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Engaged to Succeed: Understanding First-Year Engineering Students' Course Engagement and Performance Through Analytics

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ABSTRACT The use of analytics in education provides researchers the opportunity to uncover student engagement habits by utilizing data generated through online platforms such as course learning management systems (LMS). Student engagement has been shown to vary based on student-instructor interaction. We examined LMS usage of first-year engineering students in a large research university in the United States to examine the following three research questions: 1) How do course grades vary based on the students' instructor and the overall number of LMS sessions per student, 2) How do course grades vary based on the students' instructor and the number of LMS sessions per student for different course tools, and 3) How does the timing and frequency of LMS tool usage relate to course grades and vary across instructors? We found a positive relationship between LMS usage and course grades; however, the relationship is dependent upon the instructor of the course, as well as for the specific type of tool used. We also found that the day of the week on which the LMS was used is a strong predictor of student course grades. The results empirically demonstrate that better engagement with a course leads to better outcomes and there are variations in how instructors use an LMS which ultimately influences student usage and performance. We also illustrate an opportunity for researchers and instructors to capture, analyze, and use LMS data to inform and improve teaching practices and policies.

INDEX TERMS Assessment, engagement, engineering education, first-year engineering, learning management systems.

I. INTRODUCTION

The emergence of learning analytics has created excitement about student assessment with respect to the information and new knowledge that can be garnered from the vast amount of student data that have been and continue to be collected [1]. There are many factors that are driving the development and expansion of learning analytics, including the ability to access big data, new online learning opportunities, and politics [2]. Just as businesses first utilized big data to advance their understanding of customers' preferences and purchasing behaviors, colleges and universities have similarly found value in those approaches within the educational space through learning analytics [3]. For example, with the increase in students' online learning experiences in new environments, such as MOOCs, there has been an explosion in the amount of student data available, which may be used to understand learners in greater detail.

Within more traditional educational environments, where face-to-face classes are still the norm, colleges and universities find themselves with a myriad of student data collected via learning management systems (LMS), which similarly can be analyzed to uncover new insights about students' learning processes. In fact, almost 99 percent of postsecondary institutions have reported having an LMS in use and approximately half of faculty members at those institutions reporting using the systems on a regular basis [4]. While these systems have become more pervasive, they also tend to be considered transactional warehouses rather than an opportunity to understand student learning and engagement with course materials. In line with other emerging instructional technologies, proponents of LMS as an

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instructional resource have advocated for increased opportunities to train instructors on and demonstrate the value of the technology.

Prior research has demonstrated associations between different aspects of LMS usage and students' performance in a course. This study seeks to extend that prior work by investigating how variation in instructor usage of an LMS can associate with course outcomes. Specifically, this research focuses on course-level activities of students within an LMS (i.e., both magnitude and timing), variation across instructors, and insights that can be gained from analyzing specific tools within LMS student data quantitatively. Some researchers have shown relationships between LMS engagement and higher course grades [5], yet little research has been done to investigate LMS usage in more traditional learning environments across multiple instructors. Additionally, as LMSs continue to evolve and incorporate more instructional resources, more detailed investigations should examine how instructors utilize these different tools and how student usage can relate to course performance. This research seeks insights on how student interactions with an LMS can differentially relate to course performance. Of strong interest throughout this study is an emphasis on instructor differences in usage-performance relationships. We explicate this relationship to show the relationship between usage and performace. Comparisons are afforded through a first-year engineering course with multiple instructors and a common curriculum. We use the Academic Plan Model (APM) as a framework to help tease out the relationship of interest in this study – how instructors shape student learning. By explicating how curricular decisions that faculty members make at the course, program, and/or institutional levels effect student learning, the APM provides a conceptual model to pose and study the right research questions.

II. BACKGROUND

A. LEARNING MANAGEMENT SYSTEMS

In parallel with the increased usage of LMSs to facilitate instructional and learning processes, there has also been an increase in published research that has examined how instructors and learners interact with LMS tools and the association of those interactions and learning outcomes. Often, the modeled relationships involve a summative assessment that examines the associations between LMS usage and final course grades [6]. On the other hand, the aspects of LMS usage are quite varied, and most often include some measure of usage intensity. Rafaeli and Ravid [7] found a positive relationship between the number of LMS pages read and final grade. Zacharis [8] found statistically significant positive associations with the number of links and files viewed with final grade. Additional research has found positive correlations with final course grades and discussion forums [5], messages sent [9], and total time online [10]. With the advent of LMS as a potential instructional resource, many researchers have sought to understand factors behind faculty use, and, as previously demonstrated, have made considerable progress. One overlooked area of research in this regard, however, is how faculty differences can manifest in student course performance. To frame our study, we will explore the ways in which faculty differences can influence different LMS usage—and by extension, students' experience of the course.

1) DIFFERENCES IN FACULTY USAGE

Prior studies in higher education have described differences in teaching across faculty members, even those who have the same credentials [11]–[15]. Much of this related work has led to the creation of the Academic Plan model to acknowledge the importance of these of how these differences combine and relate to educational outcomes. Innovative uses of technology, in this case LMS, fit squarely into how instructors use instructional resources to inform their instructional process and the student experience. Although we do not directly examine these specifc variables, their prior investigation provides a useful context and motivation for exploring differential instructional usage of technology.

2) DIFFERENCES IN LMS TOOL USAGE

The means in which instructors can differentiate their LMS utilization is further amplified by the numerous LMS features that can be added or modified for instructor use. As previously mentioned, prior work has identified associations between frequency and intensity of usage of different LMS tools and course outcomes. Fathema and Sutton [16] sought a more nuanced exploration of student usage of LMS tools and found that not all functions are used with equal emphasis. They found that document uploading, grade posting, and assignments were the most frequently used features. Similar to findings of influences on faculty usage of LMS as a whole, instructor perceptions of specific LMS tool utility and ease of use play an important role in course emphasis and, by extension, student use [17].

3) DIFFERENCES IN TIMING AND FREQUENCY OF USAGE

In addition to exploring differential instructor LMS usage and its relationship to student course outcomes, this study seeks to examine another less studied aspect of LMS interactions: timing of usage. As previously identified, usage frequency and frequency across different LMS tools have been a major component of studies on associations between LMS usage and course outcomes; prior research on the timing of LMS usage is more limited. Although, not examining specific timing of LMS usage, Jo et al. [18] found that regularity of LMS use was the best predictor of course performance. In addition, Hu et al. [19] and Schell et al. [20] found that the predictive accuracy of LMS usage increases over time. We seek to extend these examinations by exploring the timing of student LMS usage with more specificity, specifically incorporating the proximity of LMS usage around assignment deadlines and major examinations.

