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Using LMS Data to Provide Early Alerts to Struggling Students

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Abstract – **The traditional model of having mid-semester grades prompt meetings with an advisor is inherently flawed. They come after mid-semester (i.e., week 9) making it often difficulty for students to recover from their early poor performance. Early, behavior-based prediction modeling and intervention avoids these weaknesses. A learning management system (LMS) can serve as a comprehensive platform for delivering rich multimedia content to learners, managing discussions, organizing collaborative and problem-based learning activities, and conducting assessments. This project utilized a LMS to provide digital content to students in a face-to-face lecture course and improve the efficacy of early warnings to struggling students by using students' LMS usage to trigger early alerts to struggling students. Students use of LMS-hosted digital resources were observed using Splunk software, and data mining methods were also to produce a prediction algorithm based on digital course material usage. Students' usage of course resources were found to correlate to performance ($r_{LMSevents} = .44$, $r_{folders\_accessed} = .42$, $r_{LectureNoteDownloads} = .39$).**

A logistic regression model to predict student performance was developed using LMS behavioral data from weeks 1-5 of the course The cross-validated prediction model accurately classified 75% of students as C or Better vs. C- or worse learners (Kappa = 0.48) based upon LMS content usage patterns. The model identified learners likely to perform poorly well before mid-semester grades. It accurately identified 48 of 79 students who ultimately failed to obtain a C or better during the training and testing phase of prediction model development. This degree of specificity (61%) provided sufficient accuracy that the prediction algorithm was programmed back into Splunk to provide real time predictions of students' success projections. An initial intervention study is ongoing to 1) identify students likely to struggle in the course, and 2) alert these students and provide them additional learning resources.

Index Terms – Learning Management System, First Year Experience, Learning Enrichment, Student Intervention

INTRODUCTION

University of Nevada, Las Vegas (UNLV) students are required to complete a First-year Experience (FYE) course within their first 30 semester hours of coursework. Students can take an approved FYE course in any discipline; the Howard R. Hughes College of Engineering offers multiple sections of EGG 101 Introduction to Engineering to satisfy the requirement. EGG 101 introduces students to engineering and the UNLV engineering curriculum while developing skills essential for academic success. The course currently consists of a 1 semester-hour lecture portion and a 1 semester hour laboratory component with smaller sessions. This study focused only on the lecture portion of the course.

EGG 101 students reflect a broad spectrum of preparation. Only about 30% of the students take calculus concurrent with EGG 101 with a similar number in remedial math (i.e., unable to qualify for pre-calculus). Only 42% of the students had a parent with a Bachelor's degree or higher; i.e. most of the students were first-generation college students. UNLV is a designated minority-serving institution. Combined, these result in an unusually low completion rate with less than 30% of incoming engineering students earning degrees within 6 years. While the reasons vary, lack of fundamental study, time management, and organizational skills seem to be major components. Attempts to hone these skills in EGG 101 are often thwarted by the lack of those same skills. Anecdotal evidence suggests that students who struggle in EGG 101 also struggle in more demanding courses. The purposes of this study were to 1) build a prediction model to identify poor performers early so that intervention measures (i.e., alert messages recommending advice from successful students, learning skill trainings) have time to improve success, and 2) test whether messaging these students could improve their achievement and retention. Intervention offered too late could cause students to miss an opportunity to change their ineffective learning behaviors and even gain successful results. Therefore, it is important to take action quickly with students identified as at risk to avoid failure [1,2].

METHODS

I. Data

The university LMS, Blackboard Learn, captures and records student use of materials hosted on course sites. When enriched with sufficient metadata, these data can be made to describe learning events conducted by students [3]. EGG 101 course materials were developed, organized, and deployed within the LMS. In addition to traditional course materials, students were also provided with self-help modules and materials that described proven learning strategies and advice from former students. The frequency, rate, and timing of students accessing course materials were collected throughout the semester using a data management and visualization tool called Splunk and their use patterns were correlated to learning progress using statistical software.

II. Participants

Model Development Sample

A sample of 185 students enrolled in two sections of EGG 101 in Fall 2016 were examined to develop the prediction model. The students in this sample were 80% male, 26% Caucasian, 7% African American, 16% Asian, 36% Hispanic/Latino, 11% Multi, and 0.5% Native American/Pacific Island. The ethnic distribution was similar for males and females.

