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Using Registration Timing as an Early Indicator of At-Risk Students in an Online STEM Course

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Abstract

Aim/Purpose	Early identification of students at risk of not achieving course learning objectives enables instructors to intervene earlier to help students succeed. One of the first student course engagement activities is registration. This study aims to determine if registration timing correlates with student success in an online STEM course.
Background	Student success is based on achieving course learning outcomes. Students who register very late may have a lower probability of successfully passing challenging courses, adversely impacting student retention. Earlier instructor intervention with at-risk students may improve student academic achievement.
Methodology	This study analyzed historical data of 193 student numerical course scores and registration timings for a recently updated introductory management information systems and data analysis course at a university in the southeast United States. The course was delivered online over nine-week periods, by two different instructors, over two calendar years comprising one academic year. The response variable, overall course score, was evaluated based on the student's course registration timing relative to the course start date.
Contribution	We examined the relationship between registration timing relative to course start date and academic performance as measured by overall course score and letter grade. At a statistically significant level, we found that students who registered very late earned, on average, one letter grade lower than students that registered earlier in the registration window.

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Findings	The analysis reveals that registration timing correlates to course scores. Also, 45% of students that registered after the course start date failed the course, and the overall course scores of late registrants were lower, indicating that very late registration may identify at-risk students.
Recommendations for Practitioners	For students, carefully consider the decision to register for a STEM course late and understand why you delayed registering. Can you purchase the text and access codes to catch up on the first week's assignments? Will you have the time to work harder in the first few weeks of the course to catch up? For instructors, be aware that students that register late for a course are at risk of not doing well and intervene if you observe the student falling behind the rest of the class or not engaging with the course. Administrators should carefully consider policies allowing late registration for STEM courses and its effects on student success and retention. What might seem like a promising idea in the short term (allowing a student to register late) may have deleterious long-term effects on student success and retention.
Recommendation for Researchers	Researchers may consider the relationship between course registration timing and learning outcomes. Additional data collection on registration timings and course outcomes combined with data collected from students through surveys could shed light on the decision-making behavior of students that register for courses late in the registration window.
Impact on Society	Improved student academic performance enables better use of academic resources. Students with higher academic performance qualify for scholarships, internships, and better job opportunities. For teachers, less time spent on low-performing students allows the instructor to challenge students academically to achieve higher levels of understanding. Finally, universities may enjoy higher student retention, and society will benefit from better use of financial resources dedicated to higher education.
Future Research	Expanding the dataset to include other schools, courses, and learning modalities may provide additional insight into students' registration behavior. Research on intervention strategies' effectiveness based on student characteristics could be beneficial. Additional research on factors affecting students' course registration decision-making process is required. Finally, a longitudinal study considering student registration timing throughout a degree program could identify chronic late registration behavior. Further study of the relationship between late registration and degree completion could provide valuable insights.

Keywords	higher education, academic achievement, student retention, course registration behavior, learning interventions, at-risk students, linear regression

INTRODUCTION

Student retention has been the focus of many research articles (Muljana & Luo, 2019) and is a common point of discussion for educators. The genesis of this study came from a discussion between two instructors of a science, technology, engineering, and mathematics (STEM) course that had recently been modified to include additional statistics and writing assignments when one of the instructors noted in passing that it seemed that students that registered for the course after the official start date of their online course seemed to struggle more with course assignments. The other instructor concurred, having noticed the same phenomenon. However, both instructors were unsure if the effect was significant or just a perception. Identifying struggling students became increasingly important during the COVID-19 pandemic and the disruption to learning environments (Cao et al., 2022). Institutions incorporated more remote learning opportunities to enable students to continue their academic journey, but online courses can make it harder for instructors to engage with students and identify at-risk students resulting in lower retention rates (Muljana & Luo, 2019).

Students who struggle academically in a course may require additional interaction with the instructor to achieve the course learning objectives and complete the course of instruction, as success is determined by more than just talent (Buzzetto-Hollywood et al., 2019). An at-risk student may drop, withdraw, or fail the course without timely intervention, and identifying them early across various phases of education is essential (Chen et al., 2020). However, the idea that identifying at-risk students could start at course registration became apparent after an initial data review. Late registration may indicate a particular student needs additional motivation or learning resources. This insight prompted the authors of this study to conclude that further analysis should be conducted on registration timing and student performance. Fortunately, the learning management system being used by their organization had captured the date a student registered for the course, which could then be paired with the overall course score of recently completed courses.

