Investigating Systematic Variation in Academic Procrastination Behavior by Course, Assignment, and Student Characteristics

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Abstract

Procrastination has been linked to lower academic performance and sociodemographic achievement gaps in a variety of educational contexts, posing challenges to student success and educational equity. While prior research acknowledges that learning environments play a crucial role in shaping student procrastination alongside personal traits, there is a lack of solid empirical evidence on the connection between specific variations in learning environments and academic procrastination. This study provides a large-scale evaluation of the relationship between course and assignment characteristics and student procrastination behavior using a sample of 33,514 students across 3,169 courses at a US university. Using fixed effects linear regression models, we find that students tend to procrastinate less in courses with larger enrollment, non-introductory content, and well-structured deadlines. Procrastination is also lower for assignments with spaced-out deadlines, weekend deadlines, and a quiz or discussion post format. However, these patterns do not apply equally across all student groups. Male, ethnic minority, and first-generation college students exhibit higher levels of procrastination than their peers, especially for courses and assignments with specific characteristics. We suggest two instructional design strategies to help manage procrastination across student populations: (1) allowing more time before the first assignment deadline, and (2) ensuring adequate spacing between deadlines. This study provides large-scale evidence of the complex relationship between learning environment design, student characteristics, and procrastination.

CCS Concepts

• **Applied computing** → **Learning management systems**.

Keywords

Academic Procrastination, Instructional Design, Disparities in Learning Behaviors, Learning Management System

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1 Introduction

Procrastination is defined as the act of postponing the initiation or completion of an intended task despite potential negative consequences, and it is a widespread phenomenon in higher education and beyond [24]. While previous research has studied strategic procrastination used by some individuals to improve outcomes [8], the majority of current research suggests that procrastination is generally unfavorable and has negative effects on academic performance in academic settings [13]. Furthermore, recent empirical studies revealed the existence of sociodemographic gaps in students' procrastination behaviors, which can partially explain achievement gaps among college students [3, 21]. These findings highlight procrastination as a significant barrier to academic success, with the potential to further exacerbate educational inequities between groups of students with different identities and backgrounds.

While the socioeconomic, cultural, and psychological drivers of procrastination may be complex and difficult to change, there may be features of learning environments that educators can control to develop effective interventions that help students overcome procrastination [25, 32]. Survey-based research has suggested that course characteristics, such as the level of instructor support and deadline pressure, are related to the emergence of student procrastination [4, 9]. Prior research has also indicated that procrastination behaviors are influenced by academic task characteristics, such as the perceived interest, importance, and difficulty of course assignments [15, 25]. However, it remains unclear whether these findings hold true on a large scale and equally across diverse student populations. Overlooking potential disparities in procrastination patterns and underlying mechanisms across student groups poses the risk of misunderstanding the unique experiences of marginalized student populations, which may render interventions ineffective or even counterproductive and further exacerbate achievement gaps in higher education.

To better understand the relationships between academic procrastination, student characteristics, and learning environments –

specifically, course structure and assignment design – we perform a large-scale analysis of 4,171,584 assignment submissions by 33,514 students on a popular learning management system (LMS) deployed at a U.S. university. Following prior research, we operationalize procrastination behavior as the lateness of assignment submissions. We explored how procrastination relates to course and assignment characteristics across different student groups to answer the following three research questions:

RQ1: How are course structure and assignment design associated with students' procrastination behavior?
RQ2: How does student procrastination behavior vary across different student groups?
RQ3: Do the relationships between procrastination and course structure, as well as procrastination and assignment design, vary across different student groups?

The contribution of this study is three-fold. First, by leveraging large-scale educational data mining to examine the relationship between learning environment features and student procrastination, our study strengthens empirical understanding of how academic contexts relate to procrastination. This work expands existing research, which has primarily relied on theoretical discussions and self-report surveys with limited sample sizes. Our findings provide robust evidence that procrastination is not solely attributed to individual traits, but also linked to the social, contextual, and organizational aspects of learning environments.

Second, by taking students' sociodemographic backgrounds into consideration when analyzing their procrastination behavior, we contribute to the growing body of evidence on disparities in procrastination levels across different student populations, highlighting the need to address these gaps as part of the efforts to close the achievement gaps in higher education.

Finally, and most importantly, by investigating how the relationships between procrastination and learning environment features vary across student groups, we fill a critical gap in understanding how course and assignment characteristics correlate to student disparities in procrastination.

Our findings show that students with different identities and backgrounds exhibit different patterns in how attributes of the learning environment relate to their procrastination behavior. This underscores the need for both researchers and instructors to further explore the underlying mechanisms driving these disparities and to create more inclusive learning environments that minimize academic procrastination for all students.

2 Related Work

Procrastination has been studied in psychology and education research for many years. While some empirical studies suggest that the relationship between procrastination and achievement can be non-significant (e.g. [23]), or even positive if students functionally delay tasks to manage their time [8], most research considers procrastination as a failure in self-regulation. Two prior meta-analyses reported strong support for an overall negative relationship between procrastination and academic achievement [13, 28].