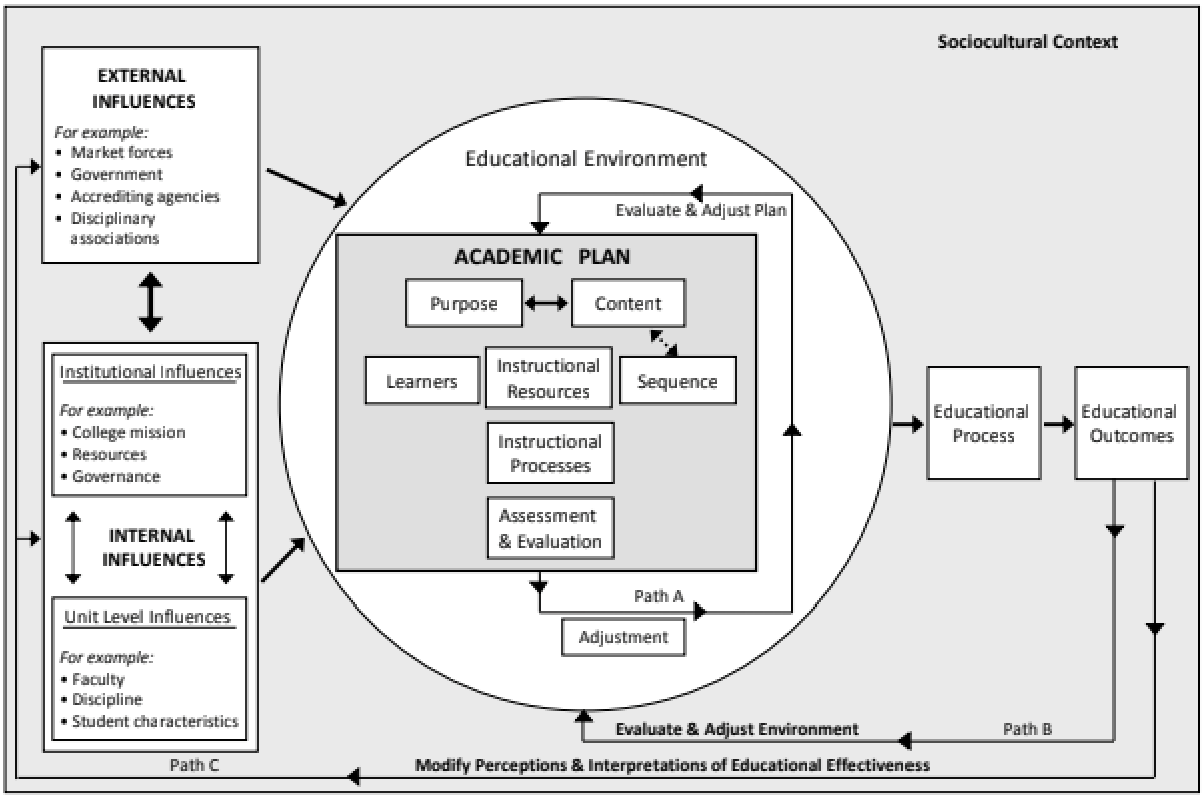

FIGURE 1. The academic plan model by lattuca and stark, 2011.

B. THE ACADEMIC PLAN MODEL AS A FRAMEWORK TO EXAMINE LMS USE

This research study seeks to examine how differential usage of LMS by instructors and students associates with course outcomes, namely course grades. We ground our study theoretically with the Academic Plan Model [21], which outlines how instructor considerations influence the learning process and student outcomes. The Academic Plan Model details the curricular decisions that faculty members make that apply at the course, program, and/or institutional levels (Fig. 1). Operating in response to a set of external (e.g., market forces, government, accrediting agencies, and disciplinary associations) and internal influences (e.g., resources, faculty beliefs, student characteristics), the "Academic Plan" which consists of a set of seven elements that instructors address, whether intentionally or not, as they develop courses and programs: purposes (the views of education that inform faculty members' decisions about the goals of a course or program), content (selecting subject matter), learners (taking into account student characteristics, goals, and abilities), sequence (the organization of content), instructional processes (learning and teaching activities), instructional resources (the learning material and technologies used), assessment (of student learning) and evaluation (of the course/program).

The Academic Plan Model states that individual instructor considerations in course planning can have a strong influence on student experience and outcomes. Our element of interest is the use of instructional resources (LMS) and its interactions with learners to produce learning outcomes. Analyzing the LMS that instructors use is a way to easily determine differences in how students interact and engage with a course and determine differences between instructors. Based on instructors' views of educational purposes and utilization of different instructional processes, instructor usage of LMS can be quite varied. Much of the prior research on faculty member adoption of LMS classroom usage is framed using the Technology Acceptance Model, a frequently used framework for understanding usage of new technologies (e.g. [22]). Factors within the model that are often investigated in the context of LMS usage are faculty member attitudes toward the technology, particularly perceived usefulness and ease of use [23]. Technological self-efficacy can also play a significant role in how instructors implement LMS into their classroom [24], [25].

The APM, as [26] empirically demonstrated, allows an understanding of how a specific technological tool is perceived by educators to support their pedagogical and organizational goals. In the APM, all aspects of the Educational Environment, including instructional resources, are part of a complex equation that ultimately produces educational outcomes. Establishing strong relationships between varied instructional practices and student outcomes can provide a workable foundation from which adjustments and innovations can be made. This study seeks to contribute to that foundation. In the context of multiple instructors across a common, first-year engineering course, we will investigate how these differences can manifest in variation in course grades. In another study, in relation to the Academic Plan Model, [22] identified how differences in instructional tasks (processes) can produce different usage rates of LMS tools (resources) used to perform them. The study found that LMSs are consistently used for the distribution of online materials, and less frequently used for instructor-student communication or collaborative learning. These studies provide an illuminating look at the relationship between LMS and student learning, but often neglect the important role that instructors have in the overlap of curricular design, pedagogical practices, and LMS.

Viewed through the lens of the Academic Plan Model, these considerations can create crucial differences in LMS usage and student course performance. Within the context of a common, first-year engineering course, this study seeks to explore how these differences can manifest. This differential usage is further amplified by different LMS tools that can be incorporated for student and instructor use. We address the following research questions:

(1) How do course grades vary based on the students' instructor and the overall number of LMS sessions per student?
(2) How do course grades vary based on the students' instructor and the number of LMS sessions per student for different course tools?
(3) How does the timing and frequency of LMS tool usage relate to course grades and vary across instructors?

Across all three research questions, consistent factors that will be included in the statistical modeling are student characteristics. In line with the learner element of the Academic Plan Model, demographic characteristics, such as gender, can play a significant role in how instructors utilize different processes and resources, and how students navigate those pedagogical components. In fact, the consideration of student characteristics is a limitation of prior LMS usage studies [27] despite being known to be an important characteristic in investigations of student learning [11], [28], [29]. The research described in this manuscript incorporates these additional elements for students enrolled in a traditional, first-year engineering course.

III. DATA AND METHODS

Data for this study were collected via the University's learning management system (LMS) as well as from student records (i.e., grades in the course). After obtaining approval from the Institutional Review Board, LMS data were obtained from the system administrator who compiled the data into text files, which initially comprised over 15 million rows of data. To glean information, the data was first processed through R, an open-source statistical package. Once data were cleaned and processed, statistical analyses were conducted to address each of the three research questions.

The study sample (post-data cleaning) consists of 876 students who were enrolled in the first-year engineering course at a large, Mid-Atlantic research university and agreed to have their data be used in an ongoing research project. Any student who did not receive a final grade in the course or a formally recorded Withdrawal ("W") was also removed.

A. COURSE BACKGROUND

The first-year engineering course analyzed for this study consisted of two components each week: 1) a lecture, and 2) a smaller workshop. Each week all of the 876 students would attend both a larger lecture and a smaller workshop, which comprised the two-credit course. For the lecture component, students met once each week for 50 minutes in sections that enrolled upwards of 140 students. Five different lecturers taught various sections of the same lecture course, and each utilized the same LMS site (i.e., one main LMS site for the lecture portion of the course). The smaller, hands-on workshop met once each week for 110 minutes. Each workshop consisted of up to 34 students, and there were 16 different workshop leaders in total. The roster of workshop leaders was comprised of the same instructors from the lectures as well as graduate student teaching assistants. For each workshop class, there was a unique, additional LMS site, which was organized and managed by the workshop leader for a particular section.