The two course sections were taught by different instructors, but had identical syllabi, schedule, assignments, grading rubrics and digital content. Of the 185 students enrolled in Fall 2016, 57% (n=106) earned a C or better, meaning they completed the course with a sufficient grade that they could move forward in their engineering coursework in the coming semester. The remaining 43% (n = 79) withdrew, failed to complete, or obtained a C- or worse and would need to retake the course before moving forward.

Intervention Sample

The prediction model was used to examine the effects of an intervention tested in Spring 2017 when 76 students enrolled in the two sections of EGG 101. These two sections were taught by the same two instructors using identical course design features as in Fall 2016. The students in this sample were 79% male, 32% Caucasian, 6% African American, 26% Asian, 18% Hispanic/Latino, 9% Multi, and 0% Native American/Pacific Island. The ethnicity distribution was similar for males and females.

III. Instrument

Timestamped activity logs from the Blackboard Learn LMS course site were extracted from university servers and enriched with metadata using Splunk enterprise software [4]. Data models incorporated metadata to describe individual content items and classify them by "resource type" categories to aggregate usage of course content designed to support specific learning processes (Table I). In a prior study, it was discovered that organizing individual content items into classes of resource types that describe a common learning activity supported by similar content items provided a superior feature set than did entering unique content names as features [5]. In the same study, it was discovered that a logistic regression algorithm outperformed Naïve Bayes, J-Rip, and J-48 decision tree models in terms of prediction accuracy (i.e., Kappa + confusion matrix values). In this study, we utilize these same modeling approaches, as well as a k-fold cross-validation approach (i.e., here, 10-fold, described below) which produced nearly identical models to Leave-One-Out cross-validation.

TABLE I
ALIGNMENT OF DIGITAL CONTENT ITEMS TO TYPE OF RESOURCE
(DESIGNED TO SUPPORT A LEARNING PROCESS)

Resource Type	Variety of Digital Content Items
Content Folder	Clicks on Folders and Subfolders within content areas
Environmental Structure	Clicks on LMS tools (Support/Help, Settings)
Links to Content Area	Clicks on main menu links on the LMS course site (e.g., to notes, assignments, self-assessment resources)
Lecture notes	Downloads of Class notes (lecture slide decks posted by instructor)
Knowledge Rehearsal and Monitoring Learning	Attempts at ungraded self-assessments quizzes (with automated performance feedback)
Monitoring Course Performance	Visits to "My Grades" Table of student grades on completed assignment
Monitoring Learning Process	Uses of a tool to organize a study session
Planning	Downloads of Syllabus, schedule, exam guides
Policy	Downloads of policy and procedure documents

The use of logistic regression modeling serves a second, pragmatic purpose. The data management interface used to search and summarize trace data in real time afforded reporting tools that can be combined with regression weights for features, resulting in the real-time prediction of the likelihood a student would earn a C or better in the course.

IV. Procedure

Pre-processing students' activity logs into records of "learning events"

Raw data generated by Blackboard Learn were accessed via server logs. Values containing student, course, section, and content identifiers were extracted and linked to a set of lookup tables to enrich the data with human-readable classifiers of anonymous student IDs, course sections, and content names with corresponding resource types. Data were screened by information technology staff to ensure completeness and validity, with particular attention paid to backfilling periods of down time and confirming the lack of null values for key metadata fields described above. Features to be used for prediction modeling were extracted into one report using Splunk search language, and dichotomous final grades were appended (i.e., "C or better" labeled 1 or "C- or worse labeled 0). Table II describes the types of summary variables generated using LMS usage data.

TABLE II
VARIABLE TYPE

Variable type	Description
Count of access to contents by resource type (overall, by week)	Sum of all accesses of items belonging to a resource type (per semester/week)
Distinct Count of access to contents (overall and by week)	The count of unique content items within a resource type accessed in a semester (and in a semester week)
Count of content item	The number of access to the particular piece of LMS-hosted digital content
Distinct Count of content item	Use of a unique piece of digital content (i.e., dichotomous use vs. no use)

Developing a prediction model

Students' raw LMS data were pivoted in Splunk into summary variables (Table II) and exported in tabular form to afford data mining using Rapid Miner software. Logistic regression with forward selection was used to build the prediction model, and the problem of overfitting was examined through 10-fold cross-validation. The k-fold cross validation is a process in which original data is divided into k pieces with the same size, and among k pieces, one piece is used for testing the model, and rest (k-1) of them used for training the model. This process replicates for 10 pieces, changing out a testing set (i.e., train on 90%, test on 10%, 10 times).