As is the case for other types of academic behaviors, the prevalence and causes of procrastination can vary across student populations, and these group differences can partly explain performance gaps. However, the literature examining this heterogeneity is comparatively scarce. For example, Balkis and Erdinç [3] found higher procrastination levels among male undergraduate students than their female counterparts; this gender difference also had a moderating effect on the negative relationship between procrastination and academic performance. With the prevalence of digital technologies and online learning, procrastination behavior becomes easier to measure, especially at scale. Using students' behavioral trace data in digital learning environments, Park et al. [17] identified no correlation between student background and procrastination. However, a recent large-scale study found that males, racially minoritized groups, and first-generation college students tend to exhibit higher levels of procrastination behavior compared to their peers, and that such sociodemographic differences can partially account for the gaps in students' course performance [21]. Our study adds to this emerging body of literature by systematically examining which features of the learning environment are associated with sociodemographic gaps in procrastination. Indeed, Sabnis et al. [21] identified substantial variation in procrastination behavior across courses in their sample, suggesting that future research ought to investigate sources of learning-environment-related variation.

The psychological literature theorizes procrastination as a type of self-regulatory failure associated with personal traits, intrinsic motivation, and external contextual factors [19, 24]. In academic contexts, researchers have indicated that many aspects of a course environment are malleable to enhance students' capacity to engage in self-regulation to mitigate academic procrastination [25]. For example, instructor support – such as prompt feedback – can increase students' awareness of their progress toward long-term learning goals and identify harmful learning habits, thereby reducing the likelihood of procrastination [25]. Empirical studies based on student self-reports have provided preliminary evidence that such support is associated with a reduction in procrastination [4, 9, 11]. Moreover, Paden and Stell [15] suggest that assigning well-structured tasks with appropriate deadlines and difficulty level can reduce procrastination. Empirical studies have supported this theory, with Tuckman [27] finding that weekly quizzes can motivate continuous learning, in lieu of procrastinating on reviewing learning materials until the final exam. Similarly, a more recent study [4] observed that students tend to procrastinate less in courses with incremental assignments compared to those with infrequent, high-stake assignments. Additionally, social factors such as peer influence, social norms, and instructor press have also been identified as important factors related to student procrastination behavior [4, 9, 25].

Aside from course-level characteristics, researchers also have identified assignment design as a key factor associated with student procrastination on corresponding assignment tasks [32]. For instance, the difficulty of assignments is considered to be an important trigger of procrastination, as challenging tasks can lead students to avert or avoid engaging with them [1, 15, 22, 25]. Conversely, assignments that require a variety of skills and that are perceived as interesting have been shown to reduce the likelihood of procrastination by fostering students' intrinsic motivation [1, 4]. The impact of many assignment characteristics on procrastination remains uncertain at this time. For example, while longer deadlines

may encourage students to dedicate more time and effort to assignments, they can also create conditions conducive to procrastination by allowing students to delay action [25, 33].

Most existing studies on the impact of learning environments on procrastination are typically based on student self-reported surveys or small-scale experiments, and often overlook potential disparities in how different student groups experience these environments. To contribute more robust and generalizable knowledge about how learning environment features are associated with procrastination, this study uses large-scale data from a learning management system. We assess the relationship between course/assignment characteristics and procrastination at scale and carefully examine the patterns across different student populations, aiming at capturing ecologically valid procrastination patterns of college students as evidence to inform future course and assignment design.

3 Data and Method

3.1 Dataset

This study was conducted at a land-grant university in the United States with over 25,000 students enrolled at any given time. The university adopted Canvas as its primary LMS in 2019. We obtained de-identified data from the university's IT office, including Canvas assignment submission records, metadata for assignments, and the registrar's office that includes students' sociodemographic characteristics and transcript data. The sociodemographic information includes gender (male, female, or unspecified), ethnic minority status (whether a student identifies as Black/African American, Hispanic/Latino, Native American, or Native Hawaiians and other Pacific Islanders), and first-generation college status (whether neither of the student's parents completed a bachelor's degree). Both registrar and LMS datasets were de-identified using the same hashing algorithm applied to the student IDs, enabling us to join these data on the hashed IDs and course codes to form a combined dataset of student sociodemographic characteristics, administrative course information, and LMS assignment submission records. For course assignments that permit multiple submissions, only the final submission record is kept in the joint dataset. The joint data covers 12,416 courses offered by the university from the semester of Fall 2019 to Fall 2022.

3.1.1 Data Cleaning. We systematically cleaned the joint dataset of student Canvas submission records and university registrar data, focusing on courses with moderate to large enrollments that extensively use Canvas for pedagogical purposes. We first excluded courses with fewer than 20 enrolled students. Next, we filtered out optional assignments by removing those with submission rates lower than 50%, and then excluded courses with fewer than three non-optional assignments. Finally, we excluded courses where all students' final grades on Canvas were zero, as those courses likely did not use Canvas sufficiently as an assignment submission and grading tool. After applying these data-cleaning procedures, the dataset consisted of 4,492,112 submission records from 33,721 students for 53,132 assignments across 3,351 courses.

Additionally, we observed that some assignments in the dataset had zero or null possible points, or over half of the students received null submission grades. These assignments appeared to be optional tasks within the course and to focus on students' procrastination behavior in relation to the main assignments, we removed these assignments from the dataset. Furthermore, we excluded courses with fewer than three remaining assignments. This procedure reduced the sample size of the dataset to 4,195,893 submission records from 33,531 students for 48,245 assignments across 3,170 courses.

We excluded data for 14 students with invalid (or unspecified) sociodemographic data in the sample, maintaining all courses and assignments in the sample. This reduced the sample size of students to 33,517.

Finally, when calculating measures of learning environment features, we identified 327 assignments with abnormal records where the assignment creation or release time occurred after most students had already submitted their work. To mitigate the impact of these outliers, we excluded these assignments from our study. The characteristics of the final student-course-assignment level dataset are shown in Table 1.