This work aims to identify if a simple analysis of registration data could be used to identify students that could benefit from early interventions. Specifically, this research asks:

R.Q. 1: Is there a statistically significant relationship between course registration timing and course score?

R.Q. 2: Can instructors use registration timing as a signal to identify at-risk students?

This research includes three key objectives. First, we set out to understand if there is a relationship between course outcomes and registration timing. Second, if a relationship is observed, we explore the implications of that relationship to academic success. Third, we seek to demonstrate the feasibility of using data analysis to identify at-risk students before the course starts. In other words, could registration timing be used to identify at-risk students in an online STEM course?

This paper is organized as follows: The next section presents the background for this research related to factors affecting the registration decision, predictors of student success, and intervention strategies to help at-risk students. After the background, the following sections present the research methodology, data collection, analysis results, and findings. This research concludes by highlighting implications for educators and researchers, study limitations, and a conclusion. This research should interest our colleagues seeking to use data analysis to identify students that could benefit from early intervention to promote student success.

BACKGROUND

The background for this research begins with a review of factors that influence registration and research related to the predictors of student success, followed by a discussion on intervention strategies.

FACTORS AFFECTING THE REGISTRATION DECISION

There is no standard demographic profile of late registrants because of significant variations in individual behavior, college cultures and processes, and definitions of late registration. However, common reasons students used to explain late registrations were institution policies, bureaucracy, medical and financial difficulties, work schedules, transportation, and general life circumstances in the modern world (Tompkins & Williams, 2015).

According to Maalouf (2012), the most frequently reported reasons for late registration were related to late decision-making on attending college, financial aid processing, lack of awareness regarding the start of classes, failed plans to attend another college, delayed processing in college procedures, habits of procrastination, and family obligations. Maalouf recommends that educators meet with late registrants outside class to review the course syllabus and expectations, carefully discussing missed assignments. Educators should encourage and support all students, especially late registrants, to engage with their peers in and out of the classroom.

Predictors of Student Success

Several efforts have been made to research the indicators of student engagement as predictors of course outcome success in higher learning. Few have used registration timelines as an independent variable (Siefken, 2017). Li et al. (2021) selected several engagement metrics (not including the registration timeline) and found a linear mixed model showing that all engagement metrics positively relate to the final grade. While positively correlated, the relationships were not linear, inviting further investigation. However, student engagement is a precursor to student success in most blended learning environments (Gong et al., 2018).

Another multivariate investigation found 14 variables of significance. The study used a stepwise regression analysis to find that only four variables – reading and posting messages, content creation contribution, quiz efforts, and the number of files viewed – accounted for 52% of the student final grade contribution (Zacharis, 2015). None of the variables examined included course registration timing.

Hu et al. (2021) constructed a student engagement model developed using the environment of a programming course in a blended learning format. The model used login files, class attendance, assignments, forum participation, peer evaluation, homework, quiz results, question-and-answer participation, and other variables. Again, Hu et al., did not appear to consider registration timing. The correlation coefficients of the variables to the final course grade varied greatly and were not intuitive, inviting more research.

Liu et al. (2021) used a survey approach to delineate the most appropriate inputs for several dependent variables and then used structural equation modeling to determine the correlation of these factors. Their mixed linear model explained 42% (R^2) of the variance in final grades, showing a partially linear relationship between learning engagement as defined by the metrics and final grades. Researchers have found that behavioral engagements affect student outcomes in distance learning formats. In one study (Hsueh et al., 2022), watching course-relevant videos correlated with better student learning outcomes, and indicators of cognitive engagement were found to be more reliable predictors of student success, suggesting that dependent variables should be refined to define this more precisely above simple student engagement.

Some limited studies have been published on whether registration timing has influenced student performance. Siefken (2017) found that the time from when a student was allowed to register to when they registered impacted student performance and suggested that delayed registration is an indicator of the student's diligence. Siefken used 16 years of university registration and grade information and found that the overall G.P.A. of the students declined if they registered later but also cautioned on generalization and several confounding factors that may influence the results, such as the student's G.P.A. influencing their registration timing. Siefken suggested that registration timing be included in performance models. While this study suggested an overall decline in G.P.A., the extent to which students were at risk was not clear, and it called for additional study due to the limitation of the sample to a single system.

