Large-Scale Student Data Reveal Sociodemographic Gaps in Procrastination Behavior

Sunil Sabnis
Cornell University
Ithaca, NY, USA
svs57@cornell.edu

Renzhe Yu
University of California, Irvine
Irvine, CA, USA
renzhey@uci.edu

René F. Kizilcec
Cornell University
Ithaca, NY, USA
kizilcec@cornell.edu

ABSTRACT

University students have to manage complex and demanding schedules to keep up with coursework across multiple classes while navigating formative personal, cultural, and financial events. Procrastination, the act of deferring study effort until the task deadline, is therefore a prevalent phenomenon, but whether it is more common among historically disadvantaged students is unknown. If systematic differences in procrastination behavior exist across sociodemographic groups, they may also contribute to achievement gaps, considering that procrastination is largely negatively associated with academic performance in prior research. We therefore investigate these questions in the context of assignment submission using campus-wide learning management system (LMS) data from a large U.S. research university. We analyze 2,631,893 submission records by 25,659 students across 2,153 courses and propose a context-agnostic procrastination score for each student in each course based on their assignment submission times relative to classmates. Based on this procrastination score, we find significantly higher levels of procrastination behavior among males, racial minorities, and first-generation college students than their peers. However, these differences only explain performance gaps to a very limited extent and the negative association between procrastination behavior and performance remains relatively stable across student groups. This large-scale behavioral study advances the understanding of academic procrastination through an equity lens and informs the development of scalable interventions to mitigate the negative effects of procrastination.

CCS CONCEPTS

• **Applied computing → Learning management systems**; *Law, social and behavioral sciences.*

KEYWORDS

Procrastination, Higher Education, Learning Analytics, Learning Management System, Self-Regulated Learning, Educational Equity

ACM Reference Format:
Sunil Sabnis, Renzhe Yu, and René F. Kizilcec. 2022. Large-Scale Student Data Reveal Sociodemographic Gaps in Procrastination Behavior. In *Proceedings of the Ninth ACM Conference on Learning @ Scale (L@S '22), June 1–3, 2022, New York City, NY, USA.* ACM, New York, NY, USA, 9 pages. https://doi.org/10.1145/3491140.3528285

ACM ISBN 978-1-4503-9158-0/22/06…$15.00
https://doi.org/10.1145/3491140.3528285

1 INTRODUCTION

Postsecondary education is a sound investment for young adults to gain advanced knowledge and skills that prepare them for careers in a highly dynamic labor market [8]. However, succeeding in college requires overcoming numerous challenges simultaneously: students have to manage complex and demanding schedules to keep up with coursework across multiple classes while navigating formative personal, cultural, and financial events. This complexity often exposes students from marginalized backgrounds to additional obstacles due to systemic issues of equity and inclusion, such as prevailing stereotypes on campus [29, 36, 39], experiences of cultural mismatch [40], and financial hardship [16, 18]. These challenges contribute to the long-standing patterns of lower persistence and graduation rates and post-graduation earnings among students from historically underrepresented groups, especially ethnic and racial minorities and first-generation college students [17]. Empirical insights into how these gaps develop throughout students' college experience can advance our theoretical understanding of inequities and inform academic policies to better support students.

During academic terms, students can encounter academic, health, or social challenges that cause them to fall behind with coursework and miss deadlines. Prior studies have emphasized the important role of self-regulated learning skills in the largely autonomous collegiate learning experience [6, 49]: self-regulated learners manage their study time effectively across multiple tasks. Issues with self-regulation can contribute to procrastination, which in most educational contexts refers to a student's voluntary delay of learning effort when they expect negative educational outcomes [37]. For example, a student may delay studying for an examination or submitting and assignment until right before it is due. This behavior limits the amount of time they can spend on the task and therefore may compromise the quality of their work. Procrastination is prevalent among college students, with nearly 90% reporting to do so on coursework[1], and a large body of empirical research has shown a negative relationship between procrastination and academic performance [22]. Insofar as students from marginalized backgrounds encounter additional challenges that increase their risk of procrastinating, procrastination can provide a new behavioral approach to understand the development of achievement gaps.

Early studies of procrastination relied primarily on survey measures [34, 35], but these instruments are hard to scale and suffer

[1] https://www.prnewswire.com/news-releases/eighty-seven-percent-of-high-school-and-college-students-are-self-proclaimed-procrastinators-260750441.html

from selection and reflection biases. The rise of learning analytics and educational data mining has created opportunities for capturing procrastination in an authentic and scalable manner based on students' fine-grained behavioral interaction traces in digital learning environments [26, 31]. Large-scale analytics can not only identify behavioral correlates of sociodemographic gaps in academic performance, but also inform efforts to create interventions to mitigate them. For example, racially minoritized students may experience increased anxiety and reduced self-efficacy due to prevailing stereotypes in their educational environment [29, 36, 39]; this may contribute to increased procrastination behavior and reduced performance, which in turn lowers self-efficacy and raises anxiety in a negative feedback loop [14, 27]. This psychological feedback loop could manifest in students' real-time digital learning behaviors and it could be easily tracked at scale through learning analytics to pinpoint opportune moments for intervention.

Building on prior research on procrastination and motivated by its prevalence among college students, this study provides one of the first large-scale analyses of sociodemographic inequality in academic procrastination and achievement across a wide range of instructional contexts. We specifically answer the following research questions:

(1) How does procrastination behavior vary across sociodemographic student groups?
(2) To what extent can procrastination behavior explain achievement gaps?
(3) How does the association between procrastination and achievement vary across sociodemographic student groups and across courses of different size?

This study contributes to the literature on procrastination in several ways. First, we propose a procrastination index based on students' behavioral traces in learning management systems (LMS) relative to their classmates, without having to know the details of individual tasks and courses. Given the widespread deployment of LMS at higher education institutions [19], this index can be applied to a variety of institutional and instructional contexts to depict students' time management. Second, we unveil sociodemographic inequalities in academic procrastination and connect them to inequality in educational outcomes in one of the largest and most granular datasets on this topic. We position issues of educational inequalities in the procrastination literature to model and stimulate more computational behavioral science research on social inequalities in education. Insights from this study can inform the development of more equitable learning analytics interventions to support self-regulation and mitigate negative consequences of procrastination.