Table 1: Study sample size (top panel) and student-level distributions of sociodemographic attributes (bottom panel)

Number of Students	33,514
Number of Courses	3,169[1]
Number of Assignments	47,918
Number of Student-Course Pairs	253,603
Number of Submissions	4,171,584
Gender	53.3% female, 46.7% male
Ethnic Minority Students	21.6%
First-Generation Students	14.6%

[1] The courses span a wide range of subjects covering both non-STEM and STEM fields, such as Economics, Policy Analysis and Management, Mechanical and Aerospace Engineering, Electrical and Computer Engineering.

3.2 Key Measures

3.2.1 Procrastination. Lateness in task submission is a widely-used behavioral measure of academic procrastination [e.g., 10, 21, 31]. While a late submission can be the result of a variety of factors aside from procrastination, such as time conflicts due to part-time jobs or family obligations, striving for perfection through continuous revisions, or unexpected life emergencies, education researchers have argued that it is reasonable to infer that students who submit assignments earlier are less likely to procrastinate [10]. This inference is further supported by the recent finding that earlier assignment submission is consistently associated with higher course grades across student groups [21]. While procrastination is not solely defined by late submissions, it is a good indicator of student procrastination behavior. Following this common approach, procrastination in this study is operationalized at the student-assignment level as the time difference (in hours) between a student's final submission time and the assignment deadline. We chose not to use group-mean centering or ranking as previous research did to compare a student's submission lateness with that of their peers, as relative delay could complicate distinguishing between an individual student's procrastination level and the overall procrastination level of the class. By using absolute submission lateness, our measure provides

a simple and easily interpretable indicator of a student's tendency to procrastinate on task completion.

Some assignments do not have specified deadlines in the Canvas LMS and we therefore imputed the approximate deadlines of all assignments using the 80% percentile of students' assignment submission times. Among the 44,597 assignments with deadlines on record, this deadline approximation approach achieves 80.8% on the precision of the days, which we confirmed to be higher than other nearby percentile thresholds (70%, 75%, 85%, and 90%). A negative procrastination score indicates that the student submitted the assignment prior to the deadline, while a positive procrastination score indicates that the student submitted the assignment after the deadline. To reduce the influence of extreme outliers, we trimmed the bottom and top 5% of procrastination scores by replacing them with the 5th and 95th percentiles, respectively.

3.2.2 Course Structure. To explore how course contexts are associated with student procrastination, we characterized courses in our dataset according to their administrative, assignment, and feedback structure. The first three panels of Table 2 show descriptive statistics of the features we calculated for each course.

Prior research has shown the important role of course administrative characteristics, such as class size and course level, in shaping students' learning behavior and achievement [e.g., 12, 29], but not its relationships with procrastination. Our study investigates the relationship between course administrative structure and student procrastination based on the following three attributes: ***Class Size*** is a continuous variable referring to the total number of students enrolled in a course. ***Course Level*** is a binary indicator of whether a course is at the introductory level, which includes non-degree applicable courses and lower-level undergraduate courses (at or lower than 2000 level according to the university course numbering system), while the advanced level includes upper-level undergraduate courses and graduate-level courses. ***Course Discussion*** is a binary indicator of whether a course has associated discussion (or lab) sessions.

Four course-level measures were computed to capture the assignment structure of a course. Prior research indicates that breaking down large assignments into smaller, more manageable tasks can enhance student self-efficacy and task organization, potentially mitigating procrastination [4, 25]. In our study, we use ***Number of Assignments*** as a proximate indicator of this course characteristic to explore its relationship with academic procrastination at a large scale. With this operationalization, a larger number of assignments reflects an assignment structure that emphasizes continuous and incremental tasks, while a smaller number of assignments indicates a structure with fewer, larger tasks assigned intermittently. ***First Deadline*** is another assignment structure feature defined as the time difference (in hours) between the start of instruction and the first assignment of a course, relative to the total length of the semester. While little research has studied this design attribute, we expected that a later first assignment would be associated with lower levels of procrastination, as it allows students more time to acquaint themselves with the course material and devise better plans. Furthermore, recognizing that task difficulty is often considered a key factor influencing student procrastination [1, 15, 22, 25], we computed two measures of the overall difficulty level of assignments within a course: ***Assignment Difficulty (Variation)*** and ***Assignment Difficulty (Median)***. The first is the average variation in students' submission grades, expressed as a percentage of the assignment's possible points, across all assignments of a course. A higher value indicates that assignments are more sensitive in distinguishing students across different learning levels. *Assignment Difficulty (Median)* is the average of the median scores achieved by all students, expressed as a percentage of the assignment's possible points, across all assignments of a course. A higher value suggests that the assignments are generally more challenging for students to achieve high scores. Finally, we calculated the ***Average Assignment Period***, defined as the average *Assignment Period* (introduced in the next section) for a given course. This feature serves as an indicator of the average amount of time students have to complete an assignment in the course.