Examining registration timing and grades at community colleges has also found that late registration can be a factor that can influence success and has led to policy changes at some institutions, including disallowing late registration (Nourie-Manuele, 2018; O'Banion & Wilson, 2013; Smith et al., 2002; Tompkins et al., 2019; Tompkins & Williams, 2015). The studies on community college students found that student performance and retention were worse among late-registering students. However, the studies did not detail performance within the groups of students.

Additional research on online education by Pathak (2019) found that late registration may cause students who wait to register to have a limited selection of face-to-face courses and may not match their appropriate learning style. Overall, the literature indicates that determining factors that hinder student success or identify at-risk students is a topic of interest. However, the research on using registration timing to determine student success at four-year institutions offering online courses was limited. However, registration timing could provide an easily accessible early indicator for instructors of at-risk students who may need an intervention at institutions where late registration is allowed.

Intervention Strategies

Educators have options for intervening with at-risk students to avoid poor performance once identified. However, one must be careful as to how performance is measured. Instructors must develop and validate a conceptual framework for learning outcomes and assessment of achievement and learning (Shavelson, 2007). In contrast, Priddy (2007) found that carefully examining the learning outcome framework is essential—indicating class performance and learning divergence. However, for this paper, the authors confined the research focus to outcomes in final grades, which does not strategically address the learning, in contrast to the performance outcomes referred to by Priddy and Shavelson. The authors of this study accept that the transition from apparent class performance to ultimate learning outcomes is an area for future research.

Assessments of learning outcomes should be part of a "coherent conceptual framework that aligns assessments with desired learning outcomes" (Shavelson & Huang, 2003). The framework could vary greatly and should acknowledge that learning outcomes differ from class performance. These authors contend that intervention based on learning outcomes across multiple courses may be the best strategy and that others suggest a need to foster a change in mindset (Buzzetto-Hollywood et al., 2019; Buzzetto-Hollywood & Mitchell, 2019). While this research examines performance in one course, we hypothesize that earlier identification of at-risk students by noting registration timing may allow more significant opportunities for earlier and more effective interventions.

Muljana and Luo (2019) conducted a systematic review and grouped the interventions by what an institution could do and what an instructor could do. Institutions could provide support such as tutoring services, orientation, and curriculum design, while instructors could foster engagement, facilitate learning, and evaluate course design. According to Gong et al. (2018), educators can use strategic methods to promote student engagement and achievement when teaching occurs in blended learning environments, such as interventions based on learning analytics. These authors proposed using indicators to determine which students should receive social media intervention via messages on a preferred social medium. The social media interventions provided by the instructor escalated from no intervention at all or a generalized intervention when indicators were low for a high percentage of students to private messages to individual students when indicators were high. The response to these actions was positive and encouraging.

However, a conversation with the student may indicate that the cost of resources deterred their success, as late registration may indicate economic distress for students. In such cases, an intervention may be providing free open-source or unlimited book subscriptions to improve success (Buzzetto-Hollywood & Thomas-Banks, 2022) or ensuring that the student has access to the proper networks and technology (Parkes et al., 2015). Other instructors have worked to create custom video libraries so that students may have free access to the material across multiple courses (Larson et al., 2021).

To find appropriate responses to registration timelines to indicate a higher risk level for individual students, the authors have formulated several intervention strategies that may reduce the risk of poor class performance. These are not canonical and could be altered, supplemented, or redacted as an educator sees fit. This list is designed to provide practical actions and stimulate further discussions to determine the root cause of a potential negative learning result.

The list of interventions includes, but is not limited to, the following:

- Instructor Interventions:
  - Contact at-risk students (those registered within seven days of the course start date) and discuss the peril of falling behind early.
  - Provide graded assignments early in the term to confirm the identification of at-risk students.
  - Review of student engagement analytics in the L.M.S. and appropriate engagement with students with low engagement (Foster & Siddle, 2020)
  - Immediately contact students that fail to turn in the first graded assignment.
  - Provide additional access to relevant course resources (videos, extra practice assignments, and other resources.)
  - Provide access to free resources to help students that may not have the academic foundation to excel in a STEM course (Buzzetto-Hollywood & Thomas-Banks, 2022; Larson et al., 2021).
  - Promote a sense of community in the online course, a task that can be difficult in remote learning situations.
- Administration Interventions:
  - Limit late registration for students with low GPAs for specific courses.
  - Institute a policy requiring late registration students to call/meet/video chat with the instructor.
  - Track at-risk students' registration timing. If late registration becomes chronic, schedule an intervention with the student.
  - Carefully consider the institutions' late registration policy (Keck, 2007).