2 RELATED WORK

2.1 Self-Regulated Learning and Procrastination

Research on self-regulated learning (SRL) has distinguished between its metacognitive, motivational, and behavioral components that are manifested in specific SRL strategies [32, 44]. Some of these strategies support the regulation of internal resources, such as effective ways of memorizing information. Others help regulate external resources, including setting goals, managing time, etc. Empirical studies have identified time management skills as a strong predictor of academic success [24, 46], and procrastination is often considered evidence that students struggle with time management [6].

The concept of procrastination originally means "to defer intended action", which can occur for a variety of reasons. For some students, procrastination is a strategic delay in tasks to achieve positive outcomes [12]. These students tend to perform better under pressure and completing tasks closer to deadlines can create such an environment for them [11, 13]. However, the majority of modern research focuses on passive procrastination, i.e., delaying action when knowing that the delay will make them worse off [37]. Across a large body of empirical studies, this type of procrastination is mostly harmful, sometimes harmless, but never helpful for students' academic performance and wellbeing [6, 22, 37].

Prior research has also identified a number of intrinsic and external factors that contribute to procrastination. Intrinsic factors include established psychological characteristics and personality traits, such as conscientiousness, distractibility, organization, achievement motivation, and the gap between one's intentions and actions [37]. While some of these intrinsic factors are stable traits across contexts (e.g., conscientiousness), others are malleable (e.g., organization skills, achievement motivation) and can therefore be affected by interventions. External factors include a diverse range of task attributes (e.g., the format and complexity of the task) and environmental attributes (e.g., distractions in the study environment) [38]. In formal classroom settings, a multitude of intrinsic and external factors jointly shape students' procrastination behavior. Practically speaking, this multifaceted process warrants more systematic investigation to better understand which factors that instructors and institutions can control contribute the most to procrastination.

2.2 Behavioral Measures of Procrastination

The measurement of procrastination largely focuses on temporal aspects of students' learning effort, because procrastination is associated with (lapses in) time management. Early studies developed survey instruments that collect students' self-reports of their procrastination behavior and associated psychological processes [34, 35]. However, depending on the context of survey administration, students might either exaggerate their delay in carrying out work due to the common belief that procrastination is ubiquitous [22], or underestimate their procrastination because they are not aware of this behavior when it happens [33]. The emergence of digital learning tools and learning analytics research enable researchers to track students' learning actions and quantify procrastination with timestamped traces in a more authentic manner [3].

Among many types of learning activities, procrastination is most studied in the context of assessments because they are tasks with relatively higher stakes and clear deadlines. A majority of empirical studies quantify procrastination by the lateness of task engagement or submission in relation to the task release time or deadline [9, 21, 26, 33, 48]. For example, You [48] counted assignment submissions past the corresponding deadlines in a Korean e-learning course with 569 college students; Cerezo et al. [9] quantified procrastination within a course of 140 students by tabulating the number of days a student took to hand in an assignment since it was released. Other studies employ more complex computational models to characterize nuances of procrastination behavior, such as temporal dependencies at different stages of the course and time management strategies [2, 31, 47].

While learning analytics could advance the understanding of learning processes at scale, only a small fraction of procrastination studies have analyzed this behavior across diverse instructional contexts. Cormack et al. [15] analyzed 73,608 assignment submissions over 9 years at an British university and computed procrastination as the difference between students' submission times and assignment deadlines. Agnihotri et al. [1] examined over 100,000 students across over 1,000 institutions from a major online learning platform and computed procrastination as a binary indicator based on whether a student started working on an assignment later than 75% of their classmates. This rank-based approach has the advantage of accounting for differences in task or course contexts when concrete variables about the contexts are not available in analyses across diverse contexts. The current study contributes a new large-scale analysis of procrastination behavior that builds on the rank-based approach to quantify procrastination but uses a continuous (instead of dichotomous) ranking of submission times to capture more granular individual differences.

2.3 Learning Analytics and Educational Equity

Education researchers, policy makers and practitioners have prioritized the improvement of educational equity as a central objective. This pursuit of equity is motivated by long-standing disparities in educational access, experiences, and outcomes across students from different sociodemographic groups [17] resulting from systemic injustice in society. In learning analytics, centering equity advances the promise of challenging inequitable structures and improving the education system [41]. This vision requires approaching learning analytics research and applications through a few different perspectives, such as algorithmic fairness [4, 23], value-sensitive and human-centered design [7, 10], and critical theories [45].

The foundation of these inquiries is that the identities of individual students involved are known, so that researchers or practitioners can observe the unique experience of vulnerable and marginalized student populations, which might differ from that of their majority counterparts and be masked in population-level analyses. However, due to administrative constraints, privacy concerns, and other limitations, a large share of existing learning analytics research does not analyze students' sociodemographic characteristics [30, 43] and therefore runs the risk of misunderstanding students from underserved communities and reproducing existing inequities even with technically sound models. Among the smaller body of literature that explicitly examines learning behavior in regard to students' demographics, Kizilcec et al. [25] compared engagement trajectories in MOOCs between learners of different genders, ages and employment conditions; Nguyen et al. [28] focused on racial gaps in a distance learning setting and identified higher levels of behavioral engagement and lower performance among racial minority groups. As learning analytics become increasingly used to augment and personalize educational resources and opportunities at scale, studies of this kind have taken steps forward towards equity-oriented learning analytics. The current study echos this commitment by revealing sociodemographic variation in procrastination behavior and connecting these behavioral inequalities to summative measures of performance.

3 METHODS

Below we describe in detail the data, measures, and modeling strategies for the main analyses. The scripts for data cleaning and analysis are available at https://github.com/sunil-2000/procrastination_ls22.

3.1 Data and Context

This study uses LMS data from a large, land-grant research university in North America. The university adopted Canvas as its primary LMS in 2017. We obtain all historical LMS data with de-identified student IDs from the university's IT office and focus on assignment submission records. For assignments that allow multiple submissions (attempts), only the last submissions from each student are included in the data. This data covers all courses offered between Fall 2017 and Summer 2021, thus including terms during the COVID-19 pandemic. We extract the timestamp of each assignment submission and the final grade in Canvas for each student in each course.

From the university registrar, we also get each student's sociodemographic characteristics, with the same set of de-identified student IDs used in the LMS data pull. The data uses standard categories for reporting student information to the U.S. Department of Education. Specifically, sex is coded as binary (male/female); first-generation college student is a binary indicator of whether both parents did not complete a bachelor's degree; underrepresented minority (URM) student is a binary indicator of whether a student is a U.S. citizen who identifies as Black/African American, Hispanic/Latino, or Native American; race and ethnicity is coded categorically.