Given that prompt feedback has been shown to help mitigate procrastination [4, 9, 25], our study also examined the feedback structure of a course, defined by four course-level measures related to the release of grades and comments. ***Grade Visibility*** measures the extent to which submission grades are accessible to students. For each assignment, we first calculated the proportion of students who received grades on Canvas. The proportion was then converted into a binary indicator: "high visibility" if 50% or more students received grades, and "low visibility" otherwise. The final *Grade Visibility* value for each course was computed as the proportion of assignments with high visibility. ***Time to Get Submission Grades*** captures how quickly students receive grades on their submission in a course. We first calculated the time difference (in hours) between an assignment's release and when each student received their grade. For submissions of which grades were not posted (6.1%), we used the time difference between the semester's instructional end date and assignment release time. Any negative feature values (11.3%) were replaced with zero. These time differences were then aggregated at the assignment level using the median value. Finally, for the course-level feature, we computed the average of the assignment-level median values. ***Comment Length*** measures the level of elaboration in comments provided as part of the evaluation process on assignments within a course. For each submission, we calculated the total length of comments received after the submission time. Specifically, if a submission received multiple comments, we summed the length of all comments; if a submission did not receive any comments, its total comment length was recorded as null. We then computed the median comment length across all submissions with non-null values for each assignment. Finally, we averaged these median values across all assignments in the course as the final measure of *Comment Length*. ***Comment Availability*** measures the extent to which comments are available for students in a course. For each assignment, we calculated the proportion of submissions that received at least one comment. We then averaged these proportions across all assignments in the course to obtain the final value of *Comment Availability*.

In the process of calculating the aforementioned features related to course characteristics, we observed extreme outliers in the assignment-level values for *Assignment Difficulty (Variation)*, *Assignment Difficulty (Median)*, and *Comment Length*. To mitigate their impact, we replaced values exceeding the 98th percentile with

the 98th percentile value before computing the course-level feature values. This adjustment prevented extreme outliers from disproportionately skewing the representativeness of the course-level means.

Table 2: Course-level features describing administrative structure (first panel), assignment structure (second panel), feedback structure (third panel), and assignment-level features describing assignment design (forth panel)

Class Size	Mean = 73, SD = 90.29
Course Level[1]	Intro: 1477, Advanced: 1755
Course Discussion[2]	True: 784, False: 2405
Number of Assignments	Mean = 15, SD = 15.53
First Deadline	Mean = 0.17, SD = 0.18
Course Difficulty (Median)	Mean = 0.94, SD = 0.08
Course Difficulty (Variation)	Mean = 0.09, SD = 0.05
Average Assignment Period	Mean = 638.30, SD = 657.27
Grade Visibility	Mean = 0.94, SD = 0.17
Time to Get Submission Grades	Mean = 384.40, SD = 331.79
Comment Length	Mean = 157.10, SD = 156.81
Comment Availability	Mean = 0.32, SD = 0.31
Assignment Period	Mean = 688.18, SD = 923.55
Assignment Interval	Mean = 155.80, SD = 189.75
Weekend Deadline	Yes: 6187, No: 41731
Assignment Type: Quiz	Yes: 16271, No: 31647
Assignment Type: Discussion	Yes: 3104, No: 44814

[1] **Course Level:** Sixty-three courses were categorized as both introductory and advanced. Students could choose to enroll in one of the levels.
[2] **Course Discussion:** A course may have both "true" and "false" values, as not all students would enroll in the supporting sections.

3.2.3 Assignment Design. Aside from course characteristics, we studied the relationship between assignment design and procrastination by examining the assignment characteristics shown at the bottom of Table 2.

Assignment Period is an assignment-level variable referring to the time difference (in hours) between the assignment publishing time and its deadline. This feature allows us to examine the debated role of long deadlines in either fostering or mitigating student procrastination [25, 33]. Since this variable contained outliers with extremely large values, we trimmed them at the 98th percentile by replacing larger values with the 98th percentile value. ***Assignment Interval*** is an assignment-level variable defined as the time difference (in hours) between the deadline of an assignment and the most recent deadline before that assignment, or in the case of the first assignment in the course, the beginning of instruction in that academic term. ***Weekend Deadline*** is an assignment-level variable indicating if an assignment is due on a weekend. The development of the *Assignment Interval* and *Weekend Deadline* features is motivated by questions about when to set assignment deadlines, which is of interest to many instructors. Finally, we created features indicating the type of assignments. ***Assignment Type: Quiz*** is an assignment-level variable indicating that an assignment is a quiz on Canvas, while ***Assignment Type: Discussion*** indicates that an assignment is based on discussion posts. Canvas also supports other assignment types, such as text entries, online report uploads, and third-party tasks. However, our study focuses exclusively on quizzes and discussion posts, as these assignment types serve unique functions: quizzes serves as a direct assessment of students' knowledge and skills, while discussion posts promote social interaction and peer engagement. Both assignment types have the potential to enhance students' motivation for early participation and timely completion of coursework, making them particularly relevant for examining procrastination behavior.

3.3 Analytic Approach

To investigate the relationship between the learning environment and student procrastination (RQ1), we constructed two fixed effects linear regression models that predict students' procrastination scores for each submitted assignment. The first model included course structure features as the predictors, with all continuous features standardized before model fitting. Specifically, we log-transformed *Class Size* and *Number of Assignments* given their positively skewed distribution. With student IDs added as a fixed effect to adjust for individual-level variation, this model captures how course structure explains the variation in student procrastination among all the courses a student enrolled in. Only 0.36% of students in our sample had just a single procrastination score or multiple identical scores, and thus did not contribute to the estimation of key model coefficients. The second model included assignment design features as predictors with all continuous features standardized. Course IDs and student IDs were added as fixed effects to control for variance across courses and individuals. This model focuses on explaining how assignment design is associated with the variation in student procrastination across all assignments within the same course for each enrolled student. Only 1.04% of student-course pairs in our sample had just a single procrastination score or multiple identical scores and thus did not contribute to the estimation of key model coefficients.