Based on educational research, an intervention strategy should be determined for individual courses and learning modalities. However, a better learning outcome strategy for intervention, involving the entirety of the body of knowledge desired for the student and triggered by multiple indicators of risk status, should be developed and implemented for students who consistently show indicators of possible poor performance. This research does not encompass such a strategy or provide the number of indicators required to develop a complete framework for identifying at-risk students. However, it provides one dependent variable for such a strategy and a 'localized' indicator for course-level intervention.

METHODOLOGY

As stated, this research aimed to identify if there was a significant relationship between course score and registration timing, and if so, explore the nature of that relationship to determine if it could help identify at-risk students. To answer the first question, the authors used linear regression. To explore the implications of any significant relationship and answer Research Question 2, the authors examined the frequency of letter grades by registration period. Existing historical data limited the study's scope. Thus, only one aspect of student course registration activity, registration timing, significantly predicts the student's overall course score. The following sections outline the research setting for this study, the data collection, and subsequent analysis.

RESEARCH SETTING

The data for this study originated from courses completed before the instructors discussed the possibility that late registration might correlate with poor student performance. The dataset initially consisted of 193 observations of numerical course scores and related registration timings relative to the course start date. The observations were from students taking an introductory management information systems and data analytics course, a related science, technology, engineering, and mathematics (STEM) topic. The students attended a university in the southeast United States and usually took this class as a junior. The course topic is often difficult for students, as it introduces concepts about information technology, information systems, databases, data analysis, and communicating analysis results to decision-makers. The remote learning course that provided this study's data took place before the COVID-19 pandemic and was delivered over nine weeks using a learning management system with links to the textbook, assignments, content, and videos. Historical data was collected from different cohorts of students who took the course in four different terms, covering two years and two different instructors. The primary response variable is a student's course score, which could range from 0 to 100. The independent variable data was the student's course registration timing relative to the course section start date. While the instructors would have intervened by reaching out after assignments were missed, this usually occurred at least a week after the nine-week course was completed and for some assignments after two full weeks due to late registration procedures. The delay in the early identification of at-risk students is particularly problematic in the short, nine-week-term course.

DATA COLLECTION

The learning management system in use at the time provided the student course score, registration timing, instructor, term, section, and which part of the academic year the course took place. The registration window for each term was published in periodic course schedules. Two hundred forty-three initial observations included withdrawals, drops, and other missing data, leaving 193 observations for analysis. The data collected included six attributes, two continuous variables, and four categorical variables.

Continuous variables:

- RegTiming is the date the student registered for the course minus the date the course started (e.g., A positive RegTiming indicates that the student registered for the course after the course started).
- CrsScore is the numerical grade earned by the student for the course, which ranges from 0 to 1, with 1.0 representing 100%, a perfect course score.

Table 1 provides the descriptive statistics of the continuous variables, Figure 1 displays the registration timing relative to the course start date (RegTiming), and Figure 2 provides a histogram showing the distribution of course scores (CrsScore).

Table 1: Descriptive Statistics for Continuous Variables

Variable	N	Mean	Std Dev	Min	Max	Sum	Skew	Kurtosis
RegTiming	185	-14.96	13.50	-53	8	-2,767	-0.57	-0.56
CrsScore	185	0.76	0.20	0.03	0.97	140.97	-2.12	4.40

