TIMELINESS MEASURES AND ACADEMIC PERFORMANCE IN AN ONLINE QUANTITATIVE REASONING COURSE

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ABSTRACT

The purpose of this retrospective study was to test the association of simple timeliness measures with academic performance in an online quantitative reasoning course using data extracted from gradebooks (N = 157). Guided by the Social Cognitive Model, timeliness was assumed to be a consistent behavior chosen by the student based on personal goals and social patterning. Submission of assignments early in the first four weeks of the term proved to be a significant predictor of the final percentage grades (mean difference = 5.02, p = 0.006). Submitting assignments Just-in-Time was not significantly related to the final percentage grade. The significance of early submission of assignments persisted after adjusting for the effects of failing status. The results are useful for targeting students who may benefit from encouragement in the form of personal messages from the instructor.

Keywords: timeliness, early submission, lateness, online learning, higher education, asynchronous, academic performance

INTRODUCTION

Professional doctorate programs that are offered online require course work in statistical analysis. However, students often are anxious about these courses because some students have struggled with statistics in previous courses and many lack confidence in their ability to learn the material, and academic performance is shown to be lower in doctoral statistics courses than in other subjects (Rotenstein et al., 2009). Instructors may find themselves uncertain about how they can improve student competence in the material and, consequently, academic performance. If instructors knew how to identify a subset of students who are both willing and able to benefit from outreach, it might be possible to improve the grade distribution.

Background

Predictors of academic performance are of perennial interest in higher education research. This line of research is even more urgent in online programs where maintaining student motivation and commitment are ongoing challenges. Instructors who reach out to students may be able to foster a greater sense of community and increase engagement. Simple tools are needed for identifying students who might benefit from instructor intervention. Targeted outreach could be beneficial for students who desire more engagement with faculty and a greater faculty presence (McElroy & Lubich, 2013).

Studies of academic performance in online classes typically have relied on primary data collection in the form of large surveys of students with long instruments. The instruments are psychometrically valid but tend to exhibit weak effects on academic performance. They also may not be practical for use by individual instructors because they require primary data collection. A 27-item instrument designed to measure engagement was shown to correlate with academic performance among 40 undergraduates (Handelsman et al., 2005). An instrument of this length has questionable utility for use by instructors. A study of 669 largely online, nontraditional doctoral students using a short eight-item instrument measuring grit (passion and persistence for long-term goals) was able to predict grade point average with a Pearson r of .093, $p < .016$ (Cross, 2014). A follow-up study of grit and a large personality inventory in 478 doctoral students (Walsh, 2020) did not find grit to be a significant predictor of grade point average; instead, conscientiousness was significant with an r-square of 0.025 ($b = 0.089$, $p = 0.002$).

Another approach to the study of academic performance, called learning analytics, relies on secondary data in the form of activity counts obtained from learning management systems (LMS). For example, a study of 354 undergraduates analyzed eight indicators of participation and persistence and reported significant correlations with academic performance (Morris et al., 2005). Various indicators of interaction are significantly related to academic performance, but the effects might be different in different types of classes (Agudo-Peregrina et al., 2014). The LMS approach to obtaining predictors of academic performance may be convenient for the individual instructor if the instructor has access to reports about their own classes. These systems can produce alerts warning the instructor about students who are at risk of poor performance due to inactivity or lateness.

Timeliness may be a promising avenue of investigation. Time spent on academic activities is a significant predictor of academic performance (Carver et al., 2017) but timeliness is a different concept. Timeliness encompasses a range of timing that extends from very early completion of tasks to very late. Procrastination is known to increase the risk of academic failure (Rabin et al., 2011). Various studies have linked procrastination among students with anxiety (Haycock et al., 1998), perfectionism and fear of failure (Flett et al., 1992), lack of computer skills (Rahardjo et al., 2013), low self-efficacy (Haycock et al., 1998), low motivation combined with aversion for academic tasks (Brownlow & Reasinger, 2000), low say-do correspondence (Howell et al., 2006), and weak executive functioning (Rabin et al., 2011). However, procrastination appears not to be related to any Myers-Briggs personality type (Ferrari et al., 1992).