Another fixed effects linear regression model was fitted to investigate the potential disparities in procrastination across different student populations (RQ2). The model predicts students' procrastination scores for each submitted assignment using student characteristics (i.e., gender, ethnic minority status, and first-generation status) as predictors. Assignment IDs were added to the model as fixed effects to control variation across assignments. This model explains how student characteristics are associated with variation in student procrastination among students completing the same assignment within the same course.

To further investigate how the relationships between procrastination and learning environment attributes vary across student groups (RQ3), we fitted two additional linear regression models to examine the interaction effects of student characteristics with course structure and assignment design features. The first model focused on disparities in the relationship between course structure and procrastination. It predicts students' procrastination scores for each submitted assignment by incorporating (1) the main effects of student characteristics, (2) the main effects of course structure features, and (3) the interaction effects between each student characteristic and each course structure feature. The second model examines disparities in the relationship between assignment design and procrastination. Similar to the first model, it predicts students'

procrastination scores using (1) the main effects of student characteristics, (2) the main effects of assignment design features, and (3) the interaction effects between each student characteristic and each assignment design feature. Additionally, course IDs are included as a fixed effect to control variation across courses. Only one course had identical procrastination scores across its two assignments for all students and thus did not contribute to the model's key coefficient estimates.

All models included the number of submission attempts as a covariate, given that procrastination was measured by final submission time. We also controlled for course units and total semester units to account for overall student workload.

4 Results

4.1 Overview of Student Procrastination Behavior

The average student procrastination score is -21.62 hours, with a standard deviation of 36.64, indicating that, on average, students submit their assignments approximately one day before the deadline. Among students with valid official course grades in the university registrar data (193,649 student-course pairs, representing 76.4% of the total student-course pairs), we find that their official course grades are negatively correlated with the course-level average of procrastination scores ($r = -0.173, p < 2.2e-16$) – thus our data aligns with the general finding in the literature that lower levels of procrastination are associated with higher academic achievement.

4.2 Lower Procrastination in Courses with Well-Structured Deadlines, Easier Coursework, Less and Slower Feedback

Table 3 shows the results of the regression model focusing on the relationship between course structure and student procrastination (RQ1). Adjusting for covariates and variation across individuals, we find that all course structure features are significant predictors of student procrastination behavior. Specifically, the regression results indicate that students procrastinate less in courses with larger enrollment, advanced-level courses, and courses without an associated discussion or lab section. Examining assignment structure features, we find that students procrastinate less in courses with more frequent assignments, later initial deadlines, easier coursework, and longer assignment periods. Finally, examining feedback structure features, we find that students procrastinate less in courses where grades tend to be more visible and, surprisingly, in courses where grading takes longer and where comments are both less frequent and less detailed.

4.3 Lower Procrastination in Assignments with Longer Periods, Longer Intervals, Weekend Deadlines, Quizzes, and Discussions

The results of the regression model focusing on the relationship between assignment design and student procrastination (RQ1) are shown in Table 4. Adjusting for covariates and variation across courses and individuals, we find that all assignment design features are significant predictors of student procrastination behavior. Students tend to procrastinate less on assignments that have longer working periods, weekend deadlines, and a longer interval between assignments. Furthermore, students tend to procrastinate less on quizzes and discussion posts compared to other assignment types.

Table 3: Fixed Effects Linear Regression Results for Course Structure Features Predicting Student Procrastination

	Procrastination (hours)
Administrative Structure	
Class Size (log)	-1.420***
	(0.063)
Course Level: Intro	0.603***
	(0.141)
Course Discussion: Yes	3.339***
	(0.136)
Assignment Structure	
Number of Assignments (log)	-0.697***
	(0.088)
First Deadline	-1.601***
	(0.071)
Assignment Difficulty (Variation)	2.387***
	(0.072)
Assignment Difficulty (Median)	-0.447***
	(0.059)
Average Assignment Period	-4.647***
	(0.075)
Feedback Structure	
Grade Visibility	-1.250***
	(0.064)
Time to Get Submission Grades	-1.097***
	(0.067)
Comment Length	0.395***
	(0.049)
Comment Availability	1.813***
	(0.050)
Covariates	
Total Semester Units Taken	-0.061
	(0.088)
Units Taken in the Course	1.199***
	(0.069)
Number of Submission Attempts	-2.288***
	(0.049)
Student Fixed Effects	True ($n = 33,514$)
Observations	4,171,584
Adj. R^2	0.176

Note: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

4.4 Procrastination Gaps Observed across Student Groups

As shown in Table 5, the model examining procrastination disparities across student groups (RQ2) indicates that, even within the same learning environment – same course and same assignment – students exhibit varying levels of procrastination. Male, ethnic minorities, and first-generation students exhibit higher levels of procrastination than their respective peers. On average, male, ethnic minority, and first-generation students tend to submit assignments approximately 2.4, 3.5, and 1.8 hours later than their respective peers.

