 2002) and information seeking behavior (Whitmire, 2002) can vary by courses and discipline. Altogether the preponderance of evidence indicates that disciplines and courses are not cut from the same cloth and that their respective student constituents may not be of one kind.

Yet, to our knowledge, only a study by Finnegan et al. (2009) examined the possibility of a mediating role for contextual variables. Finnegan et al. (2009) found disciplinary differences in the effects of trace data to predict grades on 22 courses from English and Communication; Social Sciences; and Mathematics, Science, and Technology. Not only did the authors report on the differences in the explained variability of the final grades by multiple regression models (from 26% to 36%), but they also noted there was no single significant predictor shared across all three disciplines. Although some variables (e.g., time spent on content pages) were identified as significant predictors of academic success in regression models for individual disciplines, the same effect was not apparent when data from all three disciplines were combined. Similarly, the multiple linear regression model of the three disciplines combined showed no significant effects and/or the overestimated/underestimated importance of some variables (e.g., time spent on follow-up posts and time spent on reading discussions) compared to the regression models performed for individual disciplines.

The under-explored role of contextual variables may help explain the mixed findings in the field, with even large scale studies reporting differences in their results in relation to the overall predictive power of the same individual LMS variables. For example, where Macfadyen & Dawson (2012) identified a strong correlation between student discussion forum activity and overall academic grades at a large research intensive Canadian university (N=52,917), Lauría et al. (2012) found only weak correlations (ranging from 0.098 to 0.233) between students grades and LMS activity, including discussions read and posted, at a private liberal arts college in the USA (N=18,968). Although the approaches adopted were similar, the observed results markedly differed. Plainly, if the hypothesis that LMS tool use is predictive of student risk is valid, then there are contextual differences at work here, and plausibly these are located in the distinctive elements of the courses that comprised the studies.

There are several advantages in leveraging existing learning theory to investigate the nature of these contextual factors, discussed at length elsewhere in the literature (Gašević, Dawson, & Siemens, 2015; Rogers, Gašević, & Dawson, in press). Briefly, studies designed with clear theoretical frameworks will a) connect learning analytics research with decades of previous research in education and b) make clear what is contended by research designs, and so make explicit what the research outcomes *mean* in relation to existing models and previous findings. Rather than an empirically flat, atheoretical 'clicks and consequences' approach to LMS data, a theoretically driven approach leads to an ontologically deep engagement with intentions and causes, and the validation of models of learning, learning contexts, and learner behavior. This allows for the cumulative advancement of our understanding while maximizing the potential for findings to be disconfirmed, leading to adjustments to existing theory or the positing of new theoretical positions.

1.3 Theoretical Grounding of the Current Study

Here we suggest as theoretical grounding the constructivist, metacognitive approach to self-regulated learning expounded by Winne and Hadwin (Winne, 2006; Winne & Hadwin, 1998). According to this approach learners construct their knowledge by using tools (e.g., cognitive, physical, and digital) to operate on raw information (e.g., readings given by the course instructor or found on the web) to construct products of their learning (e.g., recall information from the course readings) (Winne & Hadwin, 1998). Learning products are evaluated with respect to internal (e.g., time budgeted to study) and external (e.g., rubrics used for grading answers) standards. As agents, learners make decisions about their learning in terms of choices of study tactics (i.e., tools) they will use and standards they will apply to evaluate their learning products against (Winne, 1996). Decisions made about learning are influenced by *conditions*, which can be internal (e.g., motivation and prior knowledge) and external (e.g., instructional scaffolds or learning task grading policy) (Winne, 2011; Winne & Hadwin, 1998). *We posit that learning analytics must account for conditions in order to make any meaningful interpretation of learning success prediction.*

For the purposes of this paper, we focus on one aspect of the Winne and Hadwin model, instructional conditions, as an important component of external conditions, in the interpretation of the results predicting learning success (Lockyer et al., 2013). The impact of instructional conditions on learners' decision making process is well evidenced across numerous studies (Azevedo, Moos, Greene, Winters, & Cromley, 2008; Cho & Kim, 2013; Garrison & Cleveland-Innes, 2005; Trigwell, Prosser, & Waterhouse, 1999). For example, Trigwell, Prosser, & Waterhouse (1999) investigated the association between students' approaches to learning and the instructional methods of teaching. The authors found that students had a strong tendency to follow surface approaches to learning in classes where teachers had adopted a more central and information transmission instructional strategy. In contrast, students had a strong tendency to follow deep approaches to learning in classes where the teachers had implemented a more student-focused instructional approach. Similarly, Garrison and Cleveland-Innes (2005) showed that students took a deep approach to learning when online courses had: i) a sound instructional scaffolding for online discussions embedded in the course design; and ii) a high level of direct facilitation and leadership of online discussions by course teachers.

Specifically, in this study, we make several predictions based on the existing educational research. First, we can predict that that the students will have a tendency to interact more extensively with tools that are directly recommended for use according to the instructional conditions of the courses they are enrolled in (Cho & Kim, 2013; Garrison & Cleveland-Innes, 2005; Palmer, Holt, & Bray, 2008; Trigwell et al., 1999). We further predict that the students' levels of interaction will be positively associated with the instructional conditions of the course – e.g., use of discussion forums for question and answers or for knowledge construction and peer feedback. Variables describing the frequency of interaction with these tools[2] will likely then have high effects on the students' learning outcomes set in specific courses, thus yielding high predictive power for academic achievement. Finally, as educational research shows that central tendency prevails (Winne, 2006), the models that aggregate variables about student interaction with tools used in different courses may lead to over- and under-estimation of the effects of

[2] A similar prediction can be made for the variables describing the quality of the use of learning tools as shown by Joksimović, Gašević, Kovanović, Riecke, & Hatala (in press) for the quality of the use of discussion boards. However, assessment of effects of the quality of use of learning tools recommended by the instructional conditions, although very important, goes beyond the scope of the current study.

some variables in the predictive models of academic achievement. As a consequence, such aggregated predictive models of academic achievement may miss to identify variables of direct relevance for instructional practice on the level of individual courses.

1.4 Research Questions

This paper reports on the findings of a study investigating the extent to which instructional conditions influence the prediction of academic success in undergraduate courses offered in a blended learning model. More specifically, the study investigated the following research questions:

1) What is the level of similarity in student characteristics and LMS usage across different courses in a blended mode of study?
2) What is the portability of a general model – e.g., as suggested in OAAI (Jayaprakash et al., 2014) – for predicting academic success across courses?
3) To what extent does the predictive power of individual variables derived from trace data differ in the prediction of academic success across courses?
4) How does the predictive power of variables derived from trace data compare to variables derived from information stored in institutional student information systems (e.g., age, gender, citizenship status, and language skills) in the prediction of academic success in different courses?

2 Methods

2.1 Study Design and Setting

The study followed a correlational (non-experimental) design (Field & Hole, 2003), as it investigated the effects of the variables derived from the trace data and the data from the institutional student information system on the prediction of students' academic success. The data for the study were extracted from a public research-intensive university in Australia. The institution consists of four divisions (convergence of multiple faculties): Health Sciences; Education, Arts and Social Sciences; Information Technology, Engineering and the Environment; and Business. The data were collected from nine first-year courses that were included in the institutional retention initiative – Enhancing Student Academic Potential (ESAP) coordinated by the central learning and teaching unit. A course is defined as a discrete unit of study constituting a part of a program. The ESAP initiative was established to provide support for transitioning first-year students identified as displaying learning behaviors that lead to disengagement and a lack of academic success. Eligibility for participation in ESAP was principally based on a consistently low level of program retention into the following year (set at less than 80% for Business and Education, Arts and Social Sciences; and at less than 85% for Health Sciences and Information Technology, Engineering and the Environment) and course success (set at less than 80% i.e. more than 20% of students must have failed). In addition, courses needed to have >150 students. Five years of data were then extracted from the institutional student information system to ensure the courses showed a consistent pattern of low success. The data examined here includes all students (n = 4134) from the nine courses finally selected, which were offered in the first semester of the 2012 academic year. In accordance with the institution's privacy and ethics process, all students enrolled in the courses were informed, via email, of their involvement in the ESAP initiative including its aims and that the course interaction data (LMS) would be collected for better understanding student online behavior in order to provide insights into the learning experience and improve course quality. Access to LMS data logs was provided through direct queries to the Moodle database. The data were de-identified before the analyses were performed.

The nine ESAP courses represented a diversity of disciplines and included one each from accounting (ACCT), communications (COMM), computer science (COMP), economics ECON), graphic design (GRAP), marketing (MARK), and mathematics (MATH), and two from biology (called here 'biology 1' and 'biology 2') (BIOL1, BIOL2). All courses were offered as a blended learning approach (Graham, 2006), where face-to-face instruction was complemented by online materials located in the institutional LMS - Moodle. That is, all courses used Moodle to share learning resources with students and build an online space for social interaction. Table 1 illustrates the differences in the use of Moodle by the students enrolled in the above mentioned nine courses. Only three Moodle features, course login, resource, and forum were consistent across all nine courses. The observed differences in LMS usage across the courses resulted from the disciplinary and course-specific needs as well as differences in instructional intentions for the use of the LMS tools as shown in Table 2. For example, the two biology courses embedded quizzes in the instructional design whereby the completion of quizzes contributed to the final mark 20% and 15%, respectively. The example of a non-embedded LMS feature, but explicitly communicated as useful tool to be incorporated into the course instructional design, was Turnitin (commercial software that detects plagiarism and can be integrated with Moodle). Turnitin was used by students in the accounting, communications, computer science, economics, marketing, and mathematics courses.

