WIP: Examining the Impact of a Flexible Extension Policy on Student Learning Experience in a Large-Scale Computing Course

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***Abstract*—This Work-In-Progress Research paper examines the measurable impacts of a flexible extension policy on course learning objectives in large-scale computing courses. In higher education, flexible extension policies have become increasingly common, where students can individually request additional time on assignments to accommodate their unique learning needs and life circumstances. This paper analyzes the effects of extensions on cultivating student learning and academic performance using flexible extension data from an undergraduate Data Science course at a U.S. R1 institution. We study how extension policies impact different groups of students based on their usage. Using the policy, students are achieving high rates of assignment submissions. While prior experience has no bearing on how students use the extension policy, students who use the policy tend to have slightly lower final exam scores. This early work aims to inform educators about the efficacy of flexible extensions and how they impact student learning and academic outcomes. Ultimately, our goal is to contribute to the creation of a supportive learning environment where all students can succeed. In this paper, we intend to answer the following research questions: 1) How does a flexible extension policy improve students' learning experience in the course? 2) How does student extension usage across a course term correlate with academic learning goals?**

***Index Terms*—Higher education [syn: College, University]; Equity; Educational Software**

I. Introduction

A common perception is that grades should be a representative measure in terms of learning and mastery of course content. This is reflected in traditional classroom settings, where students adhere to strict deadlines and are incentivized to submit assignments in a timely manner. While managing workload and time is a vital skill, this approach can present challenges for students facing unexpected extenuating circumstances, such as personal health issues and family emergencies.

Students may also encounter other significant barriers to completing assignments promptly, such as academic burnout. Mental health crises, particularly prevalent among STEM students, are often attributed to overwhelming workloads, complex assignments, or rigid classroom policies [1], [2]. These challenges may hinder students from completing assignments on time, potentially leading them to forgo assignments altogether when faced with inflexible deadlines. These issues

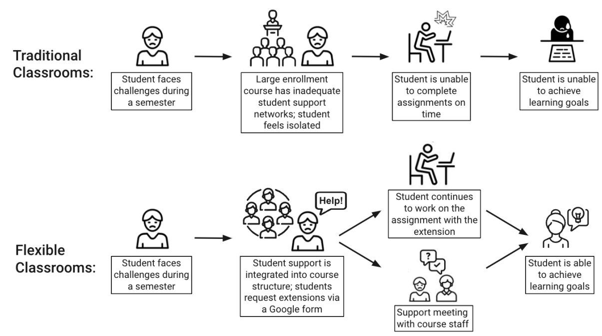

Fig. 1. A comparison of extension policies in different classroom structures.

are exacerbated for students with limited prior experience. Previous research [3], [4] has suggested that students with different prior knowledge may approach assignments and deadlines differently. Students with extensive prior experience in the course may be more adept at managing their time and completing assignments promptly; by contrast, those with less experience may require additional time to grasp concepts and complete tasks. Consequently, grading systems that penalize missing or late assignments, particularly in rigid classroom structures that do not allow for any flexibility, may not accurately assess every student's learning or understanding of the material.

In response to such concerns, many higher-education courses have adopted and studied the impacts of a flexible extension policy [5]–[7]. This classroom designrecognizes the extenuating circumstances that could be preventing some students from completing their assignments and provides several options—giving students more time on specific assignments, or incorporating an auto-grader so that students can get instant feedback on their work.

Prior work has shown that such methods where students are given ample time to achieve understanding, widely known mastery learning practices, positively affect student engagement, learning progress, and final grades [8]. However, the exact impact of such a policy is still unknown. In this Work-In-Progress paper, we collect and analyze data on student usage of extensions, class-specific student academic performance, and student background on the subject in one large-scale, college-level data science course that has implemented a flexible learning approach. This work aims to explore the impacts of this flexible extension policy on student learning experience, learning goals and performance with the following two questions:

RQ1) How does a flexible extension policy improve student learning experience in the course? Student learning experience varies by individual and course context. The Data Science course we are examining comprises small, follow-along lab assignments, longer homework assignments, and multi-week projects. For research purposes, we define a student's learning experience as whether students stay on track with course content and submit these assignments as close to their due date as possible instead of forgoing them.

RQ2) How does student extension usage across a course term correlate with academic learning goals? While academic learning encompasses more than just a student's final score at the end of the course, we define learning goals based on how well a student masters the course content by the end of the semester. To quantify this, we assessed the students' performance on corresponding questions in the final exam to determine their mastery of relevant knowledge.