Table 4: Fixed Effects Linear Regression Results for Assignment Design Features Predicting Student Procrastination

	Procrastination (hours)
Assignment Design Features	
Assignment Period	-4.537***
	(0.723)
Assignment Interval	-1.469***
	(0.120)
Weekend Deadline: Yes	-5.960***
	(0.714)
Assignment Type: Quiz	-1.754*
	(0.858)
Assignment Type: Discussion	-4.697**
	(1.603)
Covariates	
Total Semester Units Taken	-0.445***
	(0.070)
Units Taken in the Course	0.494
	(0.404)
Number of Submission Attempts	-0.808*
	(0.336)
Student Fixed Effects	True ($n = 33,514$)
Course Fixed Effects	True ($n = 3,169$)
Observations	4,171,584
Adj. R^2	0.292

Note: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 5: Fixed Effects Linear Regression Results for Student Characteristics Predicting Procrastination

	Procrastination (hours)
Socio-demographics	
Gender: Male	2.380***
	(0.038)
Ethnic Minority: Yes	3.469***
	(0.041)
First-Generation: Yes	1.794***
	(0.042)
Covariates	
Total Semester Units Taken	-1.116***
	(0.020)
Units Taken in the Course	0.762***
	(0.182)
Number of Submission Attempts	1.430***
	(0.056)
Assignment FE	True ($n = 47,918$)
Observations	4,171,584
Adj. R^2	0.352

Note: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

4.5 Variation in the Relationship between Course Structure and Procrastination across Student Groups

Table 6 presents the result of the regression model in a format that highlights sociodemographic variation in the relationship between course structure and procrastination (RQ3).

We observe several significant differences between male and female students in the relationships between course structure features and procrastination. Recall from Table 3 that advanced-level courses and a larger number of assignments are generally associated with lower levels of procrastination. However,Table 6shows that these patterns are more pronounced for male than female students. As a result, the gender gap in procrastination tends to narrow in these types of courses. Conversely, while courses without associated discussion or lab sections and those with easier assignments (lower grade variation) are generally associated with reduced procrastination, this trend is less pronounced for male than female students, contributing to a wider gender gap in procrastination in those types of courses.

Similar patterns are observed for ethnic minority students. Higher grade visibility is generally associated with lower procrastination, and we see this pattern is more pronounced for ethnic minority students, narrowing the procrastination gap with their majority group peers. While advanced course levels, a larger class size, a greater number of assignments, easier assignments (lower grade variation), and lower comment availability are generally associated with reduced procrastination, these trends are attenuated for ethnic minority students, which contributes to a wider ethnicity-based gap in procrastination. Additionally, for first-generation students, the negative relationship between assignment difficulty (median) and procrastination is less pronounced compared to their continuing-generation peers, which implies that in courses with lower assignment difficulty (higher median grades), there is a wider procrastination gap for first-generation students.

4.6 Variation in the Relationship between Assignment Design and Procrastination across Student Groups

Table 7 shows the result of the regression model focusing on the variation in the relationship between assignment design and procrastination across different student groups (RQ3).

For male students, disparities are observed in the relationships between assignment design features and procrastination compared to their female peers. While students generally tend to procrastinate less on quizzes than other assignment types, male students show a significantly greater reduction in procrastination on quizzes. Consequently, the gender gap in procrastination is narrower for quiz-based assignments. However, the reduction in procrastination associated with weekend deadlines and discussion format is less pronounced for male students compared to their peers. On these assignments, the gender gap in procrastination widens.

For both ethnic minority and first-generation students, the reduction in procrastination associated with longer assignment periods, weekend deadlines, and discussion format is less pronounced compared to their respective peers. The ethnicity-based gap and first-generation gap in procrastination are therefore wider for these types of assignments.

5 Discussion and Conclusion

Using large-scale data on student assignment submissions from a learning management system, this study provides important new insights into contextual and sociodemographic variation in student

Table 6: Examining How the Relationship between Course Structure and Procrastination Varies by Student Characteristics: Results of a Regression Model Formatted to Highlight Main Effects and Interaction Terms for Student Characteristics and Course Structure Features. The first two columns show the main effects as a reference point, while the third column presents interaction terms which can be interpreted as strengthening or weakening the baseline relationships for specific groups of students. Main effects of course structure features represent the relationship with procrastination for the largest student group in the sample: female students who are continuing-generation students and not ethnic minorities.

Student Characteristics		Course Structure Feature		Interaction Term
Gender: Male	1.600***	Course Level: Intro	1.322***	1.201***
	(0.333)		(0.231)	(0.311)
		Number of Assignments (log)	-0.423**	-0.862***
			(0.144)	(0.190)
		Discussion Availability: Yes	3.892***	-0.842**
			(0.211)	(0.273)
		Assignment Difficulty (Variation)	2.725***	-0.567***
			(0.122)	(0.155)
Ethnic Minority: Yes	4.501***	Grade Visibility	-1.053***	-0.349*
	(0.380)		(0.106)	(0.160)
		Class Size (log)	-1.676***	0.665***
			(0.106)	(0.156)
		Course Level: Intro	1.322***	-1.234***
			(0.231)	(0.366)
		Number of Assignments (log)	-0.423**	0.572**
			(0.144)	(0.211)
		Assignment Difficulty (Variation)	2.725***	-0.508**
			(0.122)	(0.173)
		Comment Availability	1.951***	-0.348**
			(0.082)	(0.127)
First Generation: Yes	1.497***	Assignment Difficulty (Median)	-0.663***	0.469**
	(0.453)		(0.107)	(0.178)

Note: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$; Only features with significant interaction terms are shown in this table. Full regression results can be found in our OSF project: https://osf.io/tr2f7/?view_only=f56344082322402db061a95d59d3e2c8

procrastination in higher education. First, we found that a higher level of procrastination in assignment submissions is associated with lower academic achievement. Then, consistent with prior research [3, 21], but using a different measure of procrastination, we observed that male, ethnic minority, and first-generation students tend to procrastinate more than their peers. These findings raise concerns about the potential negative effects of procrastination on academic success and educational equity. Moreover, we observed that course structure and assignment design are associated with procrastination, suggesting that certain course and assignment characteristics may help reduce it. However, these benefits are not experienced equally across student groups and, in some cases, could even exacerbate student gaps in procrastination.