==== Please, insert Table 1 here ====

==== Please, insert Table 2 here ====

2.2 Outcome Variables

For the study outcomes, two measures of students' academic success were evaluated. The first was **percent mark**, a continuous variable ranging from 0% to 100%. The second measure was **academic status.** A nominal variable that included three categories: 1) *pass (or succeeded),* representing students whose percent mark was 50% or more and who passed the course; 2) *fail,* a category of students who did not achieve 50% mark and who failed the course; and 3) *withdraw*; students who withdrew from the course. Given the small number of students who withdrew from the courses (n = 88), 'academic status' outcome variable was used as a dichotomous variable (pass/fail) in regression analyses.

2.3 Student Characteristics and Trace Data

The student characteristics data extracted from the institutional student information system (SIS) was based on similar previous studies (Alstete & Beutell, 2004; Barber & Sharkey, 2012; Lauría et al., 2012; Palmer, 2013) and accessibility to the research team. The characteristics included: age (a continuous variable ranging from 17 to 66); gender (male/female); international student (yes/no); language spoken at home (English/language other than English); home remoteness (urban/non-urban (rural or isolated areas)); term access (full-time/part-time student); and previous enrollment in the same course (yes/no). The variable course start access (early access/did not access the course/late access) was derived from the user-trace data in the LMS. This variable was included among the student characteristics data as it was not indicative of any specific tool use and merely represented the time and date when the student first engaged with the LMS in comparison with the formal course commencement date. Prior research by Palmer (2013) has demonstrated the importance of the course start access as a predictor of academic success.

Variables derived from the LMS trace data include information about the usage of the following Moodle tools/features: forums, course logins, resources, Turnitin file submission, assignments, book, quizzes, feedback, map, virtual classroom, lessons, and chat. The trace data were initially collected as continuous variables and represented the number of times students used a particular feature by aggregating individual operations such as page or discussion views, addition of discussion posts, and course logins. Compared to forums, course logins, resources, and assignments, the features such as quizzes, feedback, map, virtual classroom, lessons and chat were not accessed by a substantial number of students. These were, therefore, dichotomized into the *accessed* and *did not access* categories. Turnit in and book features were accessed by more students and there was a greater variability in access. However, these variables were highly skewed, and application of data transformations such as log, square root or reciprocal transformation did not correct the skewness. Therefore, these features were transformed into categorical variables and the cut-offs were decided arbitrarily to best represent the data. For example, 14% of students did not access the Turnitin feature, 43% accessed the feature 1-2 times, while the remaining 43% of students accessed this feature 3 times or more (out of which 36 % were students who accessed Turnitin feature 3-4 times). Therefore, we divided this feature in the categories 'did not log', 'logged 1-2 times', and 'logged 3 or more times' to facilitate data analyses.

2.4 Statistical analysis

Continuous data are presented as mean ± standard deviation if normally distributed or as median (25%, 75%) if skewed. Categorical data are presented as counts and percentages. Differences in continuous and categorical variables among course subjects are explored by the analysis of variance (ANOVA) and Chi-square test, respectively. Multiple linear regression models performed on a total sample and for each course were used to explore the association between student online interactions and student percent mark. Model 1 contained student characteristics described in Section 2.3. Model 2 included student characteristics from Model 1 and variables derived from trace data. A change in R square was calculated to present the percentage of variability in student percent mark explained by online interaction features offered within a course over and above student characteristics. Only continuous variables that were not normally distributed, including percent mark, access to forum, course logins, and access to resources and assignments, were transformed using the natural logarithm before carrying regression analyses (Keene, 1995)[3]. Linear regression models were explored for multicollinearity. Variance inflation factors were well below 10, indicating no multicollinearity in the data (Myers, 1990).

Two logistic regression models, performed on a sample as a whole and for each course separately, were used to explore the association between students' use of the LMS features and students' performance status (pass or fail). Model 1 contained student characteristics (see Section 2.3. for detailed description), while model 2 included student characteristics and variables derived from trace data. Using a receiver operating characteristic (ROC) curve analysis, we calculated the area under the ROC curve (AUC) that corresponded to the *c* statistic from logistic regression models 1 and 2. As a measure of discrimination, AUC of <0.5, 0.5≤AUC<0.7, 0.7≤AUC<0.8, 0.8≤AUC<0.9, and ≥0.9 represents no discrimination, poor, acceptable, excellent, and outstanding discrimination, respectively (Hosmer & Lemeshow, 2000). A step statistic was used to explore the improvement of the predictive power of model 2 compared to model 1. All analyses were performed using the Statistical Package for Social Sciences (SPSS) version 19. P values of ≤0.05 were considered statistically significant.

3 Results

3.1 Student Characteristics across Courses

Of the total participant student population (n=4134), 18% were enrolled in the accounting course, 5.3% in biology 1, 15.9% in biology 2, 12.1% in communications, 5.9% in computing science, 16% in economics, 4.6% in graphic design, 17.5% in marketing, and 4.7% in the mathematics courses. Significant differences were observed in the examined student characteristics across the courses (Table 3). For instance, students in the biology 2 course were on average older and had a higher representation of female students compared with other courses. Furthermore, within the accounting, economics, and marketing courses there was a higher percentage of international students and students who reported that "a language other than English" was spoken at their home than among students in the remaining set of courses. Students who reported living in rural or isolated areas are most prevalent in biology 2, graphic design and mathematics courses. Moreover, students from accounting, biology 2, and economics were more likely to report being a part-time student, while the greatest prevalence of students who have previously enrolled in a course was among students taking accounting, economics, and marketing. In addition, the prevalence of students who did not access a respective course or who accessed it late was higher for accounting, communications, computing science, economics, and marketing than for the other offered courses.

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[3] The natural logarithm transformation was used to correct the skewedness of not normally distributed variables in order to work with parametric statistical tests. Compared to other data transformations employed (log10, square root and reciprocal transformation), the natural logarithm best corrected the skewedness of the variables. Furthermore, we prefer the use of natural logs (that is, logarithms base e), as the coefficients on the natural-log scale are directly interpretable as approximate proportional differences; for e.g. with a coefficient of 0.05, a difference of 1 unit in x corresponds to an approximate 5% difference in y (Gelman & Hill, 2006, pp. 60–61).

==== Please, insert Table 3 here ====

3.2 Student Performance and Trace Data-based Variables across Courses

With respect to student performance, significant differences were observed across courses (Table 4). Post hoc tests (Bonferroni) revealed that the percent mark of students taking the accounting course was significantly lower compared to their counterparts taking biology 2 ($p = 0.011$), computing science ($p = 0.004$), graphic design ($p = 0.001$), and marketing ($p<0.001$). The lowest percentage of students who failed the course was observed for graphic design, while a notably higher percentage of students who failed the course was noted for the accounting and mathematics courses.

Table 4 also includes the variables derived from LMS trace data. Not all trace data-based variables are present within each course, as shown in Table 1. However, for the subset of variables consistently adopted across the courses, there was a significant difference in student use for these LMS features. Namely, the discussion forums were most frequently accessed by the biology 1 and communications students and least frequently or not at all accessed by the biology 2, computing science and graphic design students. Furthermore, biology 1, biology 2, and mathematics students were the most frequent users based on number of course logins. With respect to access to the assignments and the Turnitin tool, the least frequent access was observed among the accounting students, while communications and economics students were the ones who accessed these two features most frequently. More than 35% of the biology 2 students did not access the book feature during the course, while that percentage was lower for the accounting and economics students (approximately 20%). More than half of the computing science students did not access the course quizzes. In contrast, less than 2% of accounting students did not access the quiz tool. In addition, the usage of some features was unique for certain courses such as the light box in accounting; feedback, map and virtual classroom in biology 2; lessons in computing science; and chat in marketing.

==== Please, insert Table 4 here ====

3.3 Prediction of Student Percent Mark

Results of the multiple linear regression models featuring the association between students' use of the LMS features and student percent marks, after adjusting for student characteristics, are presented in Table 5. In the overall study sample (students from all courses taken together), approximately 5% of the variability in the student percent mark was explained by the student characteristics. The addition of the online interaction variables consistently adopted for all courses (e.g. access to forums and resources, and course logins) explained about 16% of the variability in the student percent marks (R^2 change = 0.162, $p<0.001$).

==== Please, insert Table 5 here ====

Given that the student characteristics, student performance, and the variables derived from trace data significantly differed among courses, separate multiple linear regression analyses were performed for each course. In essence, we wanted to explore whether variability in student percent marks explained by student characteristics and the variables derived from trace data varied across courses or if it was similar to that obtained from the regression model performed on the overall study sample. As demonstrated in Table 5, there are significant differences in the association between student characteristics and trace data variables and student percent marks among courses. Variability in percent mark explained by student characteristics varied across courses and ranged from 2.9% for marketing to 14.8% for biology 2. Similarly, variability in student percent marks explained by the variables derived from trace data differed across courses and ranged from 2% for graphic design to 70.3% for communications. Interestingly, for the courses with the same number of the variables derived from trace data, there was a notable difference in the variability in percent marks explained by the variables derived from trace data. For example, variability in student percent marks explained by the five LMS features offered in courses biology 1, communications, and mathematics was 5.9%, 70.3%, and 19%, respectively. Additionally, the higher the number of LMS features offered within the course did not result in a greater percent variability in the student percent marks explained by these features. For example, the percent variability in student percent marks explained by the five features offered by the communications course and eight features from biology 2 was 70.3% and 24.2%, respectively.