Thus, when students accessed the learning management system, they could visit the lecture site or the workshop site. Each site may have contained different materials even though the lecture and workshops were designed to work in tandem.

B. VARIABLE DEFINITION

With this study, our primary phenomena of interest are differences of LMS usage across instructors that manifest in differential course performance. Within the context of a common, first-year engineering course, data from five lecturers and sixteen workshop leaders were analyzed. They are included in the subsequent analyses as the following variables:

Lecturer: Control variable (categorical) which de-notes the student's lecturer for the course. There are five levels for this variable (i.e., 5 different lecturers).

Workshop Leader (WSL): Control variable (categorical) which describes the student's workshop leader for the course. There are 16 levels for this variable (i.e., 16 different workshop leaders).

Activity within the LMS are defined as follows. For each login to the LMS site, students began what we define as a unique session. Within that session, they could access different "tools". Table 1 shows the total usage of each tool across the 876 students (multiple occurrences within a single session were counted in Table 1).

Because some tools (i.e., chat, dropbox, lesson builder, mailbox, poll, and schedule) were infrequently used relative to other tools, they were not included in subsequent analyses. Variables relating to usage of unique sessions (US) were classified as utilized in either the lecture or workshop portion of the LMS with the following variable names:

Unique Sessions.Lecture: Independent continuous variable which describes the number of sessions that a student utilized

TABLE 1. LMS tool use frequency.

Overall Tools	Count	Overall Tools	Count
Homepage	128373	Syllabus	7327
Resources	123737	Chat	29
Announcements	8893	Dropbox	41
Assignments	85692	Lesson Builder	2
Gradebook	46093	Mailbox	3
Messages	1981	Poll	10
Quiz	26527	Schedule	51

the lecture portion of the LMS during the Fall semester. Min=28, Max=487, Mean = 119.6, Median = 112.5. The variable is centered at the mean for easier interpretation of model results.

Unique Sessions.WS: Independent continuous variable which describes the number of sessions that a student utilized the workshop portion of the LMS during the Fall semester. Min=23, Max=377, Mean=71.1, Median=63. The variable is centered at the mean for easier interpretation of model results.

The variable for course performance that are included in models for research questions one and two are course GPA, defined as follows:

Course GPA: Dependent continuous variable which describes a student's final grade within the course, where an A is a 4.0, A− 3.7, B+ 3.3, B 3.0, B− 2.7, C+ 2.3, C 2.0, C− 1.7, D+ 1.3, D 1.0, D− 0.7, and F 0.0. Students who withdrew from the course (W) were not included in these analyses. Min=0.0, Max=4.0, Meanz2.899, Median=3.000.

Additional unique variables that were utilized to address the timing considerations of research question 3. Those variables are defined as follows:

Day: Independent Variable (categorical), Mon, Tue, Wed, Thurs, Fri, Sat, Sun.

Semester Week: Independent Variable (continuous), 1-16, to denote the week of the fall semester.

Next Test: Independent Variable (continuous), 0-41, to denote how many days until the next test. 0 indicates test day; 41 was the maximum be-tween test days.

Grade: Control Variable (categorical), with 5 levels for a students' final course grade, (A, B, C, D/F, W).

C. MODEL SPECIFICATIONS

To understand the relationship between LMS usage and final course grade, two competing models were developed. Model 1 included an interaction effect with LMS usage and Gender, and Model 2 did not include the interaction. Both models include interaction effects for LMS usage and lecturer and workshop leader.

To minimize the chance of a random significant result we created a training set and validation set from the total pool of student participants. We then ran the following simulation on both models:

TABLE 2. Simulation model results.

Model 1		Model 2	
MSE mean	0.3876	MSE mean	0.3892
MSPE mean	0.4505	MSPE mean	0.4495
MSPE min value	532	MSPE min value	468

Step 1: 600 of the 876 students were randomly selected to be included in the training set. The 276 students that were not part of the training set comprised the validation set.

Step 2: Each of the above models used the training set data to create prediction models.

Step 3: Students from the validation set were used to calculate the model error for each of the 2 models.

Step 4: Steps 1-3 were repeated 1000 times.

Step 5: For model selection, the mean of the mean square error (MSE) and mean square predicted error (MSPE) were calculated for each, along with the frequency of minimum values in each model iteration for MSPE.

As shown in Table 2, both models performed fairly similarly. Because both models display very similar fits with the data, Model 2 was selected for further analyses because it is more parsimonious. This process was followed for analyses addressing both research questions one and two, with analyses for research question two including separate models for each LMS tool.

To address research question three, a generalized linear model was developed to understand group differences (ANOVA) as well as identify the relative relationships of independent variables and daily LMS usage (regression). However, since the dependent variable in this analysis is a count of the total number of times a student used the LMS each day, a Poisson model was most appropriate for this type of count data.

IV. RESULTS

A. DESCRIPTIVE STATISTICS

Tables 3-5 display learning management system use for the fall semester for 876 students. Table 3 depicts average overall sessions, lecture sessions, and workshop sessions for final grade bands in the course. The overall sessions do not equal the sum of the lecture sessions plus the workshop sessions because students could have interacted with both sites (i.e., lecture and workshop) during a single session. In addition, even though students could have received a grade with a '+' or '−' in the course, we binned final grades as shown in the table for easier interpretations.

Table 3 exhibits a pattern of usage with final grades, i.e. on average, students who received higher grades within the course interacted with the LMS with greater frequency. Table 4 similarly shows LMS usage for overall sessions, lecture sessions, and workshop sessions by

TABLE 3. LMS usage[1] by final course grade.

Course Grade	Count	Overall Sessions Mean	Overall Sessions Stdv	Lecture Sessions Mean	Lecture Sessions Stdv	WS Sessions Mean	WS Sessions Stdv
A	147	162.84	55.54	130.63	46.26	81.2	40.84
B	507	150.78	55.36	122.65	46.93	73.32	36.63
C	188	133.45	39.83	108.65	34.34	63.85	24.72
D/F	22	99.00	39.02	80.14	34.17	46.95	20.93
W	12	119.25	31.20	101.08	27.28	54.58	15.51
Total	876						

TABLE 4. LMS usage by gender.

Gender	Count	Overall Sessions Mean	Overall Sessions Stdv	Lecture Sessions Mean	Lecture Sessions Stdv	WS Sessions Mean	WS Sessions Stdv
Male	672	147.53	56.24	119.96	47.75	71.07	38.22
Female	204	152.65	42.87	123.55	35.18	71.99	27.00

TABLE 5. LMS usage by tool.

Tools	Count	Mean Sessions	Stdv	% Use
Resources	876	141.25	51.52	41%
Announcements	872	10.19	8.85	3%
Assignments	876	97.82	33.23	29%
Gradebook	876	52.62	40.02	15%
Messages	605	3.27	3.35	1%
Quiz	876	30.28	14.35	9%
Syllabus	867	8.45	5.40	3%

gender. The data indicate that, on average, female students (mean=152.65), interacted with the LMS more than male students (mean=147.53). Thus, subsequent analyses include gender as a predictor variable to determine if there is any significance to the relationship between gender and LMS usage.

As noted, students could access multiple tools during each session. For some tools, such as messages, only a portion of the workshop leaders granted their students' access by turning that tool function "on." Almost 70% of the time that students logged onto the LMS, they would utilize the resources and/or the assignments tools. This finding aligns with previous research that describes LMS functionality as transactional warehouses for students to retrieve and submit documents [30]. Educational technology proponents point to the potential for LMS functions to enable greater collaboration and interaction between students and their instructors [4]. However, for this first-year engineering program, over 30% of the students did not use the "messages" tool at all.