In this work, we found that students' usage of the extension policy was not significantly correlated with their prior experience. Our results also showed that the usage of extensions aids in a 95% completion rate for each assignment, improving student experience, but has a slightly negative correlation with academic learning goals, as those requesting extensions have a lower mean final exam score (see Table II-A).

II. Related Work

The current study extends previous research [9] by incorporating a grace period and an accessible extension request pipeline. Here, we aim to investigate the impact of combining a grace period with an extension request workflow for longer extensions on students' mastery of course content. Previous research also neglected to focus on the relationship between student background factors and academic outcomes. While past studies have indicated a positive correlation between prior experience and academic performance [3], [4], they did not identify possible measures to quantify this difference, particularly when considering flexible extension policies. Past research also utilized self-reporting questionnaires to quantify student academic engagement, which could be affected by self-report bias.

Our approach is similar to other studies [8], [10] that allow students to complete assignments at their own pace, framed by additional deadlines that encourage continuous learning. Students may complete assignments at their own pace up to the end of a 24-hour grace period after the original deadline; students who need additional time beyond this grace period must request the extension through a Google Form. A staff member reviews these requests and adjusts them based on the situation the student described. The process is automated through a Google Cloud backend [11], [12].

The structure of our courses aligns with the principles of Universal Design for Learning (UDL) [13], which emphasizes providing multiple means of representation, engagement, and expression to accommodate diverse learners. UDL is particularly beneficial for neurodivergent and disabled students, as it fosters an inclusive learning environment that acknowledges and addresses varied cognitive and physical needs [14]. The course encompasses a variety of elements, including synchronous elements, such as in-person or online discussions, which students are required to attend, and asynchronous elements, such as weekly assignments with varying difficulty, which students can complete at their own pace. This framework ensures that our course promotes equitable access to learning opportunities for all students.

A. Course Description

The study focuses on an intermediate-level course at an R1 institution that bridges the introductory data science course Data 1 (Foundations of Data Science) and other advanced Data Science courses, such as Data Mining. The course builds quantitative critical thinking and familiarity with fundamental principles and techniques for the data science cycle. It includes elements of synchronous learning (lecture and discussion attendance), small lab assignments, week-long homework assignments, and larger multi-week projects. Labs are direct applications of lecture material. Homework assignments require more critical thinking and application of concepts into real-world scenarios. Projects build upon previous units to solve a case study. Course prerequisites include foundations in computer science, calculus, and linear algebra. Students nevertheless enter with varying levels of competence in calculus, linear algebra, computer science, and other relevant topics.

The course is divided into 12 units based on content (described in Table II-A), with each unit having a corresponding lab, homework, and (optionally) project. The Fall 2023 semester offering had 1087 enrolled students.

- **Computational units:** Units 1, 2, 3, 4, 8, 10, 12
- **Conceptual units:** Units 5, 6, 7, 9, 11

III. Defining Student Learning Experience and Academic Learning Goals

This section clarifies our metrics for the variables in our research questions and justifies why these are appropriate working representations. The current definitions are somewhat preliminary, and the variables are still being developed. Here are the definitions we are using at present:

We define the student learning experience as the collective performance and participation in the course. Given that most assignments are expected to receive full credit, the difference in assignment scores between students who receive extensions and those who do not is minimal. Therefore, to quantify this variable, we define it as the proportion of students completing assignments as opposed to forgoing them in a traditional

TABLE I

AVERAGE UNIT FINAL SCORE IS SLIGHTLY LOWER FOR PEOPLE WHO REQUEST EXTENSIONS DURING THE UNIT.

	Mean performance on final exam	
Weekly units[1]	Without extensions (std. err)	With extensions (std. err)
1: Pandas	0.73(0.21)	0.67(0.22)
2: EDA	0.82(0.26)	0.72(0.33)
3: Regex	0.77(0.25)	0.70(0.27)
4: Visualizations	0.84(0.18)	0.77(0.19)
5: Sampling	0.85(0.17)	0.79(0.22)
6: Modeling/OLS*	0.58(0.26)	0.48(0.28)
7: Gradient Descent*	0.70(0.30)	0.53(0.32)
8: Cross-Validation & Regularization*	0.61(0.20)	0.44(0.23)
9: Probability & Bias-Variance Tradeoff	0.56(0.18)	0.51(0.17)
10: SQL*	0.69(0.24)	0.55(0.25)
11: Logistic Regression	0.62(0.22)	0.56(0.22)
12: PCA & Clustering*	0.69(0.18)	0.57(0.18)

*Units with a significant difference ($p < .01$) in performance.

classroom setting with no extension policy. We leave further exploration and definition of the student learning variable to future work, which should additionally quantify factors like engagement in various course activities, including attending class or effort in completing assignments.