When considering the associations between separate LMS features and student percent marks after the adjustment for potential student characteristics (potential contributing factors), we have observed notable differences between the results of the analyses performed on the sample as a whole and those across courses. For example, after the adjustment for student characteristics, the results of the multiple linear regression analyses performed on the total sample of students (from all courses together) indicate that the course logins variable was a significant predictor of student percent marks whereby one percent increase in course logins results in about 0.5 percent increase in student percent marks (B (95%CI) = 0.446 (0.365, 0.527), $p < 0.001$) (Table 5). However, when the analyses, adjusted for student characteristics, were performed across the individual courses, course logins showed no association with student percent marks for courses communications, biology 1, biology 2, economics, graphic design, marketing and mathematics. Similarly, access to resources was a significant predictor of student percent marks for the total sample population. However, for the separate course analysis, access to the resources variable showed no association with the outcome for courses communications, computing science, biology 1, graphic design and mathematics. These results indicate that the analyses performed on the total sample may either underestimate or overestimate the effect of certain variables derived from trace data in a particular course. Across the total sample of students and adjusting for student characteristics, a 10% increase in access to resources is associated with around a 2% increase in student percent mark (B (95%CI) = 0.223 (0.157, 0.290), $p < 0.001$). This certainly overestimates the effect of access to the resources variable in courses where this variable was found to be not significantly associated with student percent marks; and it underestimates the effect of this learning interaction variable for the courses where this effect was twice as large, such as biology 2 (B (95%CI) = 0.498 (0.298, 0.699).

On a course level, while the expectation was that students' use of the LMS features would have a positive effect on student performance, there were some contrasting results (Table 5, columns 5-7; all analyses adjusted for student characteristics). Access to the LMS feature "book" consistently showed a negative association with student percent marks. Namely, percent marks of students from accounting and economics who frequently accessed the “book” tool were on average 0.3% lower than those of their counterparts who did not access this learning interaction course feature (accounting, B (95%CI) = -0.302 (-0.467, -0.085), $p = 0.009$; economics, B (95%CI) = -0.266 (-0.390, -0.177), $p = 0.001$). Although online access to a “book” was also offered by biology 2, we observed no significant association between access to a “book” and student percent marks. Access to chat, an LMS feature that was unique for marketing, was negatively associated with student percent marks (B (95%CI) = -0.143 (-0.257, -0.010), $p = 0.036$). Similarly, a negative association was found for student access to assignments and percent marks for mathematics (B (95%CI) = -0.229 (-0.425, -0.034), $p = 0.022$), while access to assignment had a positive effect on student performance in accounting (B (95%CI) = 0.195 (0.052, 0.339), $p = 0.008$), communications (B (95%CI) = 0.127 (0.009, 0.246), $p = 0.035$), and marketing (B (95%CI) = 0.296 (0.132, 0.461), $p < 0.001$).

The effect of the use of LMS features on student performance again varied significantly across courses. No association was identified between frequent (3 or more times) access to the Turnitin feature and student percent marks for accounting and mathematics courses. However, when compared to students who did not access feature, the percent marks of the students who did frequently access Turnitin were about 60% (B (95%CI) = 59.264 (37.978, 89.107), $p < 0.001$), 6.6% (B (95%CI) = 6.629 (3.527, 11.858), < 0.001), and 5.8% higher (B (95%CI) = 5.814 (3.522, 9.268)) for communications, computing science, and economics, respectively. Similarly, while access to quizzes showed no effect on student performance for the courses biology 1 and computing science; the percent marks of the students enrolled in biology 2 and economics and accessing quizzes were about 0.7% higher than those of their counterparts not accessing quizzes (biology 2: B (95%CI) = 0.737 (0.376, 1.192), $p < 0.001$; economics: B (95%CI) = 0.685 (0.411, 1.013), $p < 0.001$).

3.4 Prediction of Course Performance Status (pass/fail)

For the entire sample population and the separate course analyses, the addition of the variables derived from trace data to the model with student characteristics significantly improved the overall accuracy of the model to discriminate between students who passed and failed the course. The exception to this finding was the course graphic design (see Table 6, columns 1-4). However, the improvement in the overall model followed by the addition of the variables derived from trace data was not uniform across all courses. With the addition of the trace data-based variables, according to the AUC, the power of the model to discriminate between students who passed and those who failed the course increased from poor to acceptable for accounting and marketing; from acceptable to excellent for biology 1, biology 2, computing science, and economics; while the largest improvement of the model was observed for mathematics where the discriminatory power of the model increased with the addition of the variables derived from trace data from poor to excellent, and for communications from poor to outstanding.

==== Please, insert Table 6 here ====

After adjusting for student characteristics (potential contributing factors), the results of the analyses performed on the total population sample indicate that each additional course login and additional access to resources decreased the odds of failing a course by 1.4% (OR (95%CI) = 0.986 (0.983, 0.990), p

< 0.001) and 0.5% (OR (95%CI) = 0.995 (0.991, 0.999), p = 0.012), respectively (Table 5, columns 5-7). However, the analyses performed for each course separately reveal no significant association of course logins and access to resources with student performance status for accounting, biology 1, biology 2, communications, economics, graphic design, and mathematics. Moreover, similar to the analyses run on the overall sample, after the adjustment for student characteristics, the course logins variable showed a negative association with failing the course among the students taking computing science (OR (95%CI) = 0.980 (0.965, 0.994), p = 0.007); however, no association was found between the access to resources and failing this course. The opposite pattern was found among students taking marketing where access to resources was found to be a significant predictor of failing a course. In this instance, each additional access to resources was associated with a decrease in odds of failing the course by 1.8% (OR (95%CI) = 0.982 (0.966, 0.999), p = 0.037). No significant association was recorded between course logins and student performance status. After adjusting for student characteristics, no variable derived from the trace data showed a significant association with student performance status among the students taking communications and mathematics. While access to Turnitin demonstrated no effect on student performance status for the communications, marketing and mathematics students, odds of failing the course were significantly lower among the accounting, computing science, and economics students who frequently accessed the Turnitin (3 or more times) when compared with their course peers who did not access the feature (Table 6). Interestingly, frequent access to a "book" and to "assignments" were associated with an increase in odds of failing the course among students taking accounting (OR (95%CI) = 2.160 (1.207, 3.865), p = 0.009) and economics (OR (95%CI) = 1.028 (1.010, 1.047), p = 0.002), respectively. In addition, the odds of failing the course were significantly lower among biology 2 (OR (95%CI) = 0.122 (0.064, 0.231), p < 0.001) and economics (OR (95%CI) = 0.280 (0.141, 0.558), p < 0.001) students who accessed compared to those who did not access the quizzes.

4 Discussion

4.1 Discussion of the Results with respect to the Research Questions

The results reported in Sections 3.1 and 3.2 revealed significant differences in student characteristics and the level of use of individual LMS features across the nine courses, as investigated in research question 1. Not only did the students use different LMS features across the nine courses (see Table 1), but significant differences in how and the extent to which the tools were utilized were also observed. For example, students enrolled in biology 1 and communications had a significantly higher use of the LMS discussion forums than the students in other courses examined in the study. The observed differences in the level of student use of the various LMS features, conceivably has two primary implications. First, there is a need to create models for academic success prediction for individual courses, incorporating instructional conditions into the analysis model. Second, there must be careful consideration in any interpretation of any predictive model of academic success, if these models do not incorporate instructional conditions. In such cases, several threats to the validity of the results may emerge such as overestimation or underestimation of certain predictors.

Significant differences in student characteristics were also observed across all the variables analyzed in the study. Such differences can have different implications on academic success and the use of the LMS.

For example, in the present study, the courses that had high enrollments of part-time students (e.g., accounting, biology 2, and marketing) also had significantly higher numbers of students with late or no access to the LMS. This finding suggests that particular courses, which may have similar technology use, may warrant separate models for academic success prediction due to the individual differences in the enrolled student cohort.

The accuracy of aggregated and course-specific models differed significantly in academic success prediction for both percent marks and course completion (pass/fail) – investigated in research question 2. The results of the analysis showed that, in both aggregate and course-specific models, the addition of the variables derived from trace data improved the accuracy in predicting course performance (Table 5). However, while the general logistic regression model had an acceptable accuracy to discriminate between students who passed and failed the course, the accuracy of the majority of course-specific models was excellent or outstanding based on Hosmer & Lemeshow's (2000) interpretation of the AUC values. The exception to this finding was the graphic design course, where accuracy of the model with both student characteristics and variables derived from trace data had a marginal increase as compared to the accuracy of the model containing only student characteristics. A plausible explanation for this finding may lie in the specific instructional requirements for technology use linked to this course. The graphic design courses requested that students use social media tools other than those provided by university IT support unit as part of the standard university process. Indeed, although graphic design had a Moodle course site, the course instructor confirmed that the students were not requested to perform all their learning activities in the LMS. Rather, they were guided to incorporate public social media tools, such as Twitter and Facebook. As such, while the course had an active online component, the majority of this activity occurred beyond the boundaries of the institutional LMS. Consequently, the lack of LMS based activity resulted in a non-significant contribution of the variables derived from traced data in the prediction of student percent marks. This example offers an important insight for learning analytics research: the importance of understanding and taking account of instructional conditions in learning activities.