B. RQ1: SESSIONS AND COURSE GRADES

The first ANOVA model for Model 2, (now referred to as "Model 2a"), indicates that there is no significant interaction effect between unique sessions on the lecture site and the lecturer; however, a significant interaction between unique sessions on the workshop site and the WSL was present. The lecture site and lecturer interaction was removed because it is non-significant, reflected in Model 2b, which was found to be significant at $F(37,826)=3.071$, *p-value* $<.001$. Model 2b retained the significant interaction between WSL and workshop site usage. Before interpreting this model, two characteristics were evaluated: 1) generalizability tested using multicollinearity and homogeneity of variances, and 2) fit tested by inspecting outliers. Results from a robust analysis accounting for these characteristics by applying Huber weights to outliers [31], Model 2c, provided almost a 15% decrease in error relative to the previous Model 2b. Results of Model 2c retain the significant WSL interaction (see Table 6).

As there were 16 different WSLs, additional analyses were conducted to facilitate post hoc comparisons. Grouping the 16 different WSLs into three groups did not harm the investigation because the goal of the research is to understand broad patterns as opposed to singling out an individual workshop leader. Table 7 shows the correlation of final course grade and LMS workshop site usage for each of the 16 workshop leaders. Three groups were formed on the basis of their correlations. The low/negative correlation group (Group 1) consists of four WSLs and correlational values ranging from -0.093 to 0.062. Group 2 consists of six WSLs with correlations ranging from 0.143 to 0.244 and Group 3 is comprised of six workshop leaders with correlations ranging from 0.320 to 0.435. Model 2d uses the three workshop leader grouping

TABLE 6. ANOVA results for Models 2a, b, and c, with grade as the dependent variable.

	F scores, N=864								
ANOVA	*US.Lecture^*	*US.WS^*	*Gender*	*Lecturer*	*WSL*	*US.L^ x Lecturer*	*US.WS^ x WSL*	*R^2-Adj*	*Residual SE*
Model 2a	6.49*	1.06	2.96	1.49	2.20**	1.76	2.11**	0.085	0.644
Model 2b	7.44**	0.62	3.23	1.65	2.08**	dropped	2.06**	0.082	0.645
Model 2c	4.79*	0.25	3.55	2.40*	1.90*	dropped	1.96*	0.073	0.554
Model 2d	5.17*	1.93	0.54	1.84	0.29	dropped	7.71***	0.101	0.568

p<.001 ***, p<.01 **, p<.05 *

^=variable is mean centered

TABLE 7. Correlation between grade and unique sessions on WS Site by workshop leader.

WSL	*Group*	*r*	*p-value*	*WSL*	*Group*	*r*	*p-value*	*WSL*	*Group*	*r*	*p-value*
WSL 2	1	0.017	.887	WSL 1	2	0.143	.506	WSL 9	3	0.357	.007
WSL 4	1	0.017	.887	WSL 3	2	0.202	.072	WSL 11	3	0.349	.016
WSL 10	1	-0.093	.684	WSL 5	2	0.237	.097	WSL 12	3	0.435	.003
WSL 14	1	0.062	.611	WSL 6	2	0.232	.262	WSL 13	3	0.320	.035
				WSL 7	2	0.244	.049	WSL 15	3	0.349	.003
				WSL 8	2	0.200	.079	WSL 16	3	0.393	.064

TABLE 8. Model 2d coefficients with grade as the dependent variable.

Term	*Estimate*	*SE*	*t Ratio*	*p-value*	*Standard Beta*
(Intercept)	2.820	0.088	32.074	*.000*	-
US^	0.002	0.001	2.273	*.023*	0.152
US.ws^	-0.002	0.002	-1.388	.165	-0.122
Male	0.039	0.054	0.731	.465	0.025
Lecturer2	0.116	0.086	1.357	.175	0.207
Lecturer3	0.028	0.089	0.317	.752	0.033
Lecturer4	0.146	0.079	1.847	.065	9.785
Lecturer5	0.203	0.101	2.014	*.044*	10.676
WSL.G 2	-0.024	0.062	-0.388	.698	-0.015
WSL.G 3	-0.047	0.062	-0.756	.450	-0.083
US.ws^ x WSL.G2	0.003	0.002	2.062	*.040*	0.004
US.ws^ x WSL.G3	0.006	0.002	3.924	*.000*	0.421

Note: Female, Lecturer 1 and Workshop Leader Group 1 are references.
^=variable is mean centered

levels within the robust generalized linear model instead of the original 16 levels.

Even though Model 2d has a small increase in residual standard error (0.014), the amount of variation the model explains increased from 7.3% to 10.1% and the significance of the WSL interaction decreased below $p < 0.001$.

Findings from the robust ANOVA indicate that only unique sessions on the lecture site and the interaction between WSL and workshop site usage have a significant relationship with a student's final grade, even while accounting for student-level differences (i.e. gender). Although the lack of a lecturer interaction effect is puzzling, this result provides strong evidence of a significant moderating effect of the association between LMS usage and final course grade. To give these differences practical value, Table 8 displays regression coefficients from this analysis and shows that students who were in workshops led by instructors in Group 3 exhibit a 0.06 higher increase in GPA for every 10 additional unique sessions on the LMS than students who are in sections with workshop leaders from Group 1. Similarly, students enrolled in sections led by instructors in Group 2 exhibited a 0.03 higher increase in GPA for every 10 additional unique sessions on the LMS relative to students who had a workshop leader in Group 1.

C. RQ2: LMS TOOLS AND COURSE GRADES

Table 9 presents an overview of the LMS tool usage by students within each workshop leader group. The results support two main findings. First, students enrolled in workshop sections led by instructors in Group 1 had the highest GPA for the course, but they generally had the lowest LMS usage on average, limited use of the messages tool, and no use of the quiz tool. Second, further supporting findings addressing research question one, a student's workshop leader helped determine the relationship between students' LMS usage and final course grade. For instance, when a student used the messages and quiz tools during the semester, they tended to

TABLE 9. Workshop site tool use by workshop leader group.

	median (MAD)						mean (sd)	
	Resources	Announce.	Assignment	Gradebook	Messages	Quiz	Course GPA	n
WSL.G 1	59 (19.27)	3 (2.97)	27 (10.38)	21.5 (12.60)	0 (1.27)	0 (0)	2.94 (0.63)	240
WSL.G 2	61 (20.76)	4 (2.97)	28 (10.38)	22 (14.83)	1 (2.08)	4 (2.97)	2.87 (0.68)	328
WSL.G 3	62 (22.24)	4 (2.97)	28 (11.86)	19.5 (14.08)	1 (3.15)	3 (4.45)	2.89 (0.70)	308
	if used Messages and Quiz tool on WS site							
WSL.G 2	69 (23.72)	4 (2.97)	29.5 (11.12)	25 (16.31)	2 (1.48)	5 (2.97)	N/A	144
WSL.G 3	69 (25.20)	5 (4.45)	28 (10.38)	23 (17.79)	3 (2.97)	6 (4.45)	N/A	127

TABLE 10. Individual tools robust generalized linear models, with grade as the dependent variable.