At the opposite end of the timeliness spectrum, early submission of academic work might indicate higher executive functioning. Procrastination is related to executive dysfunction (Rabin et al., 2011). Executive functioning includes self-regulation and the ability to plan, organize, initiate, and complete work. These skills are conducive to academic success. On the other hand, submitting papers at the last minute (labelled as Just-in-Time) can be described as pragmatic and useful (Ferket et al., 2012; Rotenstein et al., 2009). Waiting allows more time to perfect the paper and leaves open the possibility of acquiring useful information from other students who complete their assignments sooner. Despite these apparently good reasons for waiting, earlier submission has been shown to predict better scores (Rotenstein et al., 2009).

The purpose of this retrospective study was to investigate the predictive validity of simple timeliness measures that can be assessed before the middle of the term. If these measures are valid, then they could be used to target students for the special attention than many of them crave (Cung et al., 2018). This in turn could increase academic performance, motivation, engagement, student satisfaction, and a sense of community in the class.

Theory and Research Questions

Guided by the Social Cognitive Model (Bandura, 1988), timeliness is assumed to be a consistent behavior chosen by the student based on personal goals and social modeling. According to the theory, students who consistently complete assigned work early do so because they able to self-regulate and early submission meets their personal goals. Students are self-motivated based on prior academic success that has increased their self-efficacy (Zimmerman et al., 1992). Goals include professional achievements such as grades and social activities. Students who submit assignments early can be expected to be high in self-efficacy and to get better than average scores. Students who submit their work Just-in-Time have settled on this behavior pattern because they believe it helps them to achieve their goals, both social and professional. If their grades are not as good as expected, they are able to work harder and achieve higher performance. However, students who are failing may lack motivation because their poor academic performance has reduced their self-efficacy.

The research questions associated with the study are:

1. Is there an association between timeliness measure and final grades of graduate students in an online quantitative reasoning course?
2. Is there an association between timeliness measure and final grades of graduate students in an online quantitative reasoning course after adjusting for failing status?

METHODS

Setting

Students in this course were pursuing a doctorate in the health sciences, either the PhD in public health, the PhD in Health Services, or the Doctor in Health Administration. The course is entirely online and asynchronous with terms that are 12 weeks in length. Discussion posts are submitted weekly, and assignments are also submitted weekly and are due at 2:00 a.m. on Monday morning. Assignments are graded with a standard rubric provided by the course designers, and late assignments are penalized at 25% per day late. Instructors do not design the course; their role is to facilitate, answer questions, and grade papers. There are no tests. Class sizes typically are fewer than 15 students after dropouts. The course subject is quantitative reasoning. The graded assignments are exercises demonstrating the ability to use SPSS software to test hypotheses. Only one instructor taught all sections of the course analyzed in this project.

Sample

Data were obtained from the gradebooks of the class sections included in the study (14 consecutive sections beginning in the spring term of 2017 and ending after the summer term of 2020). The sample size was 157 students. The proposal was approved by the university Institutional Review Board and received administrative institutional approval.

Variables

The dependent variables were two measures of academic performance: the final percentage score and the final percentage score rank-transformed with higher values indicating higher scores. The rank-transformation was performed to reduce outliers and normalize the distributions. The primary independent variables were two measures of timeliness: (a) Early Submission (Early1×4-submission of at least one assignment more than one day early in the first four weeks of the term); and (b) Just-in-Time (JIT1×4-submission of at least one assignment in the last two hours before the deadline). Students who were classified as disabled and allowed to submit late every week without penalty were classified as Just-in-Time rather than late. Both timeliness variables were coded as a dummy variable with 1 for yes and 0 for no. Students could be classified as Yes on both measures and this happened eight times. Failing status (Fail4) was scored as 1 for yes if the percentage score was less than 80 at the end of week 4 and 0 for no. The covariates were year (2017, 2018, 2019, 2020) and term (1 = spring, 2 = summer, 3 = fall, 4 = winter).

Analysis

The statistical significance of the timeliness measures was tested via univariate analysis of variance in the means of the academic performance variables. Significance was set at $p < 0.05$. The general linear model procedure in SPSS was used to test the independent effects of the variables found to be significant in the univariate analyses.