Our results also revealed different patterns in the effect of individual variables, derived from trace data, on academic success (research question 3), which could be divided in to the following five categories. First, the variables derived from trace data were not significant predictors of academic success for some courses (e.g. graphic design, as already discussed). Second, while some variables were found significant in the general model, they were not found to be significant in the course specific models (e.g., course logins and resource views were not significant predictors in seven out of the nine courses). A highly plausible reason for the only variables found significant in the generalized model is that the variables represented those features which were common (but not necessarily important) across all courses. Third, conversely, while some variables were not found to be significant in the overall model, they were significant in the course-specific models (e.g., book in accounting and economics, quiz in economics, and Turnitin in communications, computing science, economics, marketing, and mathematics). Fourth, some LMS features had a significant association with percent marks in some courses (e.g., book was negatively associated with the student percent marks in accounting and economics), while the use of the same features had no significant association with the percent marks in the other courses (e.g., book in biology

2). Fifth, the use of the same LMS feature had a positive effect on academic success in one course, and resulted in a negative association within another. For instance, there was a positive association of assignments in marketing and a negative association in mathematics for the same LMS feature. From these five categories, we draw two important conclusions: a) generalized models of academic success prediction can overestimate or underestimate effects of individual predictors derived from trace data; and b) use of a specific LMS feature by the students within a course does not necessarily mean that the feature would have a significant effect on the students' academic success; rather, instructional conditions need to be considered in order to understand if, and why, some variables were significant in order to inform the research and practice of learning and teaching.

The level of variability associated with predicting academic success is largely attributed to the trace data in comparison with the variables associated the student characteristics data (research question 4). This is well evidenced in the observed *large* effect size for the trace data in the majority of the courses in our sample (i.e., in those with the change in R^2 greater than 25%) – based on Cohen's (1992) interpretation of R as an effect size measure (0.1 – small; 0.3 – medium; and 0.5 – large). Notable examples of the effects of trace data on the prediction of academic success were located in communications, computing science, and economics. On the other hand, the variability explained by the variables derived from trace data was smaller than that of the variables explained by student characteristics in biology 1 and graphic design. The reasons why course-specific models for these two courses had low predictive power warrants further research. A possible explanation – that needs to be studied and validated in the future research – is that these courses either i) had a low degree of instructional guidance requiring students to use the LMS features or ii) students required some other scaffolds for more effective use of the tools (Gašević, Mirriahi, & Dawson, 2014). This in turn can suggest that not only will course instructional conditions determine the use of LMS features and therefore their predictive utility, but also that the relative predictive value of trace data vis-à-vis student characteristics data is dependent on course instructional decisions, and hence overall course design. This is especially important in blended learning conditions where online and face-to-face components of instruction need to be seamlessly integrated if online tools are to be perceived as useful in order to be adopted by students (Bliuc, Ellis, Goodyear, & Piggott, 2010; Clarebout, Elen, Collazo, Lust, & Jiang, 2013).

Subtle differences in instructional intentions guiding the use of tools, as shown in Table 2, are an added plausible explanation for the observed differences in the predictive power of variables derived from trace data. We unpack this explanation further by drawing on the examples of the use of quizzes. For example, both biology 1 and 2 required students to complete assessment quizzes as part of the suite of learning activities integrated into the overall course instructional design. However, biology 1 exclusively used these quizzes for summative assessment and grading. In contrast, biology 2 provided students with the opportunity to undertake a quiz multiple times with the student's best score recorded as the final grade for that particular task (quiz). In this instructional design context it is likely that biology 2 promoted students' engagement in self-testing (Bjork, Dunlosky, & Kornell, 2013) by allowing for reflection on their level of understanding after completion of the particular quiz. Ideally, after completing a series of these quizzes, students are presumably more likely to have identified gaps in their knowledge and be seeking additional guidance and learning support. Thus, the use of the specific LMS tools in biology 2 has likely played a higher role in promoting student self –reflection than in biology 1. This may in part, reflect the higher explanatory power in the regression model in academic success for biology 2. This interpretation requires further research in understanding the study strategies employed and the results interrogated over an extended period of time and across different courses to better understand the effects of different instructional intentions as outlined in Table 2.

4.2 Implications for Research

The findings of the present study suggest that it is imperative for learning analytics research to take into account instructional conditions when developing predictive models. The differences in instructional conditions, especially those related to whether and how to use LMS features need to be determined before data are merged to create one generalized model for academic success prediction. A failure to consider instructional conditions is likely to lead to an over-estimation or under-estimation of the effects of specific LMS features on students' academic success. However, technology use even within a single course can also change as a result of the evaluation of course effectiveness (Swan, Matthews, Bogle, Boles, & Day, 2012). Thus, instructional conditions define the level of instructional guidance regarding how and when an individual uses the various LMS features. Not only can new LMS features be introduced, but also the use of existing LMS features may change as a result of course revisions e.g., discussions and quizzes in LMS are changed to a graded format and may be compared to a former non-graded approach that operated in previous course versions. Learning analytics must, and can, account for the fluid nature of technology use within a course offering rather than assume that the trace data of different offerings of the same course can be aggregated to create a single joint predictive model for academic success and retention.

The findings of this study expand on the results of Finnegan et al.'s (2009) study and imply that the differences in predicting academic success are affected by disciplinary differences and to a greater extent, technology use within individual courses. For example, in our study, we had nine courses that from four different divisions of the university, where each division represents approximately four disparate disciplines. However, our results revealed no identical predictors of academic success, derived from the trace data, even within the same discipline (e.g., science – biology 1 and biology 2 and business – accounting, economics, and marketing). While future research should advance the understanding of the effects of the LMS use in specific disciplinary contexts, our findings indicate that trace data in different courses should not be aggregated based on disciplinary assumptions alone. Technology use within individual courses also needs to be accounted for prior to making generalizations at a disciplinary level. If not, similar threats to validity can arise as encountered in this study with the use of general models for academic success prediction. An understanding of the pedagogical intent and disciplinary context in developing predictive models may increase the generalizability and accuracy of such models.

The findings of this study confirm the conclusions drawn from Lust et al.'s (2012) systematic literature survey on the importance of theoretical grounding of studies that investigate effects of technology use on learning. In this paper, we have presented evidence on the need to consider instructional conditions in order to increase the validity of learning analytics findings. A possible reason of the differences in technology use across courses lies in differences in instructional conditions and that requires further investigation. However, it is likely that instructional conditions are not the only factor that affects course-specific technology use and academic success. According to Winne & Hadwin (1998), instructional conditions are a component of external conditions. As suggested by Winne (1982, 2006), when external conditions are considered only, studies in instructional science often end with contrasting results. Reasons for such contrasting results often lie in individual differences of the students involved in studies (Winne, 1996). Both Perkins (1985) and Winne (1996) posited that this is due to the individual differences related to the internal conditions of metacognition and motivation. The results of recent studies have also confirmed the importance of internal conditions for increasing the validity of learning analytics research by showing that the distinct profiles of learners, reflective of different student motivations, conceptions of instruction, and approaches to learning, can be identified based on the use of learning tools (Clarebout et al., 2013; Lust, Elen, & Clarebout, 2013; Lust, Vandewaetere, Ceulemans, Elen, & Clarebout, 2011; Wise, Speer, Marbouti, & Hsiao, 2013). Therefore, future studies should consider the effects of interactions of internal and external conditions in order to increase the validity of learning analytics results and better inform the research and practice of learning and teaching.

The quality of integration of online and face-to-face learning components is a tangential factor that can affect educational experience and thus, courses-specific technology use in blended instructional learning models. Future research in the field of learning analytics and digital learning more broadly, should evaluate the effects of factors associated with the quality of blended learning experience. These factors are typically about educational experience and collected by self-reports (Bliuc et al., 2010; Ginns & Ellis, 2007); and could be incorporated as covariates into models of academic success prediction. To enhance interpretation of academic success prediction, it appears important to investigate the association of the quality of blended learning experience and individual differences, especially metacognitive and motivational factors related to the use of particular study tools/tactics (Clarebout et al., 2013; Winne, 2006).

This study highlights that as we are moving from generic models to course-specific models, we should be also transition from the crude measure of academic success to focus on the measurement of learning, learning processes, and learning outcomes. This would require i) connecting trace data-based predictors with learning outcomes, ii) collecting more granular data indicative of learning processes; and iii) discriminating which types of trace data are more reflective of learning and types of learning (factual vs. conceptual) compared to the types of data that are more indicative of other individual differences such as academic goal-orientation, self-management of learning, or sense of responsibility. For example, for quizzes, we would need to know for each question item the type of knowledge it measures (e.g., factual vs. application vs. transfer) and for online discussions, we would need to apply content analysis and look for traces of constructs such as Garrison's and associates' cognitive presence (Garrison, Anderson, & Archer, 1999). To achieve this, additional meta-data should be entered by course instructors and collected by LMSs. Furthermore, additional techniques for analysis of learning processes and products (e.g., process and text mining) should be applied (Kovanović, Joksimović, Gašević, & Hatala, 2014; Reimann, Markauskaite, & Bannert, 2014). Adoption of these processes for collecting finer-grained data may facilitate the maturation of the field of learning analytics to move past the "urban myth" that the greater use of technology results in better learning outcomes without explanation or contextual evidence.

Disciplinary differences, characteristics of the instructors and materials could have affected our findings. Future research should focus on more accurate ways to compare courses that have the equivalent characteristics of instructors and content within the same subject domains, changing only the students and the technology use for educational purposes. This would allow for investigating the extent to which instructional conditions, guiding students how to use technology, affected the results of the regression analyses reported in the paper.