	F scores, N=864							
Tools	US.Lecture^	US.WS^	Gender	Lecturer	WSL.G	US.L^ x Lecturer	US.WS^ x WSL.G	R^2 Adj
Resources	3.57	1.55	0.42	1.91	0.25	dropped	*8.15****	0.056
Announcements	2.08	0.84	0.01	1.33	0.26	*2.56**	2.57	0.005
Assignments	*25.96****	2.12	1.32	2.04	0.30	dropped	*5.82***	0.084
Gradebook	0.42	0.41	0.26	1.92	0.33	dropped	*6.61***	0.033
Messages	0.37	*9.01***	0.20	1.81	0.47	*2.47**	*4.63***	0.016
Quiz	*8.15****	0.02	0.04	1.65	0.26	dropped	dropped	0.006
Syllabus	0.003	N/A	0.13	1.33	0.24	dropped	N/A	-0.01

p<.001 ***, p<.01 **, p<.05 *, ^ mean centered

have higher LMS usage on all other tools on average (bottom half of Table 9).

The usage of seven different tools, which were used on either the lecture site, workshop site or both, were analyzed using a similar ANOVA modeling approach used in research question one. A separate robust generalized linear model was developed for each tool that follows the format of Model 2d. When appropriate, a new model was developed to include the LMS usage on the lecture site and lecturer interaction. Table 10 shows the F-scores for each of the models on the seven separate tools to identify significant relationships. Across all seven tools analyzed, the lecturer interaction was statistically significant across two of the models and the WSL interaction was significant across four of the models. For the messages tool, both the lecturer and WSL interaction were significant. Neither interactions were significant for the quiz and syllabus tools.

Similar to Table 8 for research question one, Table 11 displays regression coefficients that can be used to understand the relative relationship of each variable with final course grade. For example, relative to students who had a workshop leader in Group 1, students who had a workshop leader in Group 3 had a predicted increase in course GPA ranging from 0.007 to 0.111 as students used four out of five tools available more frequently. Elaborated more fully in the discussion section, these findings point to a nuanced relationship between how lecturers and WSLs combine an LMS with their existing pedagogical practices. Importantly, the alignment of student interactions with instructional intentions could play a role in course performance.

D. RQ3: TIMING, FREQUENCY, AND COURSE GRADES

The final set of analyses investigates variables related to the timing and frequency of student use of the LMS, with particular interest in differences across lecturers and workshop leaders. The ANOVA results shown in Table 12 indicate that all factors were significant at the $p<.001$ level. The adjusted r-squared value of 0.163 indicates that the model is moderately able to predict daily student usage of the LMS. Instead of showing all coefficient estimates as to not be overbearing, two examples are presented. First, the anti-log estimate for Monday (with reference to Friday) is 1.865, which can be interpreted as follows: students log on to the LMS on Monday's 1.865 times more than on Friday's. In another example for a continuous variable, -1.075 for semester week is interpreted as follows: for each unit increase in semester week, students use the LMS 7.5% less.

Focusing first on the role of timing, the results indicate that the best predictor for the timing of students' LMS usage is the day of the week. Students used the LMS 3.074 times more on Wednesday than on Friday. However, because there is an interaction effect, it is more appropriate to interpret usage on a particular day by students' final grade in the course. Fig. 2 shows the interaction of semester week and grade. Of particular note is that students who withdraw from the course with a grade 'W' used the LMS

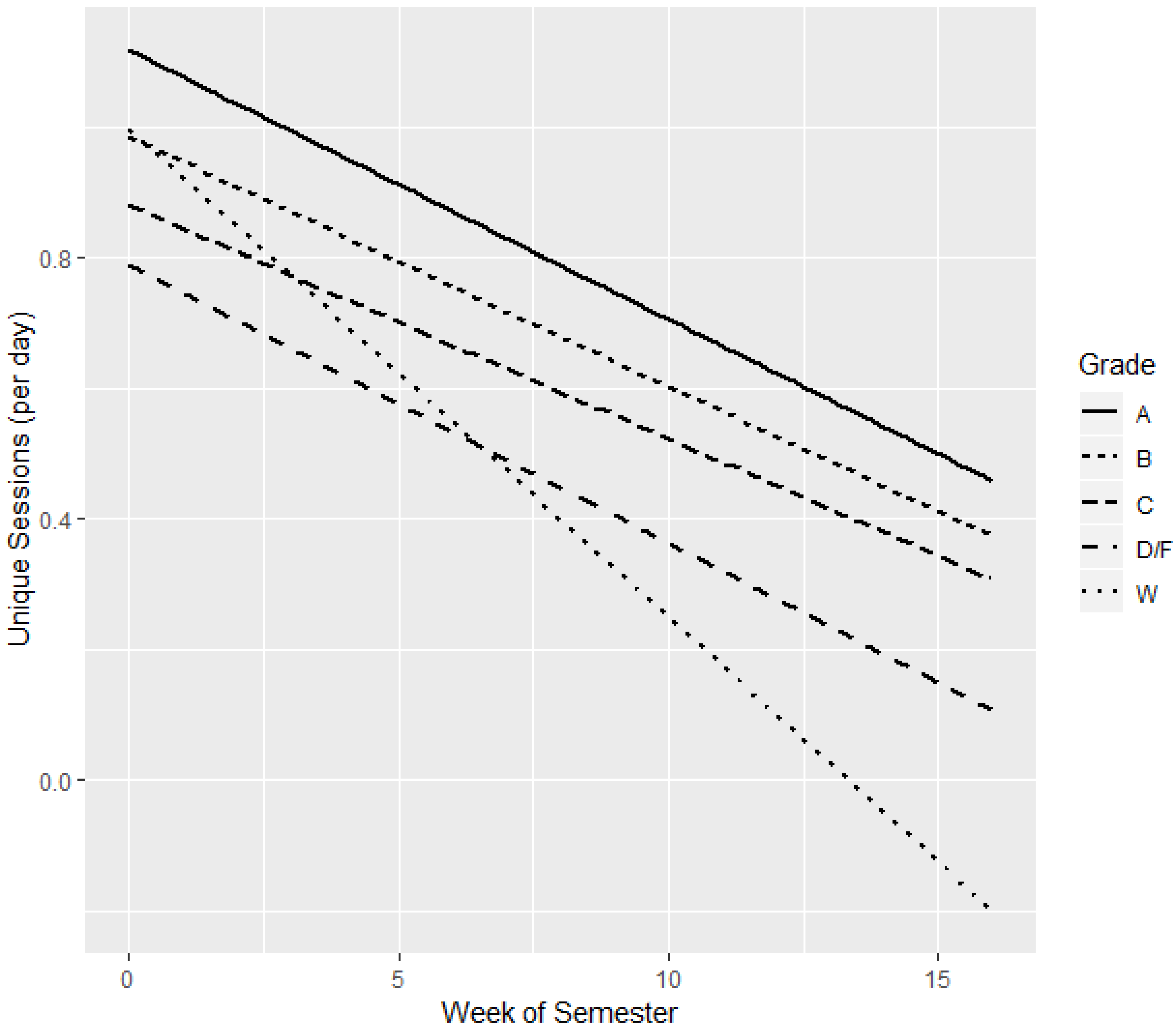

FIGURE 2. Interaction plot of grade and LMS usage by week of the semester.

during the first week at the same daily rate as students who earned an A, and at the same daily rate as students who earned a B or C by week four. At weeks 8 and 12, the 'W' students reduced daily LMS usage considerably. Thus, these findings could potentially be fed to instructors and to students to emphasize the importance of continuing to engage with course materials on the LMS throughout the semester.