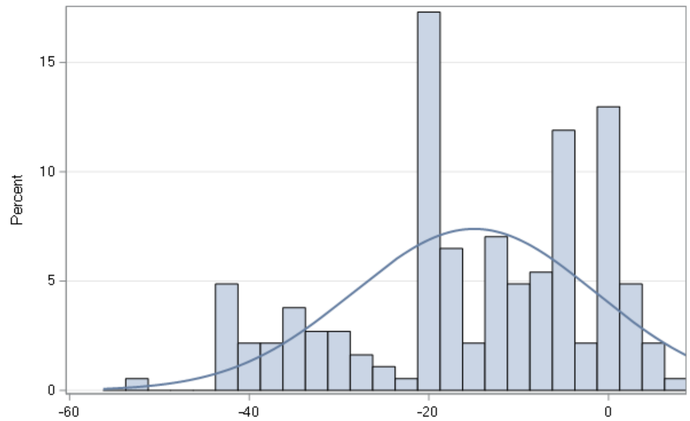

Figure 1: Histogram of RegTiming

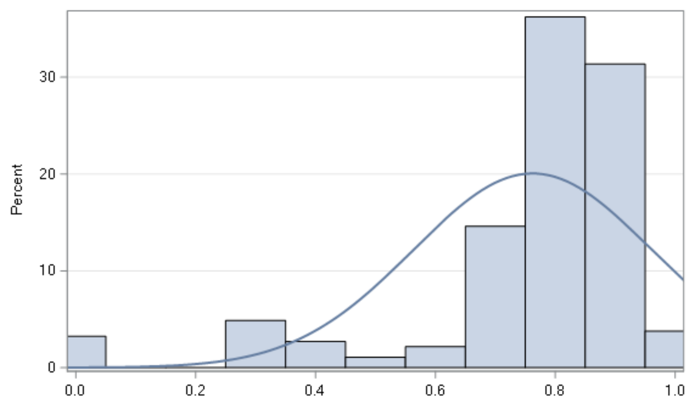

Figure 2: Histogram of CrsScore

Categorical variables:

- The Instructor variable represents the instructor for the course section, two levels, A and B.
- The Year variable is the calendar year of the course, with two levels, Y1 and Y2. The data came from one academic year, which started in the Fall and continued to the Spring semester—not used in the final linear regression model.
- The Term is nine weeks with four levels: One, Two, Three, or Four. There are two terms per semester. This variable was also not used in the final linear regression model.
- The Section variable identifies the course section for a particular Year and Term, with three levels: A, B, and C. Not all terms have all three levels.

Tables 2, 3, 4, and 5 below detail the distribution of observations of registration timing and course score by the level of various categorical variables. An analysis of RegTiming and CrsScore by Instructor, Year, Term, and Section revealed no statistically significant differences. Data diagnostics indicated skewed model residuals, with eight outliers in the independent variable RegTiming that ranged from -152 to -84 days (about three months) before the course start date. The average CrsScore for these eight observations was 80.3%. Since it was unclear how these students could register far before the official registration window, these observations were not in the data used for the linear regression. The removal of RegTiming outliers left 185 observations.

Table 2: Observation Count by Instructor

Instructor	Count	Percent
A	124	67.0%
B	61	33.0%

Table 3: Observation Count by Year

Year	Count	Percent
Y1	102	55.1%
Y2	83	44.9%

Table 4: Observation Count by Term

Term	Count	Percent
One	27	14.6%
Two	56	30.3%
Three	61	33.0%
Four	41	22.2%

Table 5: Observation Count by Section

Section	Count	Percent
A	94	50.8%
B	50	27.0%
C	41	22.2%

RESULTS AND FINDINGS

The following sections present the findings from this study exploring the use of data analysis for the effects of registration timing and early identification of at-risk students that may need intervention. The following subsections present the research questions, methodology for analysis, and findings.

RESEARCH QUESTION 1

The first research question was, "Is there a statistically significant relationship between course registration timing and course score?" A linear regression using an alpha value of 0.05 was conducted, controlling for the Instructor and Section. The Term and Year variables were redundant in that Instructor and Section were sufficient to delineate the separate groups of students. Each section was limited to 40 students or less, allowing limited control for course size.

The linear regression model was significant ($R^2 = .13$, $F(4, 180) = 6.78$, $p < .0001$). The parameter estimate for Registration Timing (RegTiming) (-0.006) was a significant predictor ($t = -4.74$, $p = <.0001$), indicating that the course score declined as RegTiming approached the course start date (Table 6). The post hoc statistical power calculation for multiple regression using three predictors and an observed R^2 of 13%, alpha of 0.05, and sample size of 185 was 0.99, indicating sufficient power.

Table 6: Parameter Estimates

Variable	Estimate	S.E.	95% CI		*p*
			LL	UL	
Intercept	0.688	0.053	0.584	0.792	<.0001
RegTiming	-0.006	0.001	-0.008	-0.003	<.0001
Instructor A	0.021	0.036	-0.049	0.092	0.551
Instructor B	0	0	.	.	.
Section A	0.026	0.037	-0.1	0.047	0.481
Section B	-0.039	0.042	-0.122	0.045	0.363
Section C	0	0	.	.	.