4.3 Implication for Practice

The results of the study indicate that translating findings obtained by generalized models for academic success prediction pose a threat to the potential of learning analytics to improve the quality of teaching and learning practice. Conversely, findings derived from more granular course-specific models can provide instructors with better insight into the factors that affect the academic success of students, so that the findings can be i) interpreted with respect to instructional conditions, and ii) directly used to improve teaching practice. In cases of exclusive use of generalized models, numerous patterns of direct importance for the practice of learning and teaching could remain undetected. For example, some LMS features had a significant effect on academic success in the course-specific models, but they had no effect in the model based on the sample of all the courses. These features were sometimes unique to individual courses and may offer important insights or suggest avenues for further investigation. The interpretation of such findings should account for course-specific requirements and instructional intent about technology use embedded in the design of courses. Although this study did not investigate the effects of instructional intent and learning design on technology use, possible implications for practices could be still be drawn. For example, the negative association between chat and student success in marketing may indicate that students tried to reach out to their peers for some help, but the peers were unable to assist them. Unexpected mismatches between LMS features and outcomes may also be salutary for curriculum design. For example, the negative association of assignments with grades in mathematics could be an indicator of a) inadequate alignment of assignments with the course expectations or b) weaknesses in integration between the face-to-face and online components of the course. In contrast, a positive association between the use of assignments and marketing grades could be an indicator of good assignment-course expectations alignment and used to identify students lagging behind the course expectations.

The course specific models of academic success can offer valuable insights for instructors regarding how to improve their instructional practice. The models may also be complemented with findings established within educational psychology to better inform teaching and learning practice. Our study illustrates that instructors often incorporate specific tools within the LMS without envisioning learners' activity in the context of their overall instructional designs[4]. As highlighted in Table 2, the adoption of the chat tool

[4] This indicates that teaching practice does not often recognize the importance of guiding and scaffolding students' use of a particular technology or tool to support their learning endeavours. This is well documented by Winne's (2006) four conditions– metacognitive awareness of the tool value, mediation to find the tool useful for a task at

had no instructionally defined purpose and no single reference as to how students would use the chat tool in any of the courses. While the MARK course offered chat the only difference – compared to all other eight courses – was that the chat tool was made available and highly visible on the home page of the course in the LMS. This likely attracted the attention of the students (23.4%) for experimentation purposes. However, as our regression analysis demonstrated the use of chats had a negative effect on the students' academic success in this course. This may suggest that students who were struggling with the course material were seeking additional methods for learning support. As the use of chats was not pedagogically crafted into the instructional conditions and only offered as an added feature, it was unlikely that the tool was used for learning, but more as a tool for seeking added support or experimentation. In the case of learning support, specific additional support measures for students adopting this tool were also required. Regardless, the fact that the use of chat was a significant negative predictor of academic success is relevant feedback for the instructors. In the given course, instructors could design learning activities or learning support through the use of the chat tool. Furthermore, in the case of student support through the use of synchronous chat a simple dashboard indicating the use of chats could act as a relevant indicator for instructors to readily identify students seeking instructional assistance.

There are important considerations that arise from these findings for both the field of learning analytics and education institutions that hope to benefit from its insights. For the field, our findings strongly suggest that learning analytics cannot be decoupled from actual, situated learning and teaching practice. Learning analytics will not be of practical value or widely adopted if it cannot offer insights that are useful for both learners and teachers (Ali, Asadi, Gašević, Jovanović, & Hatala, 2013; Clarebout et al., 2013; Swan, 2012). There are potential unintended consequences when embarking on wholesale adoption of generalized models of student success. Efforts in the field of learning analytics should be directed towards the development of actionable recommendations, and this will only be possible if the understanding of practical needs in specific instructional and learning contexts is the primary driver for the development and deployment of learning analytics methods.

The comparison of the results between course-specific and general models points to a significant tension in the field that must be resolved. On the one hand generalized models may be inaccurate in many cases, but represent a cost effective and organizationally efficient approach to identifying student risk. On the other hand, boutique models that vary by course, or even each offering of the course, may be unwieldy to implement, despite being more accurate. One approach to resolving this dilemma would be to seek generic capabilities at the software application level rather than the variable identification level, with instructors able to tap into simplified model generation programs that can analyze previous course offerings and suggest key risk variables given their instructional aims, specific student tool-use requirements and (where available) the outcomes of previous student cohorts. Even so, this does represent a fundamental adjustment to the underlying assumptions of learning analytics as applied to risk prediction. In the generic variable-based model the academics are passive consumers of a product

hand, metacognitive skills to use the tool effectively, and motivation to use the tool – the use of tools has metacognitive and motivational aspects with respect to tools use that need to be accounted for when creating instructional designs.

that predicts student risk, whereas in the model generation approach suggested here they would be engaged as producers. In this scenario, the direct involvement of the learning analytics benefactors, and assisting the benefactors to build their skills in translating learning analytics results into their practice and decision making, could be a stepping stone for the field of learning analytics to make a significant impact on educational practice.

For institutions, there are implications for strategic policy and implementation. In spite of having access to volumes of data with direct relevance to improving their performance, higher education institutions are not mature data-informed organizations (Macfadyen & Dawson, 2012; Macfadyen, Dawson, Pardo, & Gasevic, 2014; Manyika et al., 2012). A predominance of institutions have poorly developed capacity and competencies in learning analytics (Siemens et al., 2014). In recognizing this gap institutions are seeking to establish partnerships with commercial vendors to fast track adoption for a perceived competitive advantage. However, a threat of such an approach could be that the choices made on the data to be accessed and how it will be analyzed will be too “far removed from the specific learning context and learner to be able to provide an organization with any direct actionable recommendations” (Siemens et al., 2014, p. 7). In particular, where the commercial exigencies of vendors create pressures to design generic products and algorithms to be applied at scale, these will clearly be antagonistic to the development of situated solutions grounded in an analysis of the specific instructional and learning contexts. But only the latter, on the findings and analysis presented here, are likely to generate actionable knowledge and engage benefactors. Based on the results of this study, higher education institutions should proceed cautiously when outsourcing capacity building in learning analytics to ensure their strategic priorities for the ongoing development of the practice, quality, and socio-cultural aspects of learning and teaching are not compromised.

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es of trace data recorded by the LMS (Moodle) across the nine courses included in the study.

e/Moodle e	ACCT	BIOL 1	BIOL 2	COMM	COMP	ECON	GRAP	MARK	MATH
ment	X	X		X	X	X		X	X
	X		X			X			
								X	
e Logins	X	X	X	X	X	X	X	X	X
ack			X						
n	X	X	X	X	X	X	X	X	X
Box Gallery	X								
			X						
		X	X		X	X			
rce	X	X	X	X	X	X	X	X	X
in	X			X	X	X		X	X
l Classroom			X						

intentions for the use of the LMS tools used across the nine courses included in the study.

BIOL 1	BIOL 2	COMM	COMP	ECON	GRAP	MARK	MATH
Course assignments were available hosted in the LMS.		Course assignments were available hosted in the LMS. Combined use with Turnitin.	Course assignments were available hosted in the LMS. Combined use with Turnitin.	Course assignments were available hosted in the LMS. Combined use with Turnitin.		Course assignments were available hosted in the LMS. Combined use with Turnitin.	Course assignments were available hosted in the LMS. Combined use with Turnitin.
	Contained information			Contained information			

Course/Moodle feature	ACCT	BIOL 1	BIOL 2	COMM	COMP	ECON	GRAP	MARK	MATH
	were taking the course on campus and those taking fully online.		address each of the course requirements (e.g., quizzes) and deal with issues such as test anxiety.			provide the rationale for the importance for the course topics for the profession of economics, and address each of the course requirements (e.g., quizzes) and deal with issues such as test anxiety.			
Chat								Offered in the LMS, but no specific activity designed – student initiated use only.	
Feedback			Different questionnaires asking students about their study habits online, value of quizzes, virtual classrooms, and overall experience.						
Forum	Used primarily for Q&A and news sharing.	Used primarily for Q&A and news sharing.	Used primarily for Q&A and news sharing. No marks for	Used to discuss and receive peer feedback on	Used primarily for Q&A and news sharing	Used primarily for Q&A and news sharing	Intended for news sharing, but not used at all.	Used primarily for Q&A and news sharing	Used primarily for Q&A and news sharing

Course/Moodle feature	ACCT	BIOL 1	BIOL 2	COMM	COMP	ECON	GRAP	MARK	MATH
	No marks for participation in online discussions.	No marks for participation in online discussions.	participation in online discussions.	the research questions for the assignments in the course. News and Q&A. No marks for participation in online discussions.					
Light Box Gallery	Used to share the images of the course instructors to establish their teaching presence.								
Map			Asked students to enter the post codes of their locations of residences to plot on the map.						
Quiz		Had two major quizzes (weeks 7 and 13) each worth 10 marks of the final grade. Seven pre-lab quizzes – each would have 2-3	Each of the 10 course topic had 2-5 quizzes – total 34. In weeks 1-3 and 6-10, there were seven quiz-based assessment points		One practice and four assessed quizzes contributing to the final grade (4 marks each).	A practice quiz and mid-term quiz contributing 20 marks to the final grade.			