For usage on each day of the week (Monday-Sunday), the interaction effect with final course grade was also significant. Students who received an 'A' as their final grade used the LMS more than any other grade band for all days of the week except Wednesday, on which 'B' and 'C' students have the highest daily activity. Homework for the course was due on Wednesdays, with an implication that 'B' and 'C' students waited until the due date to turn in homework, while 'A' students completed this task earlier on average (Fig. 3). Such a graph could be an effective way for instructors to help students visualize a "procrastination effect" using their own data and how such decisions might influence course performance.

Most relevant to research question three, statistically significant differences were found among lecturers and WSLs in students' daily usage of the LMS. All four lecturers were statistically different than the reference lecturer and seven of fifteen WSLs were statistically different from the reference. To explore differences in usage with more specificity, an additional model was conducted that included lecturer and WSL interaction effects with both timing during the semester and during the week. As an overview of the results, there are more statistically significant differences across lecturers and WSLs for day of the week than week of the semester. Only one lecturer and one WSL reported as statistically significant from the reference, whereas an overwhelming majority of the interactions for both lecturers and WSLs reported as statistically significant for the day of the week. The differences across lecturers are demonstrated through the interaction plots in Fig. 4 and 5. As seen in Fig. 4, Lecturer 1 and 5 show

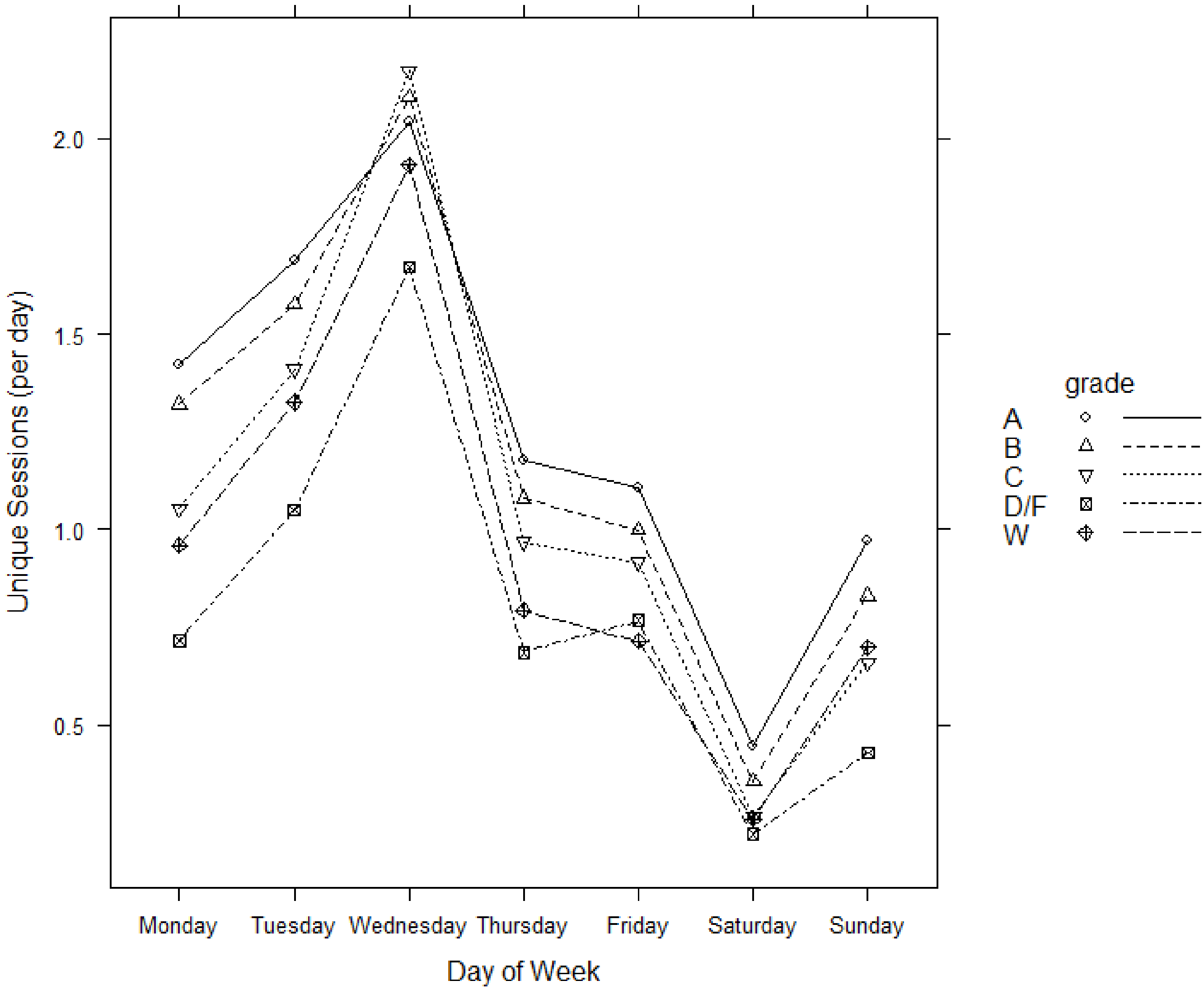

FIGURE 3. Interaction plot of grade and LMS usage by day of the week.

an increased usage throughout the semester. In comparison, day of the week differences in Fig. 5 are more fuzzy. While instructors 1 and 5 have comparable usage across the week, instructors 2, 3, and 4 are noticeably more variable.

V. DISCUSSION

This study sought an underlying examination of the differences in course performance based on LMS usage as mediated by the students' lecturer and workshop leader (WSL). One of our primary findings was a confirmation of previous studies that identified a positive relationship between student LMS usage and course performance (e.g. [7]). However, this research has extended this work by presenting a conflicting result of how differences across instructors can produce different course outcomes. First addressing the basic question of LMS usage, the full ANOVA model showed an interaction effect for WSLs, but not for lecturers. This held valid across multiple model specifications. This finding can be interpreted that the correlation between students' LMS usage and their final course grade were contingent on who was their WSL.

Prior research has established that instructors can implement LMS in their classrooms differently based on their perceived utility and ease of use of the technology [17]. These underlying mechanisms could explain the varied relationships for different students. Unfortunately, we do not currently have the means of investigating these WSLs to gain a better understanding of their usage of the LMS and its relationship to their instructional practices, but the result certainly justifies closer examination. Perhaps, some WSLs use the LMS in a more purposeful manner were increased usage can produce stronger course outcomes. More curiously, why do negative correlations exist? What LMS practices produce a negative relationship between LMS usage and course performance?

Returning to the conflicting result of significant interactions for WSLs and not for lecturers, what about the structure

TABLE 11. Unstandardized coefficients (standardized) for each tool, with grade as the dependent variable.