Applying the prediction model to the new data and sending a message

The balance of developing a sufficiently accurate prediction model based on student behaviors in the early weeks of a semester, while providing sufficient time for intervention measures to improve student grades is a challenge. The time required to gather additional data that will improve the accuracy of the predictive model reduces the time students have available to adapt their approach and overcome their grade history. In this study, an accurate alert based upon 5 weeks of data was set as the goal. By the end of the 5th week of the semester, students should have completed 4 units of course content, which includes lecture notes, links to outside resources, self-assessment quizzes, and course assignments. Most of these early topics are designed to improve important skills that students will need to be successful. For example, the first activities are online tasks and quizzes that require students to identity the contents of the syllabus, develop a weekly time schedule, and complete a library orientation. Data on student activity – and not performance – during these content units were used to inform the prediction model.

Based on the Kappa (κ) and recall, the best 5-week prediction model developed from the Fall 2017 data was applied to data from spring 2017. Students in need of an early alert message that provides learning support were identified. Students identified as at risk of poor performance by the prediction model were randomly divided into two groups. One group received a message and offered a set of learning supports. The other group did not receive this message. This allowed us to investigate the effect of the message and the use supportive materials. The salutation was personalized with each student's name, and the message body reminded the student that they had upcoming assignments due, and expressed that the instructor wishes them to be well prepared (Figure 1).

> Hi!
>
> In the coming weeks, we'll be shifting our focus to cover topics in engineering. These topics and the corresponding assignments are likely to be more challenging than the ones you have completed so far.
>
> I want to check-in to make sure each student is on top of our content, learning in appropriate ways, and able to perform well. So, I'd like to direct you to **two resources** that can help you with learning the material in this course and your future engineering courses:
>
> 1. The first is a **one-page summary of advice from students** who have completed the course in the past...
>
> 2. A set of learning modules called **"The Science of Learning to Learn."** These modules describe learning strategies you can use with our course materials...
>
> Both resources can be found on the [LMS] site at the STEM Learning Enrichments link in the left panel.
>
> I hope you find that these resources help you to learn and perform well!

FIGURE 1
MESSAGE TO STUDENTS

The personalized message directed students to two web-hosted resources to improve their learning and study methods. The first was advice from students who have completed the course in the past with excellent grades. The advice presented was solicited from actual EGG 101 students and from the course instructors. Alignment to strategies known to predict learning and achievement in engineering was also confirmed. The second resource is a set of learning modules called "The Science of Learning to Learn," which provides training to students who may not know how to employ the learning strategies recommended in the advice page. These modules describe learning science principles like retrieval practice, self-explanation and spaced practice, as well as methods to self-regulate one's learning and manage one's behaviors (i.e., mental contrasting and making implementation intentions, improving one's study environment; lessons on deleterious effects of distractions by audio and video media, parallel multi-tasking). Completion of these modules has been shown to improve undergraduate science students' exam performance in two prior studies [6, 7].

Investigating students' performances

In order to examine responsiveness to the message and subsequent effects on academic performance, we first examined whether messaged students accessed the supportive materials, confirming that they received and responded to the message as intended. According to the messaging condition assignment and the degree to which students accessed recommended materials, students were divided into four groups: 1) no message and no or partial access, 2) no message and accessed all items, 3) message and no or partial access, 4) message and accessed all items.

RESULTS

I. Building a prediction model

Using logistic regression with forward selection and 10-fold cross-validation, prediction models were developed based on the sample of 2016 fall. The best prediction model produced a Kappa value of 0.48 ($\kappa = 0.48$) with a recall of 61%, i.e. the model accurately identified ≥ 6 in 10 students who earned less than 70% of possible points (Table III). This final prediction model developed based on behaviors within the first five weeks includes six attributes. Table IV shows the intercept and the relative impact of each variable to that intercept. A negative weight represents a decreasing likelihood of failure and most of the variables show negative weights of varying degrees. Total student activity interacting with the course structure has the greatest influence at -0.3734. Interestingly, the distinct count of links to the content area during Week 4 shows a positive weight, i.e. more contacts in this area contribute to a higher likelihood of failure. Additional study is needed to understand link between the course activities and student access of course content during Week 4. One potential explanation could be that access of many content items could reflect difficulties finding or identifying the digital materials relevant to the week's tasks.