RESEARCH QUESTION 2

To address Research Question 2, "Can instructors use registration timing as a signal to identify at-risk students" we determined that looking at the frequencies of the student grades grouped by their registration timing would be a simple yet practical approach. In this way, we could determine if the probability of poor performance (low course scores) increased based on registration timing, thereby identifying at-risk students. Three additional categorical variables were derived from the collected data to accomplish this analysis. Table 7 details how the RegGroup level was determined, and the assignment of Grade Level is based on the CrsGrade value and defined below. Based on an understanding of the course work required, the researchers wanted to identify if a low assignment completion rate was evident by the occurrence of extremely low course scores (< 33%) of the overall course score and a possible cause for course failure. If so, did students that registered late have a higher frequency of extremely low scores? An additional derived variable, "Extremely Poor Performance" (E.P.P.), was created to answer this investigation aspect.

Derived categorical variables:

- RegGroup = Registration timings were divided into five logical groups based on the relationship to the course start date. RegTiming less more than 40 days (about one and a half months) before the course start date was coded as "Very Early," RegTiming less than 21 days (about three weeks) before the course start date was coded as "Early," two weeks before the course started as "Normal," less than a week as "Late," and after the course start date as "Very Late." RegGroups are delineated in Table 7.
- Grade Level = Student scores grouped by the equivalent grade level. Scores higher than or equal to 90% would result in an "A" letter grade and be recorded in the data set numerically as a "4." Five levels of Grade Level were derived, greater than 90% is an "A," greater than 80% and less than 89.9% were recorded as a "B," and so forth.
- E.P.P. (Extremely Poor Performance) = Student's course score was less than or equal to 33%: two levels, 1 for True, 0 for False.

Registration Timing is relative to the course start date. Negative numbers are days before the course started, 0 is the course start date, and positive numbers indicate registration occurred after the course started.

The purpose behind creating these derived categorical variables was to better understand the practical impact of registration timing on student course scores for the course used for this study. While a linear regression may illustrate the relationship between the independent variable and dependent variable, it is harder to understand the "real world" implications of the results as factors such as achieving their desired grade level or disengaging with the course may reduce the number of points that would otherwise have been obtained.

Table 7: RegGroup Level Assignment

RegTiming	RegGroup	Explanation
-152 to -64	Very Early	These students registered under unusual circumstances more than two months early. Online course registration usually opens about one month before the class starts. These records were removed as unusual outliers.
-63 to -22	Early	Holidays between terms can sometimes extend the registration window, but again the students in this group opted to register as soon as possible and not wait.
-21 to -8	Normal	Registration for online courses is typically open approximately three weeks before the start of class.
-7 to -1	Late	Students in this group have delayed registering and may have difficulty getting texts, access codes, and other materials ready before the class starts.
0 to 8	Very Late	This group contains students that waited until the class had already started and may already be behind. They may struggle to find open sections, and the administration may have already closed some sections due to low enrollments.

In examining the grade distributions by registration category, we found that students who registered "Very Late" had a 45% failure rate and represented 64% (14 of 22) of the failures of the course (see Table 8, and Table 9), suggesting that students registering "Very Late" had a much higher risk of course failure. While a significant percentage of the very late students failed, 29% obtained either an "A" or a "B," indicating that some students can register late and still find success. All the students who registered early obtained at least a C in the course, suggesting that students who can be more proactive in registration are less at risk.

Table 8: Distribution of Grade Level and Registration Group by Count

Grade Level	Early	Normal	Late	Very Late	Total
A	13	15	3	4	35
B	19	34	13	5	71
C	9	12	20	8	49
D	0	4	4	0	8
F	0	5	3	14	22
Total	41	70	43	31	185

Table 9: Distribution of Grade Level and Registration Group by Percentage

Grade Level	Early	Normal	Late	Very Late	Pct of Total
A	32%	21%	7%	13%	19%
B	46%	49%	30%	16%	38%
C	22%	17%	47%	26%	26%
D	0	6%	9%	0	4%
F	0	7%	7%	45%	12%
Pct of Total	22%	38%	23%	17%	100%

In examining the registration groups by looking at E.P.P. frequencies, we find that out of the 13 students who were E.P.P., 10 of the students were in the "Very Late" registration group, representing 77% of the E.P.P. population. The "Very Late" students had ten out of 31 students who failed to obtain 33% of the course score, indicating that 32% of that group were E.P.P. (see Table 10), supporting the observation that students who registered very late had a higher probability of being E.P.P. and therefore more at risk. Additionally, we examined the average scores for the registration groups and found that students who registered very late averaged a score of 0.56, nearly 30% lower than the early registering students, signaling that this group is more at risk.