	Resources	Announce.	Assignment	Gradebook	Messages	Quiz	Syllabus
Intercept	*2.83****	*2.86****	*2.82****	*2.82****	*2.74 ****	*2.85****	*2.85****
(tool).Lec^	.002 (.13)	.011(.11)	*.006 (.24)****	.001 (.06)	-.013 (-.04)	*.006 (.11)***	.000 (.00)
(tool).WS^	-0.002 (-0.11)	-.011 (-.08)	-.004 (-.09)	-.002 (-.07)	*-.106 (-.38)***	.001 (.01)	N/A
Male	.035 (.022)	.006 (.004)	.062 (.04)	.028 (.02)	.024 (.02)	.011 (.01)	.021 (.01)
Lecturer 2	.114 (.20)	.105 (.19)	.116 (.21)	.142 (.25)	.115 (.21)	.126 (.22)	.106 (.12)
Lecturer 3	.022 (.03)	.040 (.05)	.009 (.01)	.051 (.06)	.063 (.07)	.035 (.04)	.039 (.05)
Lecturer 4	.148 (9.56)	.146 (1.43)	.138 (5.42)	*.166 (7.75)**	.154 (.41)	.147 (2.84)	.144 (1.17)
Lecturer 5	*.197 (9.84)**	.169 (1.09)	*.204 (5.25)**	*.209 (8.60)**	*.249 (.89)**	.196 (1.39)	.182 (.11)
WSL.G 2	-0.025 (-.02)	-.030 (-.02)	-.039 (-.02)	-.026 (-.02)	.068 (.04)	-.036 (-.02)	-.024 (-.04)
WSL.G 3	-0.044 (-.08)	-.046 (-.08)	-.046 (-.08)	-.05 (-.09)	.045 (.08)	-.050 (-.09)	-.045 (-.05)
(tool).Lec^ x Lec 2	N/A	*-.028 (-.03)**	N/A	N/A	.027 (.03)	N/A	N/A
(tool).Lec^ x Lec 3	N/A	-.003 (-.03)	N/A	N/A	*.126 (.34)***	N/A	N/A
(tool).Lec^ x Lec 4	N/A	.010 (.06)	N/A	N/A	*.066 (.24)**	N/A	N/A
(tool).Lec^ x Lec 5	N/A	-.019 (-.01)	N/A	N/A	.067 (.04)	N/A	N/A
(tool).WS^ x WSL.G 2	*0.003 (.004)**	-.010 (-.02)	.003 (.003)	*.006 (.01)***	*.084 (.15)**	N/A	N/A
(tool).WS^ x WSL.G 3	*0.007 (.44)****	.019 (.02)	*.012 (.47) ***	*.007 (.31)***	*.111 (.13)***	N/A	N/A

p<.001 ***, p<.01 **, p<.05 *, Reference Levels: Female, Lecturer 1, WSL Group 1, ^=mean centered

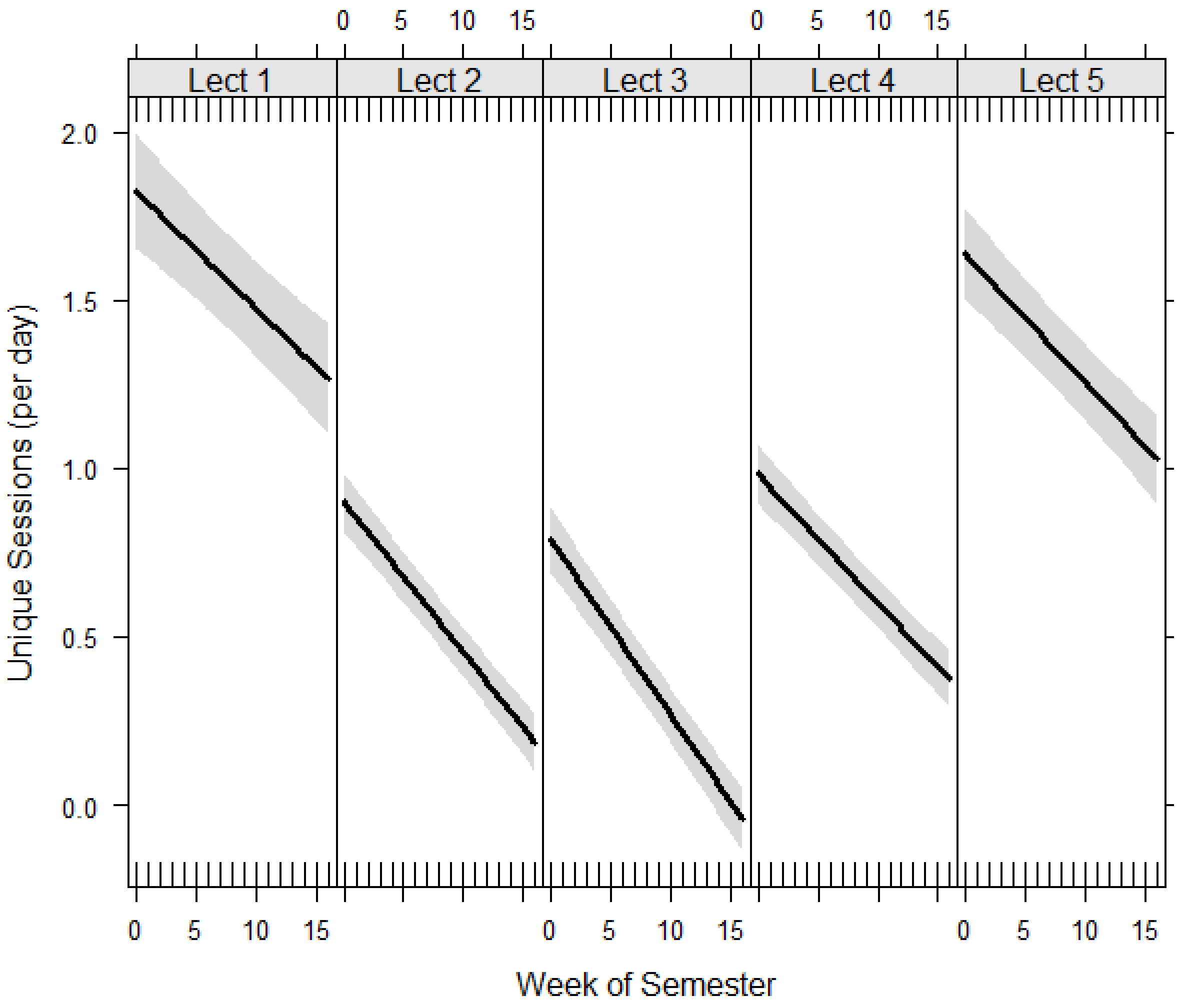

FIGURE 4. Interaction plot of lecturer and LMS usage by week of the semester.

of course could potentially drive these findings. As defined by the Academic Plan model, instructional resources, such as LMS, are one of many different influences on the overall educational experience. Further follow-up research should