Course/Moodle feature	ACCT	BIOL 1	BIOL 2	COMM	COMP	ECON	GRAP	MARK	MATH
		attempts and the last attempt was recorded. They all combined contributed 5 marks towards the final grade.	contributing 15 marks of the final grade combined. In each of those weeks, the students could try several quizzes and the highest score would be used. In week 4, the students had a mid-term quiz covering topics 1-4 and contributing 15 marks of the final grade.						
Resource	Included resources describing the eTextbook used, course content, and extra content related to the course assessment	Included multimedia resources describing some of the key concepts covered in the course. The reference to the externally hosted eTextbook (McGraw Hill) was also under	References to the recorded lectures, slide presentations, and lecture notes. Multimedia content, examples of final exams, and other course content.	Uploaded documents with the content of the assignments, weekly slide presentations and lecture notes.	Uploaded documents with the content of the assignments, weekly slide presentations, lecture notes, recorded lectures, practice notes, workshop material.	Uploaded documents with the content of the assignments, weekly slide presentations, lecture notes, and lecture recordings.	Uploaded documents with some course materials and text of the assignments.	Uploaded documents with the content of the assignments, weekly slide presentations, lecture notes, references to podcasts, and workshop material.	Uploaded documents with the content of the assignments, weekly slide presentations, lecture notes, recorded lectures, and project and practice material.

Course/Moodle feature	ACCT	BIOL 1	BIOL 2	COMM	COMP	ECON	GRAP	MARK	MATH
		Resources.							
Turnitin	Submission of the assignments had a reference Turnitin. One graded assignment – report on a given case study (25 marks).			Submission of the assignments had a reference Turnitin. Three graded assignment submissions – critical review (20 marks) and project proposal and project report (45 marks).	Submission of the assignments had a reference Turnitin. Two graded assignments – documentation of programs (10 and 15 marks).	Submission of the assignments had a reference Turnitin. Two graded assignments – learning inventory and learning profile essay (5 marks) and commenting on a news article to test understanding, application and communication of economic theory (25 marks).		Submission of the assignments had a reference Turnitin. Three assignments – minor essay (10 marks), major essay (10 marks), and group project report (20 marks.	Submission of the assignments had a reference Turnitin. One graded assignment – group project report (10 marks).
Virtual Classroom			A reference to Adobe Connect that was used for the two synchronous online sessions.						

Table 3: Characteristics of study participants across course subject

N = 4134	ACCT n = 746	BIOL 1 n = 220	BIOL 2 n = 657	COMM n = 499	COMP n = 242	ECON n = 661	GRAP n = 192	MARK n = 723	MATH n = 194	*p* value
Age (years)	22.7 ± 4.8	21.9 ± 5.3	26.8 ± 9.1	21.5 ± 4.0	22.9 ± 6.2	23.8 ± 5.6	21.5 ± 3.6	22.6 ± 4.2	22.0 ± 4.7	<0.001
Females	381 (51.1%)	143 (65.0%)	568 (86.5%)	320 (64.1%)	38 (15.7%)	328 (49.6%)	105 (54.7%)	420 (58.1%)	13 (6.7%)	<0.001
International students	255 (34.2%)	13 (5.9%)	57 (8.7%)	15 (3.0%)	15 (6.2%)	262 (39.6%)	9 (4.7%)	256 (35.4%)	35 (18.0%)	<0.001
Other language than English spoken at home	294 (39.6%)	50 (22.7%)	127 (19.3%)	29 (5.8%)	39 (16.1%)	312 (47.9%)	21 (10.9%)	289 (40.3%)	63 (32.5%)	<0.001
Living in non-urban (rural or isolated) areas	64 (11.9%)	27 (12.9%)	128 (20.8%)	60 (12.3%)	30 (12.9%)	48 (10.5%)	31 (16.6%)	60 (11.5%)	26 (15.6%)	<0.001
Part time student	82 (11.0%)	18 (8.2%)	103 (15.7%)	28 (5.6%)	16 (6.6%)	92 (13.9%)	8 (4.2%)	60 (8.3%)	13 (6.7%)	<0.001
Previously enrolled to a course	257 (34.5%)	19 (8.6%)	62 (9.4%)	28 (5.6%)	31 (12.8%)	327 (49.5%)	11 (5.7%)	226 (31.3%)	22 (11.3%)	<0.001
Course start										<0.001

N = 4134	ACCT n = 746	BIOL 1 n = 220	BIOL 2 n = 657	COMM n = 499	COMP n = 242	ECON n = 661	GRAP n = 192	MARK n = 723	MATH n = 194	*p* value
access										
Early access	184 (25.0%)	145 (66.5%)	479 (73.1%)	140 (28.3%)	97 (40.2%)	218 (35.7%)	72 (53.3%)	175 (37.1%)	75 (61.0%)	
Did not access	97 (13.1%)	25 (11.5%)	43 (6.6%)	75 (15.2%)	16 (6.6%)	99 (16.2%)	18 (13.4%)	88 (18.6%)	14 (11.4%)	
Late access	456 (61.9%)	48 (22.0%)	133 (20.3%)	279 (56.5%)	128 (53.1%)	293 (48.0%)	45 (33.3%)	209 (44.3%)	34 (27.6%)	

Age presented as mean ± standard deviation. The rest of the variables presented as counts and percentages. The difference in age across courses was explored by ANOVA. The differences in the rest of the variables across courses were explored by the Chi-square test.

Table 4: Student performance and learning interaction variables across course subject

N = 4134*	ACCT n = 746	BIOL 1 n = 220	BIOL 2 n = 657	COMM n = 499	COMP n = 242	ECON n = 661	GRAP n = 192	MARK n = 723	MATH n = 194	*Overall* *p* value
Percent mark**	39 (36, 42)	40 (35, 46)	46 (42, 50)	43 (39, 50)	52 (45, 59)	46 (42, 50)	53 (46, 62)	52 (48, 56)	45 (39, 51)	<0.001 4, 6, 7, 14
Academic Status										<0.001
Pass	513 (68.8%)	170 (77.3%)	526 (80.1%)	376 (75.4%)	179 (74.0%)	507 (76.7%)	173 (90.1%)	566 (78.3%)	138 (71.1%)	
Fail	215 (28.8%)	47 (21.3%)	120 (18.2%)	108 (21.6%)	57 (23.5%)	138 (20.9%)	17 (8.9%)	144 (19.9%)	52 (26.8%)	
Withdraw	18 (2.4%)	3 (1.4%)	11 (1.7%)	15 (3.0%)	6 (2.5%)	16 (2.4%)	2 (1.0%)	13 (1.8%)	4 (2.1%)	
Forum	17 (6, 53)	44 (18, 115)	6 (1, 60)	32 (8, 97)	0 (0, 0)	27 (8, 79)	0 (0, 0)	21 (6, 54)	12 (3, 26)	<0.001 1-6, 8, 9, 11-20, 22, 24-27, 29-36
Course logins	45 (26, 74)	117 (71, 165)	109 (69, 176)	51 (28, 79)	62 (44, 90)	65 (39, 111)	8 (4, 15)	48 (32, 76)	94 (60, 130)	<0.001 1, 2, 4-6, 8, 10-14, 16-20, 22-24, 26, 28-36
Resources	35 (20, 57)	64 (46, 93)	123 (78, 180)	21 (14, 32)	0 (0, 1)	49 (32, 72)	7 (2, 16)	51 (36, 67)	89 (51, 126)	<0.001 1-13, 15-31, 33-36
Turnitin										<0.001
Did not log	267	N/A	N/A	26 (5.2%)	25 (10.3%)	26 (3.9%)	N/A	16 (2.2%)	94 (48.5%)	

N = 4134*	ACCT n = 746	BIOL 1 n = 220	BIOL 2 n = 657	COMM n = 499	COMP n = 242	ECON n = 661	GRAP n = 192	MARK n = 723	MATH n = 194	*Overall* *p* value
	(35.8%)									
Logged 1-2 times	442 (59.2%)			72 (14.4%)	143 (59.1%)	159 (24.1%)		399 (55.2%)	79 (40.7%)	
Logged 3 or more times	37 (5.0%)			401 (80.4%)	74 (30.6%)	476 (72.0%)		308 (42.6%)	21 (10.8%)	
Assignments	7 (3, 13)	20 (13, 30)	N/A	33 (22, 48)	13 (8, 20)	36 (25, 51)	N/A	27 (19, 37)	26 (17, 38)	<0.001 [1, 3-5, 7, 8, 10-12, 14, 15, 22, 26, 27, 29, 30, 32, 33]
Book										<0.001
Did not log	164 (22.0%)	N/A	233 (35.5%)	N/A	N/A	143 (21.6%)	N/A	N/A	N/A	
Logged 1-2 times	184 (24.6%)		108 (16.4%)			267 (40.4%)				
Logged 3 or more times	398 (53.4%)		316 (48.1%)			251 (38.0%)				
Quiz										<0.001
Did not access	N/A	4 (1.8%)	123 (18.7%)	N/A	134 (55.4%)	235 (35.6%)	N/A	N/A	N/A	
Accessed once or more times		216 (98.2%)	534 (81.3%)		108 (44.6%)	426 (64.4%)				

N = 4134*	ACCT n = 746	BIOL 1 n = 220	BIOL 2 n = 657	COMM n = 499	COMP n = 242	ECON n = 661	GRAP n = 192	MARK n = 723	MATH n = 194	*Overall* *p* value
Light box Accessed by	306 (41.0%)	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	
Feedback Accessed by	N/A	N/A	432 (65.8%)	N/A	N/A	N/A	N/A	N/A	N/A	
Map Accessed by	N/A	N/A	156 (23.7%)	N/A	N/A	N/A	N/A	N/A	N/A	
Virtual classroom Accessed by	N/A	N/A	336 (51.1%)	N/A	N/A	N/A	N/A	N/A	N/A	
Lesson Accessed by	N/A	N/A	N/A	N/A	42 (17.4%)	N/A	N/A	N/A	N/A	
Chat Accessed by	N/A	N/A	N/A	N/A	N/A	N/A	N/A	169 (23.4%)	N/A	