We apply several filters to the LMS data in order to remove courses with low enrollment and few graded assignments; we describe these data cleaning steps in Section 3.2. We then join the cleaned LMS data with student-level demographic information. The characteristics of the final dataset used in this study are described in Table 1.

Table 1: Study sample characteristics (upper panel) with student-level distributions of sociodemographic attributes (lower panel)

Number of students	25,657
Number of courses (enrollments)	2,153 (M=70.8, SD=81.1)
Student-course observations	152,368
Sex	52.8% female, 47.2% male
First-generation college student	15.9%
URM student	21.1%
Race/Ethnicity	33.0% White, 19.7% International, 18.1% Asian, 12.0% Hispanic, 6.0% Black, 4.3% Multiple races, 0.4% Native/Pacific, 6.5% Unknown

3.2 Data Cleaning

The raw assignment submission records from the LMS data pull cover 166,965 unique student-course observations. Some of the course instances are not used for academic courses or do not use assignments in a pedagogically meaningful manner. Because academic procrastination typically occurs in the context of relatively higher-stakes tasks [38], we systematically clean the data to focus on academic courses with moderate to large enrollments and a sufficient number of non-optional, graded assignments on Canvas.

First, we exclude courses with fewer than 20 enrolled students, fewer than 5 assignments, or fewer than 100 submissions in total. We also remove all non-academic courses (e.g., alcohol education for incoming freshmen, COVID-19 university policies for students, and teaching modules for instructors).

Second, as our analysis examines the relationship between procrastination and academic performance, we exclude courses where the average final grade of all students in the course is zero. These courses might not be using Canvas for submitting grades or assessments. To accurately capture procrastination across all students, we exclude optional assignments due to self-selection into completing them. While there is no reliable indicator in the Canvas data of whether an assignment is optional, we approximate this by excluding assignments submitted by less than 50% of enrolled students.

Third, we exclude students who likely dropped a course but remain enrolled in its Canvas course instance. While the registrar data we obtained do not contain this information, we approximate this by excluding students who submitted fewer then half of the non-optional assignments in each course instance.

Finally, we remove any assignment submission without a valid submission time and any student for whom sociodemographic information is not available.

The steps above reduce the sample size to 152,368 unique student-course observations, as shown in Table 1.

3.3 Measures

3.3.1 Procrastination Score. We measure academic procrastination based on the submission times of assignments, following prior research on procrastination [15]. In contrast to prior work that focuses on the discrepancy between submission times and corresponding assignment deadlines, we compute the percentile rank of each submission based on its relative order among all submissions to the same assignment. Specifically, let $S_{jc} = \{s_{ijc}; i = 1, \cdots, N_c\}$ denote the set of all students' submissions to assignment j in course c, where s_{ijc} represents student i's submission and N_c represents the number of enrolled students in course c. We define the procrastination score for each submission s_{ijc} as

$$P_{ijc} = \frac{rank(t_{s_{ijc}})}{|S_{jc}|} \tag{1}$$

where $t_{s_{ijc}}$ is the timestamp of the submission, $|S_{jc}|$ is the total number of submissions to the same assignment, and

$$rank(t_{s_{ijc}}) = |t_{s_{kjc}} \leq t_{s_{ijc}}; s_{kjt} \in S_{jc}|$$

is the rank order in terms of the submission time. Ties between submission times are assigned their average rank. By this definition, the later the submission, the more the student procrastinates on this assignment, and the higher this score. We also illustrate in Figure 1 how this assignment-level procrastination score varies for three arbitrary students in a course with 30 assignments. Compared to,

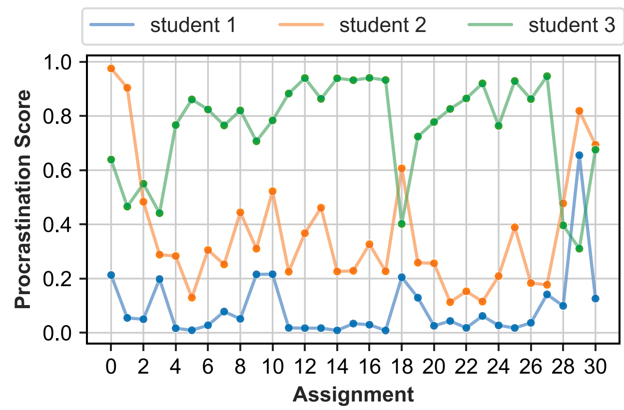

Figure 1: Assignment-level procrastination scores for three students in a course, corresponding to aggregate procrastination scores of 0.09 (student 1), 0.32 (student 2), and 0.76 (student 3).

for instance, the absolute time difference between the submission and deadline, this approach is highly scalable for two reasons. First, it does not rely on information about due dates, which instructors across thousands of courses may implement in inconsistent ways. Second, a percentile rank is normalized for assignments and courses, which makes it easy to aggregate and compare them across assignments, courses, and students.

For the main analysis, we aggregate the procrastination score to the student-course level by averaging over assignments in a course:

$$P_{ic} = \frac{1}{|A_c|} \sum_{j} P_{ijc} \tag{2}$$

where $A_c = \{a_{jc}\}$ is the set of all assignments in course c and $|A_c|$ is the count of these assignments.

A general limitation to this and other submission-based measures of procrastination is that they do not account for missing submissions where students do not submit anything. It may make sense to assign a value of 1 (the largest percentile rank) if a student procrastinates to the degree that they miss the assignment altogether. However, some instructors permit students to miss a certain number of assignments without penalty. Without knowledge of specific course policies, there are trade-offs between choosing to assign values for missing submissions or excluding them in the analysis. Here we opt for the latter approach which is arguably conservative and introduces less bias.

3.3.2 Course Grade. We measure students' academic performance based on their final course score on Canvas, which can be a percentage or a sum of points. This score aggregates across assignments and any other graded components of the course that are tracked through Canvas (e.g., attendance and participation scores, online discussion, peer assessments). This provides a holistic measure of academic performance in any specific course contexts. The continuous final score also provides a finer-grained measure than the discrete letter grade in the registrar. We normalize the raw final scores in each course via percentile ranks to mirror the procrastination score. Specifically, let $G_c = \{g_{ic}; i = 1, \cdots, N_c\}$ denote the set of all students' final scores in course c, where g_{ic} represents student i's score and N_c represents the number of enrolled students in course c. The normalized score for student i, which we also refer to as "course grade", is given by

$$\tilde{g}_{ic} = \frac{rank(g_{ic})}{|G_c|} \tag{3}$$

where $|G_c|$ is the total number of students in course c, and

$$rank(g_{ic}) = |g_{kc} \geq g_{ic}; g_{kc} \in G_c|$$

is the rank order in terms of the final score. Here, students with higher final course scores also get higher course grades.