TABLE III
CONFUSION MATRIX CATEGORIZING ACCURACY OF IDENTIFICATIONS WHO EARNED C OR BETTER VS. C- OR WORSE

Data Set	True: Predicted (to earn ≥ C)				K	Accuracy (%)	Precision (%)	Recall (%)
	1:1	1:0	0:1	0:0				
Fall 2016	91	15	31	48	0.48	75	74	61

TABLE IV
FORWARD SELECTION LOGISTIC REGRESSION MODEL PREDICTING A STUDENTS' LIKELIHOOD OF FAILURE TO OBTAIN C OR BETTER

Attributes	Weight
Total count of accesses of content items	-0.0157
Total count of environmental structure resources	-0.3745
Distinct Count of Week 3 Lecture Notes-Partial	-0.0765
Distinct Count of Week 4 Link to Content Area	0.1751
Total Distinct Count of Tools	-0.1358
Count of Week 1 Course Content	-0.0141
Intercept	1.7816

II. Observing learning behavior, achievement and retention in the Spring 2017 sample

Descriptive and correlational analyses to were utilized to investigate relations between student activity, learning behavior, achievement and retention variables. The results of those analyses are provided in Table V. To understand students' typical behavior in the course, we first examined general trends and the typical level of achievement in the course and intention to remain in the major. Overall, students used course content and monitoring resources extensively, and policy-related materials minimally throughout the semester. The standard deviations show the disparate use of LMS resources by EGG 101 students.

TABLE V
DESCRIPTIVE STATISTICS FOR BEHAVIORAL, ACHIEVEMENT AND RETENTION VARIABLES

Variable	Mean	SD
Use of digital EGG content		
Assignment	205.3	143.6
Content Folder	165.8	117.3
Link To Content Area	229.7	124.9
Communication Tool	0.1	0.4
Lecture Notes-Complete	6.1	6.2
Lecture Notes-Partial	15.4	13.2
Use of monitoring resources		
Monitoring Learning (Self-Assessment)	259.7	145.6
Monitoring Performance	9.0	15.0
Monitoring Process	1.1	1.8
Use of system		
Environmental Structure	1.3	0.9
Course policy resources		
Planning	1.6	3.5
Policy	0.6	2.5
Achievement data		
Final Score	76.2	23.9
Retention		
I intend to leave the program or switch my program.	2.72*	0.72

* 1-Strongly Disagree, 2-Disagree, 3-Somewhat Disagree, 4-Somewhat Agree, 5-Agree, 6-Strongly Agree

We next examined the data in a descriptive and systematic fashion to understand how students' general use of digital resources in the course correlate with key course outcomes - achievement indicators (including course grades, grades on summative assignment) and an indicator related to retention (intention to leave/continue in engineering, course withdrawals as indicated by final grade). The partial correlations that control for students' absences are shown in Table VI. Retention Risk is the likelihood that a student will change majors; thus, negative values reflect a reduced likelihood of changing major, i.e. larger negative values are desirable. Positive values are desirable for all other columns. It is not surprising that final scores are positively impacted by higher levels of student engagement with digital resources, but specific association of achievement with individual resource types provides insight about their value for learning. For instance, certain types of resources are only indirectly associated with assignments (e.g., lecture notes, self-assessment quizzes) but correlate with achievement as highly as do items specifically related to grade assignments.

III. Applying the Fall 2016 prediction model to Spring 2017 students and sending an intervention message

On Monday in Week 6 of the Spring 2017 semester, we identified students who were unlikely to achieve C (≥ 70% points) or better based on the result of the prediction model (i.e., similar 5-week levels and types of activity with students who struggled in Fall 2017). Among 78 students, 61 were predicted to complete the course with a C or better, whereas, 17 students were predicted to earn a grade of C- or worse, meaning they would need to retake the course in order to advance toward their degree.

3 of the 78 students had withdrawn from the course by the end of Week 6 and were excluded from the messaging phase (n = 75). Based on the prediction model, 16 out of 75 students were predicted to be C- or Worse. Of these, six more students were also identified as having withdrawn (through lack of activity) and excluded from analyses which were conducted with 12 remaining in the group predicted to earn a C- or worse.