Academic learning is defined as the corresponding score on the final exam out of 90 points, conditioned on the student's extension usage category, and the unit-specific scores on the exam (standardized to be between 0 and 1), conditioned on whether students received an extension during that unit. This definition allows us to measure the overall mastery of course content by students who utilize the extension policy differently and provides a granular view of their understanding of each unit. This enables us to discern differences in unit-specific performance based on extension usage. We note that our focus on grades is a cautious but early metric of student learning; prior work has found limitations in how grades capture mastery of course content [15], and future work should address this limitation.

IV. METHODS

A. Flexible Extension Policy

In a traditional classroom, students are subject to rigid deadlines, and failure to comply with the deadline reduces course credit. As demonstrated in Figure 1 under "Traditional Classrooms," this system strongly favors students with prior experience and does not consider the life emergencies that students face and the additional support needed to learn the content. The current extension policy in the flexible classroom we are studying, as outlined in 1 under "Flexible Classrooms," includes a 24-hour grace period for assignment due dates. This grace period is designed to account for minor last-minute emergencies, such as internet issues. For more significant problems (e.g., family emergency, sickness), referred to in the course as "extenuating circumstances," students complete a Google Form. This form serves as the starting point between the communication of students and instructors and allows students to receive additional support, such as extensions on assignments or additional content resources.

Upon receiving the form submission from students, course staff members review request details to determine an appropriate accommodation, including the number of granted extension days for the student. Course staff members then initiate a workflow to inform the student of the decision through email and update corresponding due date on the assignment submission platform.

Internally, the form submission is connected to a Google Sheet backend, the primary interface for course staff to manage requests. Utilizing Google Cloud Services, the Google Sheet automates emails to each student and updates their due date on Gradescope, the central system where students submit assignments at the institution. More details on the services this workflow utilizes can be found in [11].

Unlike the traditional classroom, this approach allows instructors to receive student requests centrally and formalizes communication methods between students and the teaching team. In this way, instructors can encourage students to complete assignments with extended time instead of skipping assignments and missing out on learning opportunities. While the traditional classroom compels students to abandon assignments when faced with difficulties, flexible classrooms encourage their completion so that the students can achieve their learning goals.

B. Data Collection

Data was collected during the Fall 2023 semester, including five datasets described in Table II. The student prior experience dataset consisted of questions about a student's familiarity (from 0 to 3) with eight topics: calculus, probability, linear algebra, inference (e.g., bootstrapping), SQL, Python, NumPy, and Python visualization tools (e.g., matplotlib, seaborn). A student's prior experience score ranges from 0 to 24. During the semester, this data was only accessible to course instructors and lead TAs. All data used in this work was collected according to Institutional Review Board (IRB) protocols.

TABLE II

FIVE DATASETS COLLECTED FOR A FALL 2023 DATA SCIENCE COURSE.

Information Collected	**Method of Collection**
Student grade on every assignment in the semester	Downloaded from Gradescope and anonymized
Number of days each student received for each assignment	Recorded and organized in a Google Sheet throughout the semester, anonymized for this study
Student prior experience with relevant topics of the class	Recorded and organized in a Google Sheet at the start of the semester, anonymized for this study
Midterm score for each student	Downloaded from Gradescope and anonymized
Midterm score for each student	Downloaded from Gradescope and anonymized

C. Subpopulations of Student Extension Usage

We divided the students into four groups based on extension policy usage patterns throughout the semester:

- **On Time** (Group 1): No extensions and not frequent grace period users. $N = 633$ students. (lower 75th percentile of lateness) This is also referenced as our control.
- **Grace Period** (Group 2): No extensions, frequent grace period users. At least 8 assignments out of 28 were late. $N = 118$ students.
- **Extensions** (Group 3): 1-2 extensions. $N = 222$ students.
- **Extenuating Circumstance** (Group 4): 3 or more extensions. n = 105 students.

To study the impact of prior experience on extension usage, we also split students into even groups of least to most experience based on the quartile of their prior experience score (as mentioned in Data Collection). The groups were split as follows: scores $[0, 13)$ ($N = 246$), scores $[13, 16)$ ($N = 268$), scores $[16, 19)$ ($N = 279$), and scores $[19, 24]$ ($N = 210$).