3.4 Analytical Strategies

We use linear regression models to assess how procrastination varies with sociodemographic characteristics (RQ1) and how academic performance is explained by sociodemographic information and the variation in procrastination (RQ2). For all these regression models, we compute clustered standard errors at the course level to account for the nested structure of student observations within courses. Additionally, we compute the Pearson correlation coefficient between procrastination and performance for different student groups and courses (RQ3). All these analyses are conducted at the student-course level and the analytical details will be described along with the results in Section 4.

4 RESULTS

4.1 Sociodemographic Differences in Procrastination

To answer the first research question, we investigate sociodemographic variations in student procrastination. We visually inspect group differences by graphing the distribution of the procrastination score in Figure 2. We find that procrastination scores are normally distributed and centered around 0.5, but the distribution is shifted up for male students, first-generation college students, and especially URM students. This suggests that these groups of students exhibit more procrastination behavior on average compared to their peers.

To understand the magnitude of these differences, we plot the mean procrastination score for each subgroup on the same scale in Figure 3. A mean procrastination score of 0.5 indicates that, on average, students in this group tend to submit their assignments neither early nor late relative to others; for instance, in a class of 40 students, they tend to be the 20$^{\text{th}}$ person to submit. We find that this is the case for female students, continuing-generation college students, and non-URM students, but not their counterparts. For instance, the mean procrastination score among URM students is 5 percentage points higher ($\overline{P} = 0.55$). Moreover, disaggregating ethnic and racial groups shows substantial variation in procrastination behavior, with the highest average score among Black students ($\overline{P} = 0.59$) and the lowest among White students ($\overline{P} = 0.49$).

We identify several identity-based sources of variation in procrastination. To understand their concurrent relationship with procrastination behavior, we fit a multiple regression model predicting the procrastination score with all the student characteristics in Figure 2 except for the URM indicator due to its collinearity with the specific racial and ethnic categories. Table 2 reports the model estimates. The predictors are coded such that the intercept represents the largest subgroup, which also happens to have the lowest mean procrastination score: White female continuing-generation college students. We find that the gaps in average procrastination visualized in Figure 3 are all statistically significant with similar magnitude. Overall, sociodemographic characteristics do not have strong predictive power, accounting for just 3% of variation in procrastination scores, but this is common in complex social systems and does not itself reduce the significance of the finding [20].[2]

Table 2: Linear regression model predicting procrastination scores

Coefficient	Estimate [95% CI]
(Intercept)	0.47 [0.47; 0.47]*
Sex:Male	0.03 [0.02; 0.03]*
IsFirstGen	0.02 [0.02; 0.03]*
Eth:Asian	0.02 [0.01; 0.02]*
Eth:Black	0.10 [0.09; 0.10]*
Eth:Hispanic	0.04 [0.04; 0.04]*
Eth:International	0.03 [0.03; 0.03]*
Eth:Multiple	0.02 [0.02; 0.03]*
Eth:Native/Pacific	0.05 [0.04; 0.07]*
Eth:Unknown	0.01 [0.00; 0.01]*
R^2 (adj.)	0.03 (0.03)
RMSE	0.19
N obs.	152, 368
N clusters	2, 153

95% CIs based on course-clustered SEs in square brackets
* Zero outside of 95% CI

4.2 Procrastination and Achievement Gaps

To answer the second research question, we examine the relationship between procrastination and academic performance. We fit three separate but related regression models that predict students' course grades with only their procrastination scores (Table 3 Model 1), only their sociodemographic characteristics (Model 2), or both (Model 3). Sociodemographic predictors are coded the same way as in Table 2 and the procrastination score is mean-centered. Model 1 shows that the procrastination score is a significant negative predictor of course grade, and it accounts for 7% of variation in course grade. This replicates the well-established result in the literature that procrastination is linked to lower academic achievement [22].

Model 2 shows that there are significant achievement gaps for all sociodemographic groups: male and first-generation college students perform 4% to 5% worse than their counterparts; students from racial and ethnic minority groups also have lower average course grades than their White peers. These significant gaps, while

[2]For comparison, the established sociodemographic gaps in grades, which are deemed a critical issue in education research, account for only 4% of the variation in this sample (see Table 3 Model 3).

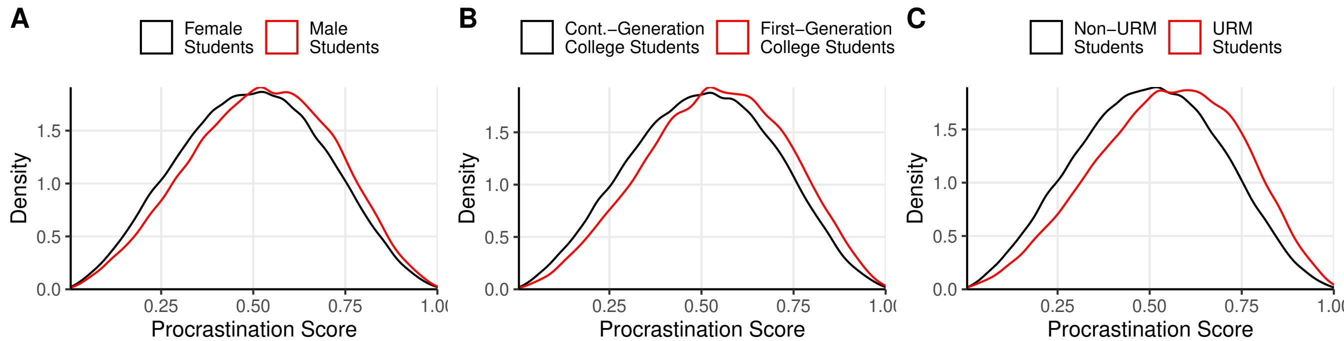

Figure 2: Sociodemographic differences in procrastination scores by students' sex (A), first-generation college status (B), and underrepresented minority status (C)

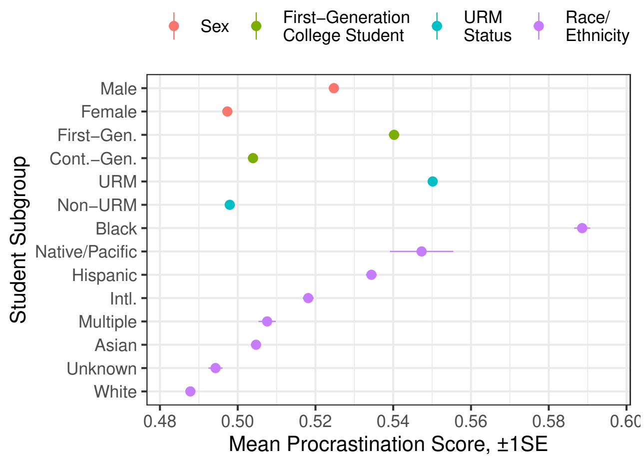

Figure 3: Average procrastination score for different sociodemographic groups

reflecting a serious issue of educational inequity, only account for 4% of the variation in course grades.