TABLE VI
PARTIAL CORRELATION MATRIX OF STUDENT USE OF DIGITAL RESOURCES TO ACHIEVEMENT AND RETENTION INDICATORS CONTROLLING FOR ABSENCES

Resource type	Retention Risk	Quiz	Final Score	Count vs Distinct
Assignment	0.016	0.113	0.403**	0.496**
Content Folder	-0.019	0.031	0.387**	0.625**
Environmental Structure	0.081	0.147	0.125	0.150
Lecture Notes-Complete	-0.070	0.330*	0.307*	0.819**
Lecture Notes-Partial	-0.150	-0.081	0.219	0.584**
Link to Content Area	0.018	0.182	0.373**	0.342**
Monitoring Learning / Self-Assessment	-0.288*	0.306*	0.392**	0.594**
Monitoring Performance	-0.109	-0.03	-0.207	0.677**
Monitoring Process	-0.052	-0.004	0.092	0.709**
Planning	0.055	0.060	0.151	0.508**
Policy	-0.103	0.031	0.079	0.830**
Retention	1.00			
Quiz	0.03	1.00		
Final Score	-0.311*	0.465**	1.00	

*significant at the 0.05 level
**significant at the 0.01 level
General notes: *Retention Risk* is the likelihood that a student will change majors; thus, negative values reflect a reduced likelihood of changing major, i.e. larger negative values are desirable. Positive values are desirable for *Quiz* and *Final Score* columns. *Count vs. Distinct* represents the ratio of unique students using the resource to total uses.

To examine the effects of a messaging intervention on students at risk of needing to retake the course versus students likely to successfully complete the course, we randomly assigned students to receive or not receive the message regardless of their predicted success (i.e., so we could examine effects of messages on students at risk and compare against both unmassaged at risk [control] and messaged/unmassaged not-at-risk [negative control]). We then messaged 50% of the sample on Monday of Week 6. The following sections examine overall trends in response to messaging. More specific analyses were conducted on our focal sample: those predicted to perform poorly enough to necessitate re-enrollment in the course. Because only 12 remaining students were predicted to perform poorly based on their early learning behaviors, we conducted primarily descriptive analyses. We also periodically employed non-parametric analyses to examine differences in behaviors and outcome variables between students who were predicted to perform poorly vs. not, and those who did vs. did not receive messages.

Responsiveness to Messaging

The message sent to students encouraged them to access and utilize support materials that provided advice from successful students in previous semester and directed students to digital learning modules designed to teach effective learning strategies. These modules were later included as assignments near the end of the course and accounted for 10% of the final grade. As a result, we analyze only students' completeness of module activities as an indicator of engagement beyond the requirement to simply access these items and assigned students to "complete access", "partial access", and "no access" groups.

In addition, we tracked the time between when the message was sent to students and the date students first accessed materials to assess responsiveness to the message. Tables VII and VIII show student distribution by predicted achievement, messaging group, and access. Among the seven students who were messaged and who were predicted to earn a C- or worse, only one student (14%) accessed the advice page. In contrast, 31% (nine students) of students who received a message and were predicted to earn a C or better visited the advice page (Table VII).

TABLE VII
ACCESS TO ADVICE FROM SUCCESSFUL STUDENTS

	No Access	Access	Total
Students predicted to obtain C- or Worse			
No Message	5	0	5
Message	6	1	7
Total	11	1	12
Students predicted to obtain C or Better			
No Message	18	10	28
Message	20	9	29
Total	38	19	57

TABLE VIII
ACCESS TO LEARNING TO LEARN MODULE

	No Access	Partial Access	Complete Access	Total
Students predicted to obtain C- or Worse				
No Message	1	2	2	5
Message	1	2	4	7
Total	2	4	6	12
Students predicted to obtain C or Better				
No Message	1	15	12	28
Message	2	17	10	29
Total	3	32	22	57

With respect to the learning modules, Table VIII shows that more students in the messaged group who were predicted to obtain a C- or Worse (4) completely accessed the Learning to Learn modules than those who were not messaged (2). For those predicted to earn a C or better, access rates were similar across Message and No Message groups. Finally, a Mann-Whitney test confirmed that of those students who did access learning supports, students identified to perform better accessed STEM Modules earlier than those identified to earn less than a C (Table IX).

TABLE IX
DAYS UNTIL ACCESS OF ADVICE OR LEARNING TO LEARN MODULE AFTER RECEIVING MESSAGE BY C OR BETTER VS. C- OR WORSE EARNERS

Advice Page, Skill Training Module No.	C- or Worse			C or Better		
	n	M	SD	n	M	SD
Advice	1	0	1	19	13.8	20.6
1	9	7.7	1.3	51	5.8	2.6
2	9	7.2	1.8	42	5.6	2.4
3	7	7.1	2.3	45	5.7	2.6
4	8	8.4	1.6	42	7.0	2.1
5	8	6.6	3.0	37	5.4	2.9
6	7	7.7	1.3	27	5.6	2.7

n = number of students accessing module
M = mean number of days after messaging that module was accessed
SD = standard deviation of days after messaging that module was accessed

We ended our analysis by examining course performance of those who did and did not access learning support. We examined quiz scores by access to advice and learning to learn modules (Tables X and XI) and found that, except for the Week 10 Quiz, students who accessed the advice pages performed better for all quizzes after the messaging period than those who did not access the advice.