Our findings indicate that student procrastination is associated with course administrative characteristics. First, in contrast to previous studies that report a negative effect of large class sizes on student academic behaviors [e.g., 5, 7], we observed that students in large classes tend to procrastinate less. One possible explanation is that larger classes often implement more structured and rigid assignment submission policies with limited flexibility and personalized extensions to facilitate efficient class management. These policies may create a classroom atmosphere where students are urged to complete assignments on time. Additionally, while students in large classes may develop fewer close connections [5], they might still experience stronger peer pressure which could motivate earlier engagement with assignments. Further research is needed to test these hypotheses or explore other instructional, social, and psychological factors contributing to variation in procrastination in large versus small classes. Nonetheless, our results suggest that smaller class sizes are not always advantageous and that instructors should attend to students' behavioral challenges, including procrastination, regardless of class size. Notably, the negative association between class size and procrastination is significantly less pronounced for ethnic minority students. This may point to challenges of social integration in large classes, which has been identified as a factor linked to academic procrastination [18]. While further research is needed to explore the underlying mechanism of these procrastination patterns, this finding underscores the importance of supporting the learning experience of underrepresented student groups in the instructional design of large classes.

Second, students procrastinated less in advanced courses. This pattern may be related to students' development of self-regulation skills as they progress through college studies and take higher-level courses. Indeed, first-year college students are known to prioritize socializing and work obligations over academics [26]. This suggests that additional guidance on self-regulation development could be particularly beneficial in introductory-level courses. Instructors of these courses could incorporate instructional design strategies

Table 7: Examining How the Relationship between Assignment Design and Procrastination Varies by Student Characteristics: Results of a Regression Model Formatted to Highlight Main Effects and Interaction Terms for Student Characteristics and Assignment Design Features. The first two columns show the main effects as a reference point, while the third column presents interaction terms which can be interpreted as strengthening or weakening the baseline relationships for specific groups of students. Main effects of assignment design features represent the relationship with procrastination for the largest student group in the sample: female students who are continuing-generation students and not ethnic minorities.

Student Characteristics		Assignment Design Feature		Interaction Term
Gender: Male	2.441*** (0.216)	Assignment Type: Quiz	-1.518 (0.932)	-0.748** (0.288)
		Weekend Deadline: Yes	-7.097*** (0.776)	1.652*** (0.334)
		Assignment Type: Discussion	-6.232*** (1.739)	1.922** (0.665)
Ethnic Minority: Yes	2.950*** (0.236)	Assignment Period	-4.915*** (0.761)	0.578* (0.245)
		Weekend Deadline: Yes	-7.097*** (0.776)	1.050** (0.336)
		Assignment Type: Discussion	-6.232*** (1.739)	1.164* (0.577)
First Generation: Yes	1.609*** (0.248)	Assignment Period	-4.915*** (0.761)	0.456* (0.202)
		Weekend Deadline: Yes	-7.097*** (0.776)	0.772* (0.325)
		Assignment Type: Discussion	-6.232*** (1.739)	1.450* (0.588)

Note: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$; Only features with significant interaction terms are shown in this table. Full regression results can be found in our OSF project: https://osf.io/tr2f7/?view_only=f56344082322402db061a95d59d3e2c8

proven to foster self-regulation, such as prompting students to reflect on their learning approaches, adding activities on planning and time management [14], and providing exemplars of effective study strategies [20]. Additionally, we note gender and ethnicity-based disparities in the relationship between course level and procrastination, which highlights the need for further research into the social, cultural, and economic factors that may contribute to systematic differences in procrastination and self-regulation development across student populations. A deeper understanding of these factors would help instructors refine their instructional practice to better support the diverse needs of their students.

Third, students were found to procrastinate less in courses without associated discussion or lab sections. A possible explanation is that sections are usually designed to provide assignment support, and therefore students may delay starting assignments until after these sections, relying on them for support and leading to later submissions. We do not advocate for eliminating discussion sections based on this finding; instead, our findings provide preliminary evidence of course sections' potential influence on student learning behaviors. Future research should explore how section design can foster assignment engagement without prompting overreliance and procrastination. Additionally, given the significant gender difference observed in the relationship between discussion availability and procrastination, further studies should also examine how section design affects different student groups to assess its effectiveness and inclusiveness.

Our findings also highlight the association between student procrastination behavior and the assignment structure of a course. First, consistent with previous literature [e.g., 4, 15], our findings support the argument that breaking down learning tasks into smaller, incremental assignments may help mitigate student procrastination. Moreover, this pattern is particularly evident for male students, but it is attenuated for ethnic minority students. These distinctions add to the current literature that suggests a more nuanced approach to assignment design. While breaking large assignments into smaller tasks is generally beneficial, some students may not fully grasp the purpose of such a structure, or external factors may limit its effectiveness for them. Therefore, additional support tailored to those students' specific situations may be necessary to maximize the benefits of incremental assignments. Second, consistent with previous findings [1, 15, 22, 25], we observe that lower assignment difficulty correlates with reduced procrastination. However, the reduction in procrastination for easier coursework is smaller for male, ethnic minority, and first-generation students, suggesting instructors pay particular attention to these students as procrastination challenges may persist for these groups even in less demanding courses. Third, our study also found that a later first deadline is associated with lower procrastination levels, and this pattern holds consistently across different student groups. This suggests that allowing students more time to familiarize themselves with the course could be an effective strategy for instructors to support all students in managing their procrastination behavior.