Model 3 shows that adding the procrastination score attenuates most of the coefficients on concerning sociodemographic predictors. Specifically, it reduces the gaps between male and female students, first- and continuing-generation college students, and minority and White students. This indicates that procrastination explains a portion of these sociodemographic gaps, but it adds additional predictive power independent of sociodemographic characteristics, because Model 3 explains 10% of the variation in course grades. We also fit a structural equation model that resembles a mediation model with three independent variables (sex, URM status, first-generation status), one moderator (procrastination score), and one dependent variable (course grade). This yields a significant indirect effect estimate of sociodemographic variables on course grade via procrastination score ($a * b = -0.037, se = 0.001, z = -29.56, p < 0.001$ clustered at the course level). This indirect effect estimate accounts for 20% of the total effect estimate ($tot = -0.184, se = 0.003, z = -53.405, p < 0.001$). Overall, this provides evidence

Table 3: Linear regression models predicting course grades (percentile rank)

	(1)	(2)	(3)
(Intercept)	0.51*	0.54*	0.53*
	[0.51; 0.51]	[0.54; 0.55]	[0.53; 0.53]
PScore (ctr.)	−0.40*		−0.37*
	[−0.42; −0.38]		[−0.39; −0.35]
Sex:Male		−0.04*	−0.03*
		[−0.04; −0.04]	[−0.03; −0.03]
IsFirstGen		−0.05*	−0.04*
		[−0.05; −0.05]	[−0.05; −0.04]
Ethn:Asian		0.04*	0.05*
		[0.04; 0.05]	[0.04; 0.05]
Ethn:Black		−0.15*	−0.11*
		[−0.16; −0.14]	[−0.12; −0.11]
Ethn:Hispanic		−0.06*	−0.04*
		[−0.06; −0.05]	[−0.05; −0.04]
Ethn:Intl.		−0.00	0.01*
		[−0.01; 0.00]	[0.00; 0.01]
Ethn:Multiple		−0.02*	−0.01*
		[−0.03; −0.01]	[−0.02; −0.01]
Ethn::Native/Pa.		−0.13*	−0.11*
		[−0.15; −0.10]	[−0.13; −0.08]
Ethn:Unknown		0.01*	0.01*
		[0.00; 0.01]	[0.00; 0.02]
R^2 (adj.)	0.07 (0.07)	0.04 (0.04)	0.10 (0.10)
RMSE	0.28	0.28	0.27
N obs.	152, 368	152, 368	152, 368
N clusters	2, 153	2, 153	2, 153

95% CIs based on course-clustered SEs in square brackets
* Zero outside of 95% CI

that the procrastination score can partially explain the observed achievement gaps.

4.3 Variation in the Procrastination-Performance Relationship

To answer the third research question, we examine how the relationship between procrastination and academic performance varies

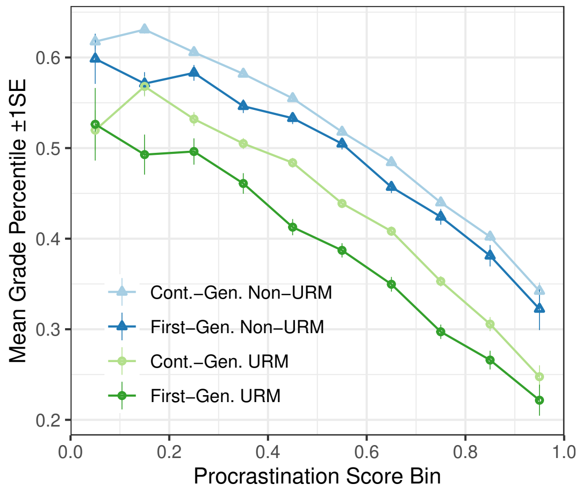

Figure 4: Mean course grade by procrastination score (bins) for intersectional student groups defined by URM and first-generation college status; error bars indicating one standard error

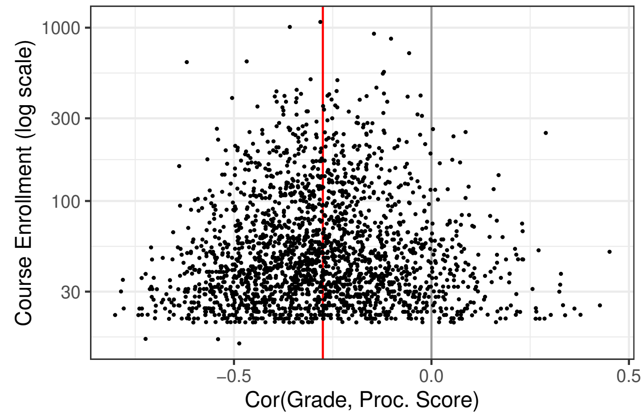

Figure 5: Procrastination-grade correlation (Pearson's r) and course enrollment (log scale); average $r = -0.275$, shown in red line

across sociodemographic groups. We visualize the average course grade for students with different procrastination scores in Figure 4. The figure draws four lines of different colors to distinguishe between intersectional groups of students based on their URM and first-generation college student status. The bins are defined based on a fixed range of the procrastination score (0.1), such that, for instance, the first bin includes students with a score between 0 and 0.1. For each bin, the average course grades are plotted at its midpoint on the x-axis. The figure shows a negative and predominantly linear relationship between procrastination and performance. The strength of that relationship (depicted by the slope) is also remarkably constant across the sociodemographic groups while the intercept is shifted.