Table 10: Distribution of Extremely Poor Performance (E.P.P.) by Registration Group

RegGroup	N	Pct of Obs	N E.P.P.	% E.P.P.	Avg CrsScore
Early	41	22%	0	0%	0.85
Normal	70	38%	3	4%	0.80
Late	43	23%	0	0%	0.76
Very Late	31	17%	10	32%	0.56
Total / Pct	185	100%	13	7%	0.76

While the instructors attempted to intervene by engaging students after seeing initial assessment results online, contacting the students is limited once students have disengaged with the course. Therefore, identifying potential E.P.P. students may be more critical than regular poor performers as the intervention needs to be earlier in online courses. Using registration timing as a proxy to signal potential E.P.P. students will allow the instructor to focus early interventions on that group of students.

DISCUSSION

The results of this study address two key research questions: 1) Is there a statistically significant relationship between course registration timing and course score? Furthermore, 2) Can instructors use registration timing as a signal to identify at-risk students? To begin, the findings from this study do show that students' overall course scores were correlated with registration delay. This finding suggests that students who delayed course registration had a higher failure rate for the course than students who registered earlier in the registration window, with a correlation between when the students registered and their ultimate grade showing a correlation, which is consistent with findings in other studies at other universities and junior colleges (Nourie-Manuele, 2018; O'Banion & Wilson, 2013; Siefken, 2017; Smith et al., 2002; Tompkins et al., 2019).

Regarding the second research question, our results do indicate that extremely late registration may identify at-risk students, with 45% of the students who started after the course started failing and 32% of those registering after the course started not successfully earning at least one-third of the points available in the course. Very late registration may signal to the instructors that for this course, very late registrants may require early intervention as they begin the course, which is also consistent with research conducted in community colleges that examined this phenomenon, thereby extending the literature as it examines students of junior and senior standing at a four-year institution. Given the data used for this study, the researchers could not determine if late course registration was a chronic behavior or a single instance of registration timing behavior, which could be a point for future research.

While the instructors had reached out to students on any missing assignments or regular poor performance, the ability to contact online students was limited when they had disengaged from the course, so it is important to intervene before this stage has been reached. Therefore, reaching them before too many assignments are past due is essential. While using late registration to identify at-risk students in every course may be inappropriate, it should be considered in online STEM courses, especially those required by students not pursuing STEM degrees. The department has made several changes to this course since the initial course deployment to address late registration issues and general challenges involved in a course rewrite. These include the creation of a video library as a free option to support knowledge gaps in the students, switching to an online textbook that has a two-week free trial period that makes the resource available immediately, and making the other instructors aware of the potential identifier so that they can contact and monitor late registering students. These interventions, the change in learning management systems, and the pandemic made immediate follow-up research impractical. However, several potential implications for educators and researchers are still detailed below.

Implications for Education

The are several important implications from this study for educators. First, delayed registration may signal to an instructor that a specific student may require additional attention as they start the course. Specifically, the student's preparedness for the learning tasks may already be behind the rest of the class, and policies such as delaying initial deadlines for early assignments may have caused the instructors to miss early warning signs before students began to disengage from the material. This signal to the instructor can be used in several ways, including increased attention to the students' assignments (quality and timeliness) and extra material to help the student early in the course before assessments indicate a problem. While prior research identifies at-risk students, at-risk students may only be identified well into the course execution after receiving the student's assignments and learning assessments. The early detection of at-risk students, followed by reasonable interventions, may improve student success and retention. Just the additional attention of the instructor may encourage the student (Muljana & Luo, 2019). Instructors and advisors can help students consider if they have the time or ability to get resources and complete any missed work before registering late for a course. Instructors should include an early graded assignment or assessment to verify the identification of at-risk students.