RESULTS

Means of the two dependent variables for early and not-early submitters are shown in Table 1. Early submitters (42.7% of the sample) had significantly higher means on both percentage grade and the rank of the percentage grade. The difference between the means of percentage grade was 5.02% ($p < 0.006$). The means for rank of percentage grade for early and not early were 95.04 and 67.06, respectively ($p < 0.001$). The means of the dependent variables were not significantly different for JIT students in comparison to not JIT (Table 2). JIT students comprised 33.1% of the sample.

Table 1. Means of Early Submission Status

Early1×4		Percentage Grade (P=0.006)	Rank Pct Grade (p<0.001)
0	Mean	82.62	67.06
	N	90.00	90.00
	Std. Deviation	12.78	41.79
1	Mean	87.64	95.04
	N	67.00	67.00
	Std. Deviation	8.37	45.56
Total	Mean	84.76	79.00
	N	157.00	157.00
	Std. Deviation	11.36	45.47

Table 2. Means by Just-in-Time Status

JIT1x4		Percentage Grade (P=0.851)	Rank of Pct Grade (P=0.114)
0	Mean	84.64	83.04
	N	105.00	105.00
	Std. Deviation	13.24	47.74
1	Mean	85.01	70.85
	N	52.00	52.00
	Std. Deviation	6.11	39.68
Total	Mean	84.76	79.00
	N	157.00	157.00
	Std. Deviation	11.36	45.47

Table 3. Means by Failing Status

Fail4		Percentage Grade (P<0.001)	Rank of Pct Grade (P<0.001)
0	Mean	88.12	92.68
	N	122.00	122.00
	Std. Deviation	5.51	40.11
1	Mean	73.07	31.31
	N	35.00	35.00
	Std. Deviation	17.42	27.32
Total	Mean	84.76	79.00
	N	157.00	157.00
	Std. Deviation	11.36	45.47

Table 4. Means by Term

Term		Percentage Grade (P=0.986)	Rank of PCT Grade (p=0.825)
1	Mean	84.92	82.96
	N	39.00	39.00
	Std. Deviation	12.65	46.54
2	Mean	84.31	75.23
	N	55.00	55.00
	Std. Deviation	12.33	43.23
3	Mean	84.95	76.86
	N	28.00	28.00
	Std. Deviation	9.04	44.36
4	Mean	85.15	82.23
	N	35.00	35.00
	Std. Deviation	10.33	49.77
Total	Mean	84.76	79.00
	N	157.00	157.00
	Std. Deviation	11.36	45.47

Table 5. Means by Year

Year		Percentage Grade (p=0.128)	Rank of PCT Grade (p=0.139)
2017	Mean	86.85	86.84
	N	44.00	44.00
	Std. Deviation	7.46	49.35
2018	Mean	85.70	85.15
	N	46.00	46.00
	Std. Deviation	10.31	43.10
2019	Mean	81.54	67.09
	N	47.00	47.00
	Std. Deviation	15.80	43.88
2020	Mean	85.56	75.60
	N	20.00	20.00
	Std. Deviation	6.26	42.45
Total	Mean	84.76	79.00
	N	157.00	157.00
	Std. Deviation	11.36	45.47

Failing status was strongly associated with the means of the dependent variables (Table 3). Students who were failing at week 4 (22.3% of the sample) had a mean final grade of 73.07. (A grade of 80% and above is considered passing; students earning less than 80% must retake the class.) In contrast, students not failing at week 4 had a mean final grade of 88.12 ($p < .001$). The mean rank scores showed a similar pattern (mean difference 61.37, $p < .001$). No significant differences were found by either year or term (Tables 4 and 5).

The general linear model-univariate was used to test the independent effect of early submission status on the rank of percent grade (Table 6). The variance explained by the model overall indicates a strong effect (partial eta square = .353), indicating that about 35% of the variance in academic performance was explained by the two independent variables. Only the regression results for the ranked variable are shown because outliers prevented the model for the unranked grades from meeting the assumptions of linear regression analysis. Fail status had a partial eta square of .287 ($p < .001$). Early submission was significant at $p = 0.004$ but the partial eta square was weak (.052).