To formally evaluate these visual patterns, we revisit Table 3 Model 3 but add interaction terms between the procrastination score and every sociodemographic indicator. This model with interactions (not shown due to length) has a better overall model fit compared to the original model (Wald test: $F_{9,152348} = 7.48, p < 0.001$). However, only a few interaction terms are statistically significant ($p < 0.05$): Sex:Male ($b = -0.02$), Ethn:Asian ($b = 0.05$), Ethn:Multiple ($b = -0.07$), and Ethn:Unknown ($b = 0.05$). This largely echos the consistent relationship between procrastination and performance across groups in Figure 4.

In addition, we examine how the relationship between procrastination and academic performance varies across courses of different size. Figure 5 shows the Pearson correlation coefficient between course grade and procrastination score within every course in the sample, plotted against the course enrollment size. Overall, the procrastination-performance relationship is negative in the majority of the courses, but there is still substantial variation especially among smaller courses, and this variation mostly ranges between -0.5 and -0.1. This raises a further question of which course-level characteristics might explain this variation.

4.4 Robustness Analysis

The cutoff thresholds we apply in the data cleaning steps (see Section 3.2) are chosen with the goal of including as much information as possible while reducing noise. However, these cutoff thresholds represent researcher degrees of freedom that warrant further examination. We therefore conduct a systematic evaluation of alternative threshold values to confirm that our findings are robust. Specifically, we try all 108 combinations of the following exclusion thresholds (* indicates the value used in the main analysis):

- Minimum number of assignments in a course: $\{5^*, 15, 25\}$
- Minimum number of students in a course: $\{10, 20^*, 30, 40\}$
- Minimum share of students who complete an assignment: $\{0.25, 0.5^*, 0.75\}$
- Minimum share of assignments completed by a student: $\{0.25, 0.5^*, 0.75\}$

Each combination produces somewhat different coefficient estimates, primarily because the choice of thresholds affects the sample size. For example, keeping only courses with over 40 students reduces the sample to around 50,000 unique student-course observations. Still, we do not observe notable differences that would change the answers to our three research questions.

5 DISCUSSION

This paper presents a large-scale analysis of behavioral trace data to reveal systematic variations in academic procrastination among college students. Toward this end, we develop a scalable measure of procrastination that can be used in any context with timestamped behavioral data and minimal assumptions about course-specific policies. Our findings based on 2.6 million assignment submission records by 25,659 students across 2,153 courses reveal significant gaps in procrastination behavior between groups of students defined by sex, race/ethnicity, and parental education (RQ1). These gaps are mostly aligned with the direction of established inequities in higher education: URM and first-generation college students who tend to be underachieving also exhibit more procrastination behavior. Such sociodemographic variation in procrastination behavior can partially explain (20%) sociodemographic gaps in course performance (RQ2). In addition, our findings confirm the negative association between procrastination and academic performance found in prior research [22] in the vast majority of the 2,153 courses in our sample. However, the strength of this association is varied across courses, especially in smaller courses. On the other hand, this negative association is consistent across different socioeconomic groups and different performance levels (RQ3).

Our study revisits the prevalent phenomenon of academic procrastination and reaffirms on an unprecedented scale the established negative relationship between procrastination and performance [22]. More importantly, we incorporate an equity lens and extend some earlier, survey-based findings about demographic differences in procrastination and more broadly, self-regulation [5, 42]. The systematic sociodemographic gaps in the prevalence of procrastination that we identify echo existing disparities in the educational experiences across sociodemographic groups and highlight this phenomenon in broader social contexts. Social injustice, prejudice, and stereotypes based on students' different visible and invisible social identities further affect their levels of confidence, self-efficacy, academic engagement, and social interaction during their college experience. In this context, procrastination is a symptom of systemic issues in education, rather than an individual failure or a root cause of academic underperformance as early research tends to assume. On the other hand, the link between inequality in in-class procrastination and end-of-course performance gaps highlights procrastination as a behavioral antecedent of educational inequality. This micro-level behavioral factor, susceptible to structural external forces and grounded in research on meta-cognition [37], can add granular insights about the development of macro-level achievement gaps through the depiction of associated psychological processes. Practically, the behavioral nature also suggests that procrastination is a malleable factor on which educators can intervene to mitigate the negative consequences on student success and educational equity. While in our results procrastination only explains a small portion of achievement gaps, it is still desirable to reduce procrastination behavior as it shows a consistent negative relationship with performance across different sociodemographic groups.

The way we operationalize procrastination differs from prior work in that it solely relies on task submission times without having to know detailed information about the tasks per se, but the findings are consistent with previous studies that measured procrastination based on more task-specific information (e.g., difference between assignment deadline and submission time) [15, 21, 26, 33]. Given the multifaceted nature of procrastination established in psychological research [37], we acknowledge that any single behavioral measure can only capture certain aspects of procrastination, and that our approach might be a more scalable and convenient, but not necessarily more accurate, measure of procrastination. For example, even on the same platform, assignments have varying levels of importance, with some being frequent low-stakes quizzes attached to individual pieces of course material and others being high-stakes final project submissions. Our current approach quantifies procrastination without accounting for these assignment details and might overweight less problematic "procrastination" in the pooled results. Our measure also focuses on assignment submission in line with the conceptualization of procrastination as the delay of task completion [22], but we are aware that other aspects of assignment-related activities, such as the time of first access and the frequency of attempts, can also be leveraged to measure procrastination which might lead to different results. For instance, students who start early and consistently work on assignments until before the deadline would be considered as procrastinating with our measure, but not with measures based on the time of first access [35]. More broadly, online actions captured by log data are imperfect reflections of students' underlying psychological processes and the broader contexts of these actions. Students identified as procrastinating might be preoccupied with other essential tasks and consciously plan a late start on the focal assignment. A more concerning situation might be that students procrastinate as a result of anxiety and depression caused by challenging life events, such as the COVID-19 pandemic. Without additional contextual information, our procrastination measure, as much as any other purely behavior-based measure, can only be taken as an approximation.

Our study provides large-scale insights about academic procrastination behavior and inequality in the context of a large U.S. research institution. This work raises several important directions for future research. First, we identify substantial variation between courses in how strongly procrastination predicts performance. This encourages future research on how specific course and task characteristics affect this relationship, especially in small classes where this relationship varies the most and instructors have more flexibility in instructional design and policies. Such insights can inform dynamic interventions to counteract undesirable procrastination behavior. Second, using the same modeling approach, researchers can study within-individual variation (or stability) in procrastination behavior over time and across concurrent courses. Students sometimes procrastinate due to busy course schedules, new learning environments (e.g., first year of college), or other contextual factors. Students may also develop self-regulated learning skills throughout their college experience that reduce the chance of procrastination. In any case, tracking procrastination behavior at the individual level may shed light on students' educational contexts and development of study habits and help improve institutional policies to better support student success. Finally, this study exemplifies equity-oriented learning analytics research, which is a growing area of research [30, 41]. Future contributions to this research area can examine other aspects of learning behavior across demographic groups of students and in the broader context of social injustice. An understanding of how behavioral inequalities arise and contribute to gaps in educational access, experiences and outcomes can inform ways to improve justice, equity, diversity, and inclusion in education.