A second practical implication from this work is a discussion of appropriate and available intervention strategies to help at-risk students early in the course and positively influence course outcomes that their registration timing would otherwise suggest. Alternatively, the administration could also explore the need to prevent late registrations if interventions are insufficient, as failures result in reduced student retention.

From the faculty's point of view, implementing suggested interventions based on receiving a list of at-risk students provided by the Registrar should not be an onerous task. This early identification and intervention with at-risk students may result in improved learning outcomes for the student, higher scores, and contribute to student retention. Instructors in courses with fewer students may be able to identify late registration by their student rosters, but it would be good practice for learning management systems to add that designation. The authors noticed the loss of this functionality when the institution's learning management system changed. Instructors of online courses, especially new or rewritten ones, should be especially aware as the instructors would not have experience identifying potential issues.

Implications and Suggestions for Future Research

The research findings presented in this work contribute to the literature on student registration timing and course scores. This study provides a potential method to identify at-risk students early in a course before assignments and learning assessments are collected from the student. Identifying at-risk students is essential in online learning because online learning has become increasingly popular, and historically student retention rates for online courses are significantly lower than those in traditional environments (Muljana & Luo, 2019). This research topic may be significant for online instructors who may have a more challenging time identifying and contacting students who may disengage from the course if the student feels that they cannot pass after the initial assignments.

Future research might also identify more effective intervention strategies or guides for which strategies work best for at-risk students. For example, an intervention that ensures that at-risk students have their text by the first week of class or are provided with free learning resources may work for one type of student. In contrast, an intervention requiring a student to meet with the instructor via video conference to identify any barriers to success may be appropriate for other students.

More research on factors affecting the registration process and decision-making would help. Despite many studies, institutions are still searching for solutions to provide early at-risk indicators to their instructors (Muljana & Luo, 2019). Instructors with clear and timely signals can deploy effective interventions to keep at-risk students on track for success. Understanding the student perspective on registration would clarify why some students delay registration, as not all late registrants are alike. For example, future research may specifically survey students on their registration behavior and readiness to commit to learning challenging topics. Studies comparing more courses, instructors, and learning venues could be invaluable to helping instructors and administrators understand the factors associated with students' registration behaviors and establishing policies and interventions. Principle component analysis may help identify the primary factors affecting the intention to engage.

Additional research should include a longitudinal study examining chronic late registration and its correlation to degree completion. Additionally, research should be conducted to determine if late registration is a chronic condition or if new environmental factors trigger the phenomenon.

Finally, the learning venue and modality are other areas of interest. For example, this study only considered online learning sections with defined registration periods. Do the same behaviors exist for traditional face-to-face courses? Also, what impact does the length of the registration window have on students? Finally, the registration process, the registration information system, and the user interface could be fertile areas of research for administrators and faculty concerned about student retention and success.

Limitations

This research has several limitations. Specifically, this study only looked at one course at one university. Furthermore, the registration timing may be a proxy, comprised of more subtle behaviors that may be difficult to measure. Nevertheless, the findings from this work contribute to understanding student success. The use of existing historical data limited the use of demographic data that may have helped improve the analysis. This limitation could be addressed by expanding the research to other schools, courses, and learning modalities may provide additional insight into student registration behavior.

Conclusion

For the course used for this study, it appears clear that registration timing weakly correlated with course scores and might provide a signal of students at risk of disengaging from the course. Late registration can indicate that a particular student may need additional motivation to engage in the learning opportunity.

This study aimed to identify any significant correlation between a student's registration timing and course score. Based on the data available for this study, there seems to be a significant but weak relationship between delayed registration and course score. While the relationship is weak, the possible impact on students that register very late (after the course start date) is not. Students who register very late are likelier to fail the course and should be identified as at-risk.

The contributions of the paper are several. First, the overview of research on student challenges in higher education and our research findings indicate that early identification of at-risk students is possible. Specifically, our findings did show that the later in the registration window a student registers, the more likely it is that the student will struggle with meeting the learning outcomes for the course.

Secondly, the insight that late student registration is an identifier of at-risk students makes faculty more aware of the potential need for an intervention to help avoid student disengagement. Third, this research suggests several appropriate interventions for educators to help at-risk students early in a course before they fall behind in their coursework. Finally, this research provides implications for future research examining other factors that may impact the registration behavior of students and administrators' policy on late registration.

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