Continuous variables presented as median (25%, 75%), and the differences across courses were explored by ANOVA. Categorical variables presented as counts and percentages (n (%)), and the differences across courses were explored by Chi-square test. *Students who withdrew from the course were excluded (n = 88); ** Percent mark presented as geometric mean (95% CI); N/A: not available in the course. Post-hoc tests (all significant at $p<0.05$): [1] ACCT vs. BIOL1, [2] ACCT vs. BIOL2, [3] ACCT vs. COMM, [4] ACCT vs. COMP, [5] ACCT vs. ECON, [6] ACCT vs. GRAPH, [7] ACCT vs. MARK, [8] ACCT vs. MATH, [9] BIOL1 vs. BIOL2, [10] BIOL1 vs. COMM, [11] BIOL1 vs. COMP, [12] BIOL1 vs. ECON, [13] BIOL1 vs. GRAPH, [14] BIOL1 vs. MARK, [15] BIOL1 vs. MATH, [16] BIOL2 vs. COMM, [17] BIOL2 vs. COMP, [18] BIOL2 vs. ECON, [19] BIOL2 vs. GRAPH, [20] BIOL2 vs. MARK, [21] BIOL2 vs. MATH, [22] COMM vs. COMP, [23] COMM vs. ECON, [24] COMM vs. GRAPH, [25] COMM vs. MARK, [26] COMM vs. MATH, [27] COMP vs. ECON, [28] COMP vs. GRAPH, [29] COMP vs. MARK, [30] COMP vs. MATH, [31] ECON vs. GRAP, [32] ECON vs. MARK, [33] ECON vs. MATH, [34] GRAP vs. MARK, [35] GRAP vs. MATH, [36] MARK vs. MATH

Table 5: The association between the variables of students' use of the LMS features and ln student percent marks: results of multiple linear regression models

Course	Model 1 R^2 x 100*	Moodle trace data-based variables R^2 change x 100 (p value)**	(Model 1 + Moodle trace data-based) R^2 x 100***	Moodle interaction variables ‡	B (95% CI)	Significance (*p*)
Overall sample (all courses together)	4.9%	16.2% ($p < 0.001$)	21.1%	ln forums	-0.014 (-0.041, 0.013)	0.317
				ln course logins	**0.446 (0.365, 0.527)**	**< 0.001**
				ln resources	**0.223 (0.157, 0.290)**	**< 0.001**
ACCT	4.4%	22.4% ($p < 0.001$)	26.8%	**ln course logins**	0.334 (0.079, 0.589)	**0.010**
				ln resources	**0.217 (0.038, 0.395)**	**0.017**
				ln assignments	**0.195 (0.052, 0.339)**	**0.008**
				Logged to a book 1-2 times vs. did not log to a book†	-0.132 (-0.350, 0.160)	0.338
				Logged to a book 3 or more times vs. did not log†	**-0.302 (-0.467, -0.085)**	**0.009**
				ln forum	-0.007 (-0.097, 0.084)	0.888
				Logged to light box vs. did not log to light box†	0.003 (-0.176, 0.221)	0.976

Course	Model 1 R^2 x 100*	Moodle trace data-based variables R^2 change x 100 (p value)**	(Model 1 + Moodle trace data-based) R^2 x 100***	Moodle interaction variables ‡	B (95% CI)	Significance (*p*)
				Logged to Turnitin-in 1-2 times vs. did not log†	0.283 (-0.060, 0.751)	0.117
				Logged to Turnitin-in 3 or more times vs. did not log†	-0.113 (-0.494, 0.553)	0.673
BIOL 1	7.3%	5.9% (p = 0.027)	13.2%	ln forum	0.058 (-0.146, 0.263)	0.575
				ln course logins	0.321 (-0.249, 0.890)	0.268
				ln resources	-0.100 (-0.478, 0.278)	0.602
				ln assignments	0.220 (-0.165, 0.605)	-0.165
				Logged to quizzes vs. did not log to quizzes†	0.560 (-0.880, 16.219)	0.715
BIOL 2	14.8%	24.2% (p < 0.001)	39%	**ln resources**	**0.498 (0.298, 0.699)**	**< 0.001**
				Logged to quizzes vs. did not log to quizzes†	**0.737 (0.376, 1.192)**	**< 0.001**
				ln forum	-0.011 (-0.060, 0.039)	0.679
				ln course logins	0.065 (-0.162, 0.293)	0.574

Course	Model 1 R^2 x 100*	Moodle trace data-based variables R^2 change x 100 (p value)**	(Model 1 + Moodle trace data-based) R^2 x 100***	Moodle interaction variables ‡	B (95% CI)	Significance (*p*)
				Logged to a book 1-2 times vs. did not log to a book†	0.066 (-0.145, 0.331)	0.568
				Logged to a book 3 or more times vs. did not log†	-0.070 (-0.229, 0.120)	0.440
				Logged to feedback vs. did not log to feedback†	0.183 (-0.009, 0.411)	0.062
				Logged to map vs. did not log to map†	0.079 (-0.111, 0.310)	0.440
				Logged to virtual class vs. not logged to virtual class†	-0.094 (-0.248, 0.091)	0.295
COMM	3.5%	70.3% ($p < 0.001$)	73.8%	**Logged to Turnitin-in 1-2 times vs. did not log†**	**16.904 (11.073, 25.523)**	**< 0.001**
				Logged to Turnitin-in 3 or more times vs. did not log†	**59.264 (37.978, 89.107)**	**< 0.001**
				ln assignments	**0.127 (0.009, 0.246)**	**0.035**

Course	Model 1 R^2 x 100*	Moodle trace data-based variables R^2 change x 100 (p value)**	(Model 1 + Moodle trace data-based) R^2 x 100***	Moodle interaction variables ‡	B (95% CI)	Significance (*p*)
				ln forum	0.010 (-0.036, 0.055)	0.680
				ln course logins	0.038 (-0.105, 0.181)	0.600
				ln resources	0.036 (-0.077, 0.150)	0.530
COMP	7.7%	58.6% ($p < 0.001$)	66.3%	**ln course logins**	**0.408 (0.248, 0.568)**	**< 0.001**
				Logged to Turnitin-in 1-2 times vs. did not log†	**5.883 (3.464, 9.602)**	**< 0.001**
				Logged to Turnitin-in 3 or more times vs. did not log†	**6.629 (3.527, 11.858)**	**< 0.001**
				ln forum	-0.022 (-0.537, 0.493)	0.933
				ln resources	0.018 (-0.106, 0.142)	0.771
				ln assignments	0.079 (-0.086, 0.244)	0.347
				Logged to quizzes vs. did not log to quizzes†	0.063 (-0.110, 0.270)	0.496
				Logged on to lessons vs. did not log to lessons†	-0.185 (-0.355, 0.028)	0.084

Course	Model 1 R^2 x 100*	Moodle trace data-based variables R^2 change x 100 (p value)**	(Model 1 + Moodle trace data-based) R^2 x 100***	Moodle interaction variables ‡	B (95% CI)	Significance (*p*)
ECON	3.3%	47.1% ($p < 0.001$)	50.4%	**ln resources**	**0.215 (0.058, 0.372)**	**0.007**
				Logged to Turnitin-in 1-2 times vs. did not log†	**3.632 (2.139, 5.835)**	**< 0.001**
				Logged to Turnitin-in 3 or more times vs. did not log†	**5.814 (3.522, 9.268)**	**< 0.001**
				Logged to a book 1-2 times vs. did not log to a book†	**-0.201 (-0.325, -0.054)**	**0.009**
				Logged to a book 3 or more times vs. did not log†	**-0.266 (-0.390, -0.117)**	**0.001**
				Logged to quizzes vs. did not log to quizzes†	**0.685 (0.411, 1.013)**	**< 0.001**
				ln forum	0.028 (-0.037, 0.094)	0.401
				ln course logins	0.121 (-0.064, 0.306)	0.198
				ln assignments	0.058 (-0.118, 0.235)	0.516
GRAP	7.3%	2.0%	9.3%	ln forum	0.006	0.961

Course	Model 1 R^2 x 100*	Moodle trace data-based variables R^2 change x 100 (p value)**	(Model 1 + Moodle trace data-based) R^2 x 100***	Moodle interaction variables ‡	B (95% CI)	Significance (*p*)
		(p = 0.472)			(-0.228, 0.239)	
				ln course logins	0.131 (-0.214, 0.476)	0.454
				ln resources	-0.164 (-0.378, 0.050)	0.133
MARK	2.9%	32.0% (p < 0.001)	34.9%	**ln resources**	**0.358 (0.193, 0.522)**	**< 0.001**
				Logged to Turnitin-in 1-2 times vs. did not log†	**12.144 (4.119, 32.717)**	**< 0.001**
				Logged to Turnitin-in 3 or more times vs. did not log†	**13.895 (4.680, 38.095)**	**< 0.001**
				ln assignments	**0.296 (0.132, 0.461)**	**< 0.001**
				Logged on to chat vs. did not log on to chat†	**-0.143 (-0.257, -0.010)**	**0.036**
				ln forum	-0.033 (-0.096, 0.031)	0.312
				ln course logins	0.064 (-0.114, 0.242)	0.478
MATH	13.4%	19.0% (p = 0.001)	32.4%	**Logged to Turnitin-in 1-2 times vs. did not log†**	**0.292 (0.022, 0.631)**	**0.032**