REFERENCES

[1] Lalitha Agnihotri, Ryan Baker, and Steve Stalzer. 2020. A Procrastination Index for Online Learning Based on Assignment Start Time. In *Proceedings of The 13th International Conference on Educational Data Mining (EDM 2020)*. 550–554.

[2] Nora'Ayu Ahmad Uzir, Dragan Gasevic, Wannisa Matcha, Jelena Jovanovic, and Abelardo Pardo. 2020. Analytics of time management strategies in a flipped classroom. *Journal of Computer Assisted Learning* 36 (02 2020). https://doi.org/10.1111/jcal.12392

[3] Rachel Baker, Di Xu, Jihyun Park, Renzhe Yu, Qiujie Li, Bianca Cung, Christian Fischer, Fernando Rodriguez, Mark Warschauer, and Padhraic Smyth. 2020.

The benefits and caveats of using clickstream data to understand student self-regulatory behaviors: opening the black box of learning processes. *International Journal of Educational Technology in Higher Education* 17, 1 (dec 2020). https://doi.org/10.1186/s41239-020-00187-1

[4] Ryan S. Baker and Aaron Hawn. 2021. Algorithmic Bias in Education. *International Journal of Artificial Intelligence in Education* (nov 2021), 1–36. https://doi.org/10.1007/s40593-021-00285-9

[5] Temi Bidjerano. 2005. Gender Differences in Self-Regulated Learning. *Annual Meeting of the Northeastern Educational Research Association* (2005). https://eric.ed.gov/?id=ED490777

[6] J. Broadbent and W.L. Poon. 2015. Self-regulated learning strategies & academic achievement in online higher education learning environments: A systematic review. *The Internet and Higher Education* 27 (2015), 1–13. https://doi.org/10.1016/j.iheduc.2015.04.007

[7] Simon Buckingham Shum, Rebecca Ferguson, and Roberto Martinez-Maldonado. 2019. Human-centred learning analytics. *Journal of Learning Analytics* 6, 2 (2019), 1–9.

[8] Anthony P Carnevale, Tamara Jayasundera, and Artem Gulish. 2015. Good jobs are back: College graduates are first in line. (2015).

[9] Rebeca Cerezo, Miguel Sánchez-Santillán, M. Puerto Paule-Ruiz, and J. Carlos Núñez. 2016. Students' LMS interaction patterns and their relationship with achievement: A case study in higher education. *Computers & Education* 96 (2016), 42–54. https://doi.org/10.1016/j.compedu.2016.02.006

[10] Bodong Chen and Haiyi Zhu. 2019. Towards value-sensitive learning analytics design. In *Proceedings of the 9th international conference on learning analytics & knowledge*. 343–352.

[11] Jin Nam Choi and Sarah V Moran. 2009. Why not procrastinate? Development and validation of a new active procrastination scale. *The Journal of social psychology* 149, 2 (2009), 195–212.

[12] Shamarukh F. Chowdhury and Timothy A. Pychyl. 2018. A critique of the construct validity of active procrastination. *Personality and Individual Differences* 120 (2018), 7–12. https://doi.org/10.1016/j.paid.2017.08.016

[13] Angela Hsin Chun Chu and Jin Nam Choi. 2005. Rethinking procrastination: Positive effects of" active" procrastination behavior on attitudes and performance. *The Journal of social psychology* 145, 3 (2005), 245–264.

[14] Geoffrey L Cohen and Julio Garcia. 2008. Identity, belonging, and achievement: A model, interventions, implications. *Current directions in psychological science* 17, 6 (2008), 365–369.

[15] Sophie H. Cormack, Laurence A. Eagle, and Mark S. Davies. 2020. A large-scale test of the relationship between procrastination and performance using learning analytics. *Assessment & Evaluation in Higher Education* 45, 7 (2020), 1046–1059. https://doi.org/10.1080/02602938.2019.1705244

[16] Rajeev Darolia. 2014. Working (and studying) day and night: Heterogeneous effects of working on the academic performance of full-time and part-time students. *Economics of Education Review* 38 (2014), 38–50.

[17] Cristobal de Brey, Lauren Musu, Joel McFarland, Sidney Wilkinson-Flicker, Melissa Diliberti, Anlan Zhang, Claire Branstetter, and Xiaolei Wang. 2019. *Status and Trends in the Education of Racial and Ethnic Groups 2018 (NCES 2019-038)*. Technical Report. National Center for Education Statistics.

[18] Ralph Hall. 2010. The work–study relationship: experiences of full-time university students undertaking part-time employment. *Journal of education and Work* 23, 5 (2010), 439–449.

[19] Phil Hill. 2021. State of Higher Ed LMS Market for US and Canada: Year-End 2020 Edition. https://philonedtech.com/state-of-higher-ed-lms-market-for-us-and-canada-year-end-2020-edition/

[20] Jake M Hofman, Amit Sharma, and Duncan J Watts. 2017. Prediction and explanation in social systems. *Science* 355, 6324 (2017), 486–488.

[21] Ayaan M Kazerouni, Stephen H Edwards, and Clifford A Shaffer. 2017. Quantifying incremental development practices and their relationship to procrastination. In *Proceedings of the 2017 ACM Conference on International Computing Education Research*. 191–199.

[22] Kyung Ryung Kim and Eun Hee Seo. 2015. The relationship between procrastination and academic performance: A meta-analysis. *Personality and Individual Differences* 82 (2015), 26–33. https://doi.org/10.1016/j.paid.2015.02.038

[23] René F Kizilcec and Hansol Lee. 2020. Algorithmic fairness in education. *arXiv preprint arXiv:2007.05443* (2020).

[24] René F Kizilcec, Mar Pérez-Sanagustín, and Jorge J Maldonado. 2017. Self-regulated learning strategies predict learner behavior and goal attainment in Massive Open Online Courses. *Computers & education* 104 (2017), 18–33.