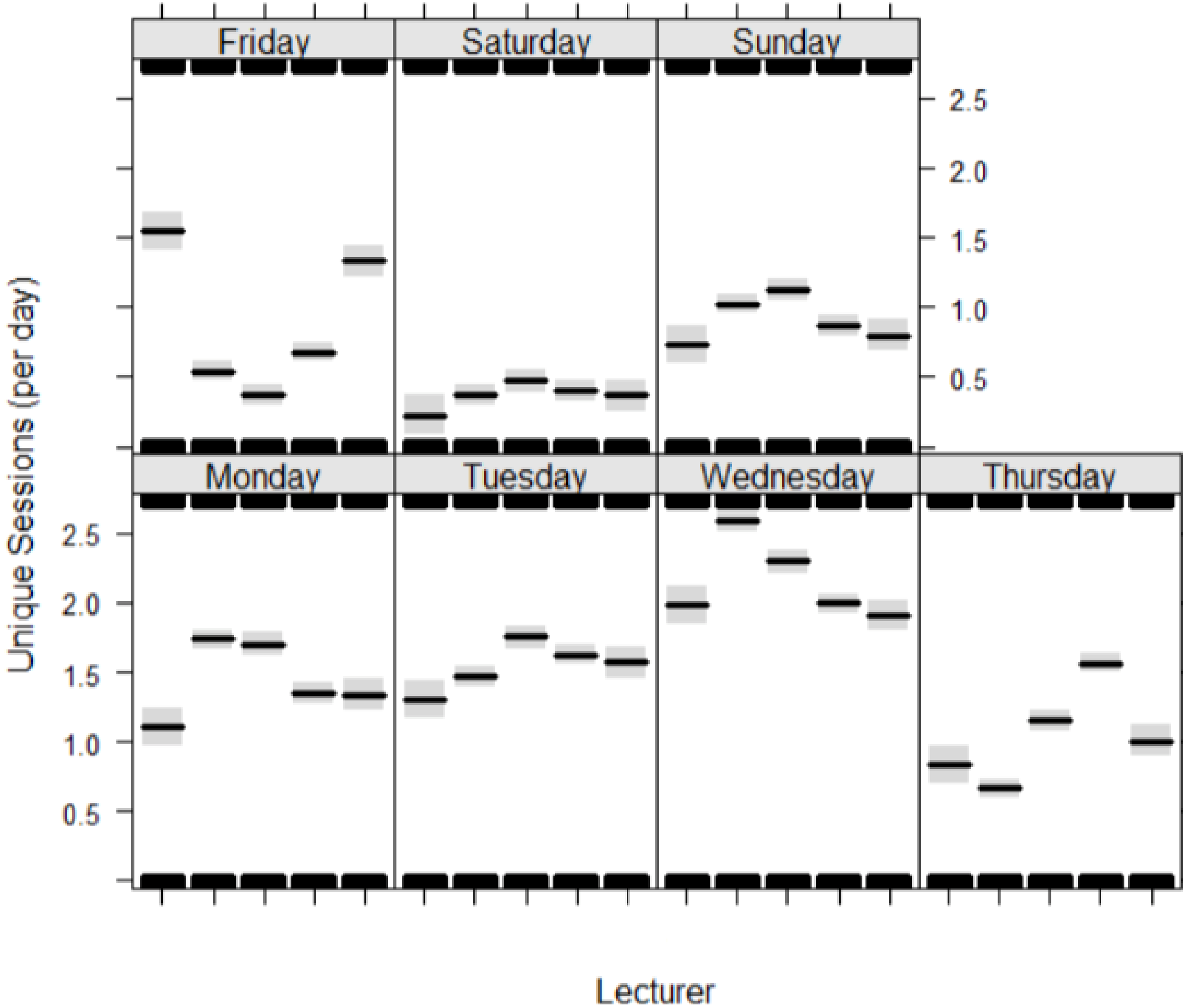

FIGURE 5. Interaction plot of instructor and LMS usage by day of the week.

include aspects of course design to gain a stronger understanding of the nuanced interactions between LMS usage and course performance.

Findings first demonstrated through research question one were confirmed and extended in research question two through the examination of different LMS tools. Not only does the usage of different LMS tools related differently to final course performance, but also the relationship can be dependent on the students' lecturer or WSL. This study's finding regarding differences across LMS tool usage are confirmations of prior investigations. For example, the assignments tool has been shown in prior literature as one of the most influential indicators of student success, which has also led some to call the LMS nothing more than a content distributor where students retrieve and submit course material and assignments [37]. However, there are other tools, such as the quiz tool, that also can be operationalized for student success. Knowing which tools are important for student success, and which tools may best capture student engagement with different aspects of a course, are vital to creating future value of using the LMS.

A more important contribution of this work resides in the associations of different LMS tool usage and the instructors that can facilitate or even require its usage. Instructors varied not only on the features they turned ''on'' for their students to use but also on how their students' course grades related to tool usage. This finding leads to a policy consideration in how instructors are trained on the LMS. Instructor and graduate teaching assistant training is an important component of developing a technological environment for student success [33]. If not all students are receiving the same level or kind of teaching and learning throughout various sections of the same course yet receive the same credential at the conclusion of the course, this finding merits further consideration. It demonstrates that analyzing LMS usage across sections may

TABLE 12. ANOVA output for the robust poisson model.

	Df	*F*	*Pr(>F)*
Day	6	476.54	.000
Semester Week	1	854.46	.000
next.test	1	788.57	.000
WSL	15	14.16	.000
Lecturer	4	8.16	.000
Gender	1	66.87	.000
Semester Week x next.test	1	281.84	.000
Day x grade	28	15.29	.000
Semester Week x grade	4	8.13	.000
Residual DF	97174		
Residual SE	1.132		
Adj-r^2	0.163		

provide insight on how learning environments differ for the same course.

As a final means of examining the nuance of LMS usage, research question three examined differences in LMS usage over time, specifically timing throughout the week and the semester. Primarily, this study identified the relevance of timing, a variable not often tied to course performance. Knowledge of a "procrastination effect" or the importance of continued course engagement, while obvious to some students, could present as a useful data point for students. In addition, knowledge of low student engagement with the LMS could represent an opportunity for instructors to intervene at timely points throughout the week or during the semester, e.g. in the lead up to an exam. Instructors often want to know how students spend their time engaging with course materials outside of class [34], and by tracking student LMS usage, a clearer picture of how students spend their time outside of class can be visualized.

In line with earlier research questions of differences across instructors, further evidence for the importance instructor differences were identified in research question three. Also in line with the prior research questions, the findings identify more areas of future research than answers. Across the two analyses, the relationship between the timing of LMS usage and course performance were identified and differences in students timing of LMS usage across lecturers and WSLs were established. This presents a further connection to the varied implementation of LMS that can be seen across instructors [22] and highlights the value of the Academic Plan model in relating differences across instructional processes. Due to data limitations, interaction effects for usage timing and instructor were not conducted. A future line of research that, when combined with more detailed information on instructional practices, will present a clearer lens to view the effects of instructional differences on the associations between LMS usage and course performance.

VI. CONCLUSION

The Academic Plan Model suggests that it is important for faculty members to understand not only the purpose of a course and the content within it but also to think purposefully about their students (i.e., learners) and understand how instructional processes and resources can be used to improve student outcomes as they plan curricula. Analyzing learning management system data provided the opportunity to uncover new insights about how learners engaged with course material in a first-year engineering program, how students derived value from its use, and how students' experiences may have varied across separate lecturers and workshop leaders (WSLs).

Across three separate research questions, this study examines how the relationship between LMS usage and course performance can vary across different instructors with increasing levels of detail by LMS tool usage and timing. The findings of this study demonstrate several different examples of how an LMS can be operationalized differently across an instructional team. Serving as a foundation for future research in instructional uses of LMS, this study provides evidence of the potential for understanding how instructional differences in LMS utilization can manifest in different course performance for students.

These and future findings could hold important implications for training programs designed to oriented instructors around LMS usage. Enhanced training for an instructional team may result in more unified LMS utilization—and even more broadly—more unified learning environments. If such training workshops can communicate how the LMS could be most effectively used to drive student usage, there is a potential for students to engage more frequently with course materials, which in turn could result in an overall increased course performance. At a broader level, this finding represents an opportunity to use LMS data to gain information about differences in the educational environments across multiple sections of the same course or between different courses in an unobtrusive manner.

We show through gathering and analyzing LMS data, there is an opportunity to capture student engagement outside the classroom; however, the LMS is limited to only one portion of student engagement. The LMS activity of students is an important first step in analytically evaluating student engagement data and correspondingly understanding their trends and habits, but there is a need for the use of other technology platforms and environments to capture the full picture of how students engage with their courses.

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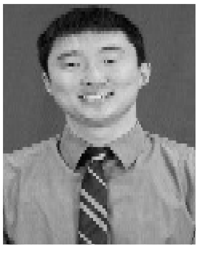

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