Unexpectedly, we found increased procrastination on courses featuring prompt grading, frequent comments, and detailed feedback. This contrasts with prior research suggesting that timely and detailed feedback is associated with decreased procrastination [4, 9, 11, 25]. One potential explanation is that the grades and comments in these courses did not serve as useful resources for students' self-monitoring, which has been emphasized as important in previous studies. For example, our analysis focused on comments provided after submissions, unlike the formative feedback examined in [11]. Grades released on Canvas may have also lacked the depth needed for students to fully understand their mistakes and progress as expected by [4, 9, 25]. In this context, feedback provided through the LMS may have heightened students' concerns about receiving low grades or critical comments, potentially increasing their procrastination. Alternatively, frequent and detailed feedback might signal a closer student-instructor relationship, which could imply greater implicit flexibility or leniency around late work. Further research is needed to explore how specific feedback characteristics – such as tone, content, and perceived usefulness – influence student procrastination behavior. Moreover, our findings provide preliminary evidence that ethnic minority students may respond differently to course feedback structures in terms of their procrastination tendencies. This highlights the need for further investigation into how cultural and demographic factors shape students' reception and interpretation of academic feedback and how these affect their procrastination behaviors [2].

Comparing assignments within the same course, we found that weekend deadlines are associated with reduced procrastination; however, this relationship is less pronounced for male, ethnic minority, and first-generation students. This may reflect distinct cultural preferences and socioeconomic constraints these students tend to face in their academic and family lives, warranting further research into their specific experiences and needs. Regarding assignment types, students tend to procrastinate less on quizzes and discussion posts. One possible explanation is that quizzes serve with a distinct assessment function, which gives students more pressure to finish them on time, while discussion posts leverage the peer influence, as students can observe their classmates completing the tasks [20, 25]. It is noteworthy that the association between quizzes and reduced procrastination is more pronounced for male students, while the pattern of discussion posts is less pronounced for all three student groups, with generally higher procrastination levels. This suggests that when incorporating diverse assignment types to mitigate student procrastination, it is crucial for instructors to ensure meaningful student engagement, as some may fall behind or miss key objectives. Lastly, our study found that longer assignment intervals are associated with reduced procrastination, with no significant differences across student groups. This suggests that avoiding deadline clustering could be an effective strategy for instructors to implement in assignment design.

In addition, both the course-level and assignment-level analyses show that a longer assignment period is associated with lower levels of procrastination. While this negative relationship may stem from the fact that assignments with longer assignment periods inherently have smaller possible minimum procrastination scores based on our measure, this finding provides preliminary evidence for the debate on the role of long deadlines in fostering procrastination [25, 33]. It suggests that students do not necessarily wait until the last minute to submit assignments when given more time. Meanwhile, our study found that ethnic minority and first-generation students exhibit a different relationship between assignment period and procrastination compared to other students. Further research is needed to explore how long deadlines influence procrastination behaviors among these student groups.

While this study provides valuable insights into the relationship between learning environments and student procrastination, we note several important limitations. First, our operationalization of procrastination, albeit aligned with prior work, only focuses on students' assignment submission records and measures procrastination behavior in terms of absolute submission lateness. Future studies may look more holistically at the entire process of students completing assignments from their first access to assignment instructions, in order to provide a more comprehensive picture of student procrastination. Second, the findings of our study do not provide causal estimates for how instructional design impacts student procrastination, despite our efforts to control many sources of variation using a fixed-effect regression-adjustment approach. Future studies could test how much the identified learning environment factors can influence student procrastination and inform instructors on course and assignment design to reduce procrastination. Finally, this study did not capture all learning environment factors potentially related to procrastination. Future work could examine additional aspects, such as fields of study and late submission policies. We also encourage further research on procrastination disparities across more diverse student characteristics, including international students, double majors, students with disabilities, and those with part-time jobs.

To conclude, our findings suggest two instructional design strategies that can help students manage procrastination across different student groups: (1) allowing more time before the first assignment deadline and (2) ensuring adequate spacing between deadlines when designing the course assignment schedule. Future research should validate the effectiveness of these strategies through intervention studies. Additionally, for course structure and assignment design features that are associated with reduced procrastination but exhibit significant differences across student groups (e.g., breaking large assignments into small incremental tasks, incorporating quizzes and discussion posts, setting deadlines on weekends), further investigation is needed to understand the underlying reasons for these distinct behavioral patterns and to develop targeted instructional supports for procrastination management. Conducting large-scale studies on student learning behavior patterns while considering diverse student experiences across student groups reduces the risk of overlooking the challenges faced by underserved and marginalized groups of students [16, 30]. The disparities in procrastination across student groups also underscore the need for personalized support in procrastination management and self-regulation development – an area where AI tools hold particular promise, as demonstrated in prior work that has leveraged large language models to provide personalized interventions [6]. Moving forward, more collaborative efforts from technologists, researchers, and instructors are essential to develop tools that help instructors create more inclusive learning environments, minimizing procrastination risks for all students.

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