[25] René F. Kizilcec, Chris Piech, and Emily Schneider. 2013. Deconstructing Disengagement: Analyzing Learner Subpopulations in Massive Open Online Courses. In *Proceedings of the Third International Conference on Learning Analytics and Knowledge* (Leuven, Belgium) *(LAK '13)*. Association for Computing Machinery, New York, NY, USA, 170–179. https://doi.org/10.1145/2460296.2460330

[26] Qiujie Li, Rachel Baker, and Mark Warschauer. 2020. Using clickstream data to measure, understand, and support self-regulated learning in online courses. *The Internet and Higher Education* 45 (2020), 100727. https://doi.org/10.1016/j.iheduc.2020.100727

[27] Dana H Lindsley, Daniel J Brass, and James B Thomas. 1995. Efficacy-performing spirals: A multilevel perspective. *Academy of management review* 20, 3 (1995), 645–678.

[28] Quan Nguyen, Bart Rienties, and John T. E. Richardson. 2019. Learning analytics to uncover inequality in behavioural engagement and academic attainment in a distance learning setting. *Assessment & Evaluation in Higher Education* (nov 2019), 1–13. https://doi.org/10.1080/02602938.2019.1679088

[29] Jason W Osborne. 2007. Linking stereotype threat and anxiety. *Educational psychology* 27, 1 (2007), 135–154.

[30] Luc Paquette, Jaclyn Ocumpaugh, Ziyue Li, Alexandra Andres, and Ryan Baker. 2020. Who's Learning? Using Demographics in EDM Research. *Journal of Educational Data Mining* 12, 3 (Oct. 2020), 1–30. https://doi.org/10.5281/zenodo.4143612

[31] Jihyun Park, Renzhe Yu, Fernando Rodriguez, Rachel Baker, Padhraic Smyth, and Mark Warschauer. 2018. Understanding Student Procrastination via Mixture Models. In *Proceedings of the 11th International Conference on Educational Data Mining (EDM 2018)*. Buffalo, NY, United States, 187–197. https://files.eric.ed.gov/fulltext/ED593094.pdf

[32] Paul R Pintrich. 2004. A conceptual framework for assessing motivation and self-regulated learning in college students. *Educational psychology review* 16, 4 (2004), 385–407.

[33] Fernando Rodriguez, Renzhe Yu, Jihyun Park, Mariela Janet Rivas, Mark Warschauer, and Brian K. Sato. 2019. Utilizing Learning Analytics to Map Students' Self-Reported Study Strategies to Click Behaviors in STEM Courses. In *Proceedings of the 9th International Conference on Learning Analytics & Knowledge (LAK '19)*. ACM Press, Tempe, AZ, USA, 456–460. https://doi.org/10.1145/3303772.3303841

[34] Henri C. Schouwenburg. 1995. *Academic Procrastination*. Springer US, Boston, MA, 71–96. https://doi.org/10.1007/978-1-4899-0227-6_4

[35] Laura J Solomon and Esther D Rothblum. 1984. Academic procrastination: frequency and cognitive-behavioral correlates. *Journal of counseling psychology* 31, 4 (1984), 503.

[36] Steven J Spencer, Claude M Steele, and Diane M Quinn. 1999. Stereotype threat and women's math performance. *Journal of experimental social psychology* 35, 1 (1999), 4–28.

[37] Piers Steel. 2007. The nature of procrastination: A meta-analytic and theoretical review of quintessential self-regulatory failure. *Psychological Bulletin* 133, 1 (2007), 65–94. https://doi.org/10.1037/0033-2909.133.1.65

[38] Piers Steel and Katrin B Klingsieck. 2016. Academic Procrastination: Psychological Antecedents Revisited. *Australian Psychologist* 51, 1 (2016), 36–46. https://doi.org/10.1111/ap.12173

[39] Claude M Steele and Joshua Aronson. 1995. Stereotype threat and the intellectual test performance of African Americans. *Journal of personality and social psychology* 69, 5 (1995), 797.

[40] Nicole M Stephens, Sarah SM Townsend, and Andrea G Dittmann. 2019. Social-class disparities in higher education and professional workplaces: The role of cultural mismatch. *Current Directions in Psychological Science* 28, 1 (2019), 67–73.

[41] Suraj Uttamchandani and Joshua Quick. 2022. An Introduction to Fairness, Absence of Bias, and Equity in Learning Analytics. In *Handbook of Learning Analytics* (2nd ed.), Charles Lang, George Siemens, Alyssa Friend Wise, Dragan Gašević, and Agathe Merceron (Eds.). SoLAR, Vancouver, Canada, Chapter 20, 205–212. https://doi.org/10.18608/hla22.020

[42] Peter E Williams and Chan M Hellman. 2004. Differences in self-regulation for online learning between first-and second-generation college students. *Research in Higher Education* 45, 1 (2004), 71–82.

[43] Kimberly Williamson and Rene Kizilcec. 2022. A Review of Learning Analytics Dashboard Research in Higher Education: Implications for Justice, Equity, Diversity, and Inclusion. In *LAK22: 12th International Learning Analytics and Knowledge Conference* (Online, USA) *(LAK22)*. Association for Computing Machinery, New York, NY, USA, 260–270. https://doi.org/10.1145/3506860.3506900

[44] Philip H Winne. 2011. A cognitive and metacognitive analysis of self-regulated learning. In *Handbook of self-regulation of learning and performance*. 15–32.

[45] Alyssa Friend Wise, Juan Pablo Sarmiento, and Maurice Boothe Jr. 2021. Subversive learning analytics. In *LAK21: 11th International Learning Analytics and Knowledge Conference*. 639–645.

[46] Christopher A Wolters and Anna C Brady. 2021. College students' time management: A self-regulated learning perspective. *Educational Psychology Review* 33, 4 (2021), 1319–1351.

[47] Mengfan Yao, Shaghayegh Sahebi, and Reza Feyzi Behnagh. 2020. Analyzing student procrastination in MOOCs: a multivariate Hawkes approach. In *Proceedings of the 13th Conference on Educational Data Mining (EDM2020)*.

[48] Ji Won You. 2015. Examining the effect of academic procrastination on achievement using LMS data in e-learning. *Journal of Educational Technology & Society* 18, 3 (2015), 64–74.

[49] Barry J. Zimmerman. 1990. Self-Regulated Learning and Academic Achievement: An Overview. *Educational Psychologist* 25, 1 (1990), 3–17. https://doi.org/10.1207/s15326985ep2501_2