TABLE X
MEAN SCORES FOR WEEKLY QUIZZES BY ACCESS TO ADVICE

Quiz	Access to Advice from successful students					
	No Access			Access		
	n	M	SD	n	M	SD
Week 7	36	84.8	17.9	18	92.9	10.9
Week 8	34	84.4	19.6	18	88.9	12.8
Week 10	32	83.2	11.8	15	82.3	11.5
Week 11	31	76.4	10.0	18	81.7	7.8
Week 12	31	86.1	15.4	18	86.4	9.8
Week 15	33	83.0	26.0	18	84.2	22.9
Week 16	31	66.5	17.6	14	76.3	13.3

n = number of students accessing quiz
M = mean of quiz scores
SD – standard deviation of quiz scores item

TABLE XI
MEAN SCORES FOR EACH QUIZ BY ACCESS TO LEARNING TO LEARN

Quiz	Access to Learning to Learn Modules								
	No Access			Partial Access			Complete Access		
	n	M	SD	N	M	SD	n	M	SD
Week 7	3	69.0	25.5	32	85.2	16.4	28	89.9	13.7
Week 8	2	65.0	35.4	30	85.7	19.1	28	87.5	11.1
Week 10	2	76.5	12.0	29	83.4	10.1	25	83.3	14.1
Week 11	3	77.9	15.7	29	77.5	9.3	25	78.2	8.1
Week 12	3	85.0	13.2	28	80.7	16.1	27	88.1	11.0
Week 15	3	66.7	30.6	28	79.3	27.2	27	92.0	15.7
Week 16	2	76.3	26.5	26	67.0	13.9	22	73.2	18.4

n = number of students accessing quiz
M = mean of quiz scores
SD – standard deviation of quiz scores item

In addition, mean scores for each quiz were examined by access to Learning to Learn modules. As shown in Table XI, the group who accessed all STEM items outperformed the other two groups.

DISCUSSION

This study demonstrates the value of developing digital materials as a resource for student learning, and the ways that usage of these resources can inform instructors about students' retention risk and course performance. Students who make greater use of digital materials tended to outperform those who use resources less. Further, data mining analyses confirm that 1) prediction models can accurately identify students who will perform poorly based on these learning behaviors and 2) prediction can occur well before students accrue the 8 weeks of poor performances that trigger the traditional mid-semester early warning system. Though models that employ behavioral data can identify these students, designing interventions that support students in ways that increase success remain a challenge. Despite direct, personalized messaging attempts, few students sought out the resources instructors recommended. This is especially true of students who were predicted to perform poorly in the course. Students predicted to perform well more commonly accessed materials, did so earlier, and performed better in the course. However, it is not possible in this sample to discern whether course performance is an artifact of timely use of learning supports, or whether timely use and superior performance are artifacts of these being more diligent or conscientious students. Additional analyses with this and future, larger samples are ongoing, which will afford additional opportunities to disentangle confounds and explore the effects of messaging and learning support with greater statistical power.

SUMMARY

Learning management systems provide excellent platforms for delivering course materials and evaluating student performance. In this study, LMS usage was analyzed to evaluate relationships between use of digital course materials and student success. A model was developed from data collected from 2 sections of the introductory engineering course in Fall 2016, then successfully applied to 2 similar sections Spring 2017. The model identified 17 students at risk of earning a C- or worse grade in the course before the 6th week of the semester.

The purpose of identifying these students was to intervene earlier than is typical and to increase the students' chances of success. Our attempts to intervene achieved only mixed success. Not surprisingly, students who access materials, and especially those who access them earlier, did better. It was somewhat surprising, however, that personal messaging did not result in an increased rate of material access. Thus, it seems access is dictated as much or more by a students' motivation and ability as it is by intervention, and we can't separate this from data on effectiveness of the interventions.

While prediction models were quite accurate in identifying students likely to perform poorly, more work is needed to improve the intervention messages triggered by the model to increase responsiveness so effects of the intervention materials can be examined and strengthened.

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