Course	Model 1 R^2 x 100*	Moodle trace data-based variables R^2 change x 100 (p value)**	(Model 1 + Moodle trace data-based) R^2 x 100***	Moodle interaction variables ‡	B (95% CI)	Significance (*p*)
				Logged to Turnitin-in-file 3 or more times vs. did not log†	0.358 (-0.063, 0.968)	0.105
				ln assignments	**-0.229 (-0.425, -0.034)**	**0.022**
				ln forum	0.041 (-0.050, 0.132)	0.375
				ln course logins	0.281 (-0.078, 0.640)	0.123
				ln resources	0.136 (-0.167, 0.439)	0.375

*Model 1: student characteristics: start access to a course (did not access, early access, late access), age, gender, being an international student, home spoken language, term access code (full time/part time student), previous enrollment, home remoteness; R^2 x 100: percent variability observed in student percent marks that can be explained by Model 1. **Percent variability in student percent marks additionally explained by the Moodle online interaction variables. ***Percent variability in student percent marks explained by the overall model (Model 1 + Moodle online interaction variables). ‡ All models adjusted for start access to a course (did not access, early access, late access), age, gender, being an international student, home spoken language, term access code (full time/part time student), previous enrollment, and home remoteness. †Beta coefficients presented as e^b-1 and interpreted as percent change in the outcome (percent mark) for one unit difference in a Moodle interaction variable. The rest of the Moodle interaction variables interpreted as a percent change in the outcome (percent mark) for one percent increase in a Moodle engagement variable.

Table 6: The association between students' use of the LMS features and their performance status (pass or fail): the results of binary logistic regression analysis

Course	Model 1 discrimination Overall C (95%CI)*	Model 2 discrimination Overall C (95%CI)*	Step statistics Chi-square (p value)**	Moodle interaction variables per course***	Odds Ratio (95%CI)	Significance (*p*)
Overall sample (all courses together)	0.658 (0.635, 0.681)	0.749 (0.728, 0.770)	259.934 (p<0.001)	Forum	0.999 (0.997, 1.001)	0.235
				Courselogins	**0.986 (0.983, 0.990)**	**< 0.001**
				Resources‡	**0.995 (0.991, 0.999)**	**0.012**
ACCT	0.674 (0.625, 0.724)	0.765 (0.721, 0.809)	64.874 (p<0.001)	Logged to light box vs. did not log to light box	0.851 (0.543, 1.134)	0.483
				Forum	0.995 (0.990, 1.000)	0.076
				Course logins	0.992 (0.982, 1.003)	0.166
				Resource	0.998 (0.989, 1.006)	0.555
				Logged to Turnitin-in 1-2 times vs. did not log	**0.388 (0.232, 0.649)**	**< 0.001**
				Logged to Turnitin-in 3 or more times vs. did not log	**0.177 (0.036, 0.865)**	**0.032**
				Assignments	1.001 (0.970, 1.033)	0.934
				Logged to a book 1-2 times vs. did not log to a book	1.377 (0.721, 2.628)	0.322
				Logged to a book 3 or more times vs. did not log	**2.160 (1.207, 3.865)**	**0.009**
BIOL 1	0.705 (0.623, 0.787)	0.816 (0.750, 0.883)	31.448 (p<0.001)	**Forum**	**0.985 (0.972, 0.999)**	**0.031**
				Course logins	0.988 (0.973, 1.004)	0.148
				Resources	1.008 (0.994, 1.023)	0.278
				Assignments	0.997 (0.956, 1.040)	0.893
				Logged to quizzes vs. did not log to quizzes	0.001 (0.000, 0.001)	0.999
BIOL 2	0.714	0.845	121.849 (p<0.001)	Forum	1.000 (0.996, 1.003)	0.948

Course	Model 1 discrimination Overall C (95%CI)*	Model 2 discrimination Overall C (95%CI)*	Step statistics Chi-square (p value)**	Moodle interaction variables per course***	Odds Ratio (95%CI)	Significance (*p*)
	(0.657, 0.771)	(0.801, 0.889)		Course logins	0.997 (0.990, 1.004)	0.411
				Resources	0.998 (0.991, 1.004)	0.472
				Logged to a book 1-2 times vs. did not log to a book	0.689 (0.321, 1.479)	0.339
				Logged to a book 3 or more times vs. did not log	0.954 (0.494, 1.844)	0.889
				Logged to quizzes vs. did not log to quizzes	**0.122 (0.064, 0.231)**	**< 0.001**
				Logged to feedback vs. did not log to feedback	**0.457 (0.254, 0.822)**	**0.009**
				Logged to map vs. did not log to map	0.931 (0.429, 2.021)	0.856
				Logged to virtual class vs. not logged to virtual class	1.688 (0.918, 3.105)	0.092
COMM	0.622 (0.560, 0.684)	0.915 (0.880, 0.949)	227.091 (p<0.001)	Forum	0.996 (0.989, 1.003)	0.213
				Course logins	0.997 (0.979, 1.014)	0.696
				Resources	1.031 (0.996, 1.068)	0.085
				Logged to Turnitin-in 1-2 times vs. did not log	0.001 (0.000, 0.001)	0.999
				Logged to Turnitin-in 3 or more times vs. did not log	0.001 (0.000, 0.001)	0.998
				Assignments	0.983 (0.960, 1.007)	0.163
COMP	0.640 (0.558, 0.723)	0.827 (0.758, 0.896)	61.224 (p<0.001)	Forum	0.001 (0.000, 0.001)	0.999
				Course logins	**0.980 (0.965, 0.994)**	**0.007**
				Resources	0.986 (0.585, 1.661)	0.958
				Logged to Turnitin-in 1-	**0.061 (0.009, 0.439)**	**0.005**

Course	Model 1 discrimination Overall C (95%CI)*	Model 2 discrimination Overall C (95%CI)*	Step statistics Chi-square (p value)**	Moodle interaction variables per course***	Odds Ratio (95%CI)	Significance (*p*)
				2 times vs. did not log		
				Logged to Turnitin-in 3 or more times vs. did not log	**0.035 (0.003, 0.352)**	**0.004**
				Assignments	0.973 (0.915, 1.035)	0.384
				Logged to quizzes vs. did not log to quizzes	1.609 (0.683, 3.792)	0.276
				Logged to lessons vs. did not log to lessons	2.584 (0.849, 7.859)	0.094
ECON	0.647 (0.586, 0.709)	0.886 (0.823, 0.909)	128.459 (p<0.001)	Forum	0.999 (0.992, 1.005)	0.719
				Course logins	0.990 (0.977, 1.002)	0.111
				Resources	0.983 (0.966, 1.000)	0.053
				Logged to Turnitin-in 1-2 times vs. did not log	0.345 (0.070, 1.698)	0.190
				Logged to Turnitin-in 3 or more times vs. did not log	**0.041 (0.008, 0.216)**	**< 0.001**
				Assignments	**1.028 (1.010, 1.047)**	**0.002**
				Logged to a book 1-2 times vs. did not log to a book	1.551 (0.723, 3.325)	0.259
				Logged to a book 3 or more times vs. did not log	1.358 (0.565, 3.264)	0.494
				Logged to quizzes vs. did not log to quizzes	**0.280 (0.141, 0.558)**	**< 0.001**
GRAP	0.830 (0.748, 0.912)	0.863 (0.792, 0.934)	3.943 (p=0.268)	Forum	0.564 (0.192, 1.659)	0.298
				Course logins	0.884 (0.747, 1.045)	0.148
				Resources	1.105 (0.991, 1.233)	0.072
MARK	0.616	0.774	43.409 (p<0.001)	Forum	1.006 (0.997, 1.015)	0.186

Course	Model 1 discrimination Overall C (95%CI)*	Model 2 discrimination Overall C (95%CI)*	Step statistics Chi-square (p value)**	Moodle interaction variables per course***	Odds Ratio (95%CI)	Significance (p)
	(0.541, 0.691)	(0.711, 0.837)		Course logins	0.989 (0.975, 1.003)	0.130
				Resources	**0.982 (0.966, 0.999)**	**0.037**
				Logged to Turnitin-in 1-2 times vs. did not log	0.001 (0.000, 0.001)	0.999
				Logged to Turnitin-in 3 or more times vs. did not log	0.001 (0.000, 0.001)	0.999
				Assignments	0.976 (0.946, 1.006)	0.121
				Logged to chat vs. did not log to chat	1.439 (0.707, 2.928)	0.315
MATH	0.639 (0.518, 0.759)	0.818 (0.727, 0.910)	20.995 (p=0.002)	Forum	0.999 (0.969, 1.029)	0.924
				Course logins	0.986 (0.964, 1.009)	0.223
				Resources	0.985 (0.965, 1.005)	0.136
				Logged to Turnitin-in 1-2 times vs. did not log	0.555 (0.179, 1.719)	0.307
				Logged to Turnitin-in 3 or more times vs. did not log	0.518 (0.059, 4.540)	0.553
				Assignments	1.035 (0.989, 1.083)	0.140

Model 1: student characteristics: start access to a course (did not access, early access, late access), age, gender, being an international student, home spoken language, term access code (full time/part time student), previous enrollment, home remoteness. Model 2: Model 1 + features derived from trace data. * Results of ROC curve analysis where the AUC corresponded to the *c* statistic from the regression models; ** The improvement in the predictive power of model 2 with the use of LMS features since model 1 (the difference in the log-likelihood between model 1 and model 2); ***variables in bold are significantly associated (p<0.05) with the outcome (pass/fail); ǂ the LMS features present in all courses