DISCUSSION

This paper reports on a study of 157 doctoral students enrolled in an online quantitative

Table 6. Independent Effects on Rank of Percent Grade

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	113910.569a	2	56955.285	42.054	.000	.353
Intercept	426979.906	1	426979.906	315.271	.000	.672
Fail4	83850.140	1	83850.140	61.913	.000	.287
Early1×4	11490.645	1	11490.645	8.484	.004	.052
Error	208566.431	154	1354.327			
Total	1302314.000	157				
Corrected Total	322477.000	156				

a. R Squared = .353 (Adjusted R Squared = .345)

reasoning class using simple and novel timeliness measures. The data collection methodology was low-tech in comparison to studies extracting data from learning management systems (LMS). For example, in a recent report LMS activity data from 4989 students was analyzed to identify predictors of academic performance (Conijn et al., 2017). Most of the r-squares reported from the multiple linear regression analysis were less than 0.25, despite the large sample size and large number of predictors. LMS studies require special permissions and data extraction skills. They also require the reader to see meaning in click counts, which might be counter-intuitive for some. In contrast, simple visual examination can be used to identify early submitters in the first four weeks and immediate action can be taken by the instructor.

Failing status was controlled in the analysis and found to be the strongest predictor of academic performance. Generous admission standards are intended to increase the accessibility of higher education to all, a laudable and achievable goal, but one consequence of this policy is enrollment of some students who are not developmentally prepared for the demands of the program. They may lack basic computer skills, reading and writing skills, or the willingness to do the necessary work. As a result, a nonzero failure rate is both expected and necessary, lest universities all become diploma mills. Academic ability is an important determinant of success in higher education (O'Connell et al., 2018) and its absence is not under the control of the instructor.

This study found statistically significant results with weak effects for one of the timeliness variables: early submission one time in the first four weeks. Studies of academic performance typically report weak effects even when statistical significance is achieved (Walsh, 2020). In this study, being an early submitter independently predicted a 5.1 percent increase in the final percentage grade. This is enough to make the difference between an A and B or between a C and B. To put this effect into perspective, we can compare it to the effect of tutoring on final percent grade in a calculus class. Three tutoring sessions were found to increase the final grade by 1 percent (Rickard & Mills, 2018).

Just-in-Time submitters were not found to have lower or higher means than other students in this analysis. Submitting at the last minute may allow student to optimize some of the personal goals but it neither helps nor hurts their final grades in this class.

LIMITATIONS OF THE STUDY

This study involves only one instructor for all the sections analyzed and may be subject to instructor bias. In addition, the sample is small, thus limiting statistical power. Demographic variables such as age, gender, and race are not included in the gradebook and were not available for analysis. The study is limited to one type of class (quantitative reasoning), one type of instruction (asynchronous online with no tests in small classes), and one type of student (doctoral students in the health sciences). The findings may not be generalizable to other type of classes, types of instruction, or types of students. Finally, the small sample offered limited statistical power.

Despite these limitations, the findings reported here are potentially useful for instructors of similar courses. Flagging early submitters creates the opportunity to reach out to them with encouragement since they might be able to apply their executive functioning skills to improve their grades. This kind of targeted outreach, perhaps via email messages, could foster a greater sense of classroom presence (Cung et al., 2018) and engagement in the class. Additional research is needed to verify the findings, test new predictors that are equally simple, and evaluate the effects of classroom interventions.

This analysis also reveals that rank transformations of academic performance variables can be useful to eliminate outliers and normalize distributions. Overall, the study demonstrates that instructors can monitor timeliness easily among their students for the purpose of improving classroom performance.

RECOMMENDATIONS

Recommendation for practice #1: Instructors should consider being flexible about office hours and accept email queries and phone calls throughout the day.

Recommendation for practice #2: Instructors should encourage students to take advantage of statistics tutors and help sessions provided by the university.

Recommendation for practice #3: Instructors should consider sending encouraging messages to students who have submitted early to reinforce the behavior and also sending messages to students who have expressed worry to see if they are feeling better about the course.

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