V. Results & Discussion

A. Extension Requests & Prior Experience

The proportion of students in each subpopulation of extension usage conditioned on experience group is approximately the same for each experience group, with slightly over a quarter of the students in each experience group being a part of the On Time subpopulation, and less than a quarter in each of the other groups. Students with more prior experience tend to request fewer extensions on average. However, the difference in means for extension requests may be due to randomness ($p > 0.1$). The distribution of number of extensions for each prior experience group is very similar, as shown in Figure 2.

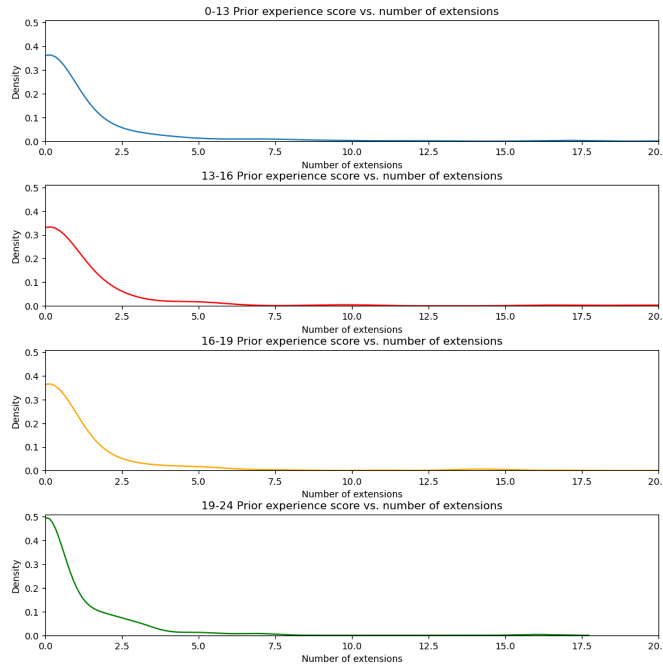

Fig. 2. The distribution of extensions is the same across each prior experience group.

B. RQ1: Learning Experience with Assignment Completion

Since prior experience does not significantly impact extension usage, we measure the extension policy's impact on student learning experience across the full course. We posit that the student learning experience is improved if students submit all assignments in a timely manner. Out of the 1078 students that ended up taking the final, 943 of them utilized the grace period or extensions, with 372 of the 943 using the extension workflow to request extra time. The resource is widely used among the students and appears to minimize the abandonment of assignments. Two-thirds of the class (711 out of the 1078 that ended up taking the final) did not miss any assignments at all. 90% (971 out of 1078) missed fewer than 5 assignments. Around 5% of the class population missed each assignment, with the lowest submission rate being Lab 7 (the assignment right before the midterm) with 88% and Project A2 (the first project assignment right after the midterm) with 89%. Respectively, these assignments were worth 1% and 3.75% of the total grade. We compared the submission times of a computational unit with a smaller final score deviation (Unit 3: Regex) to a conceptual unit with a larger final score deviation (Unit 6: Modeling/OLS) in Figure 3. More difficult units have a more left-skewed distribution, with more students opting to use the 24-hour grace period or an extension. The assignments typically reach around 95% completion within a week after the due date.

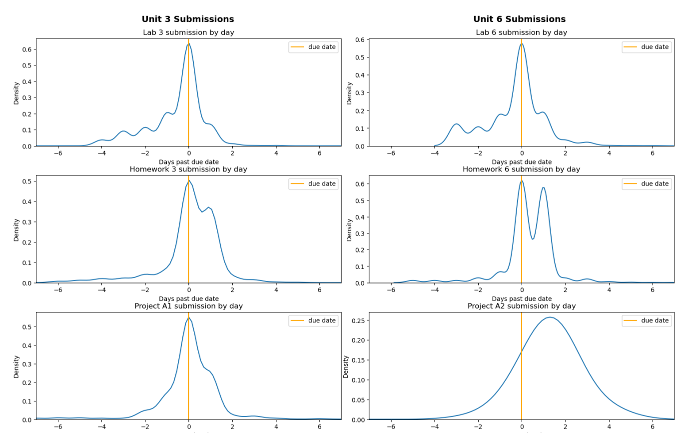

Fig. 3. The distribution of submissions for easier units (see: left) is more unimodal than for harder units, where students utilize extensions more.

C. RQ2: Learning Goals with Exam Grades

While prior experience may influence the frequency of extension requests, it does not significantly impact assignment grades or the distribution of extension usage for exams. However, there is a statistically significant difference between the On Time group and each of the other three subpopulations

(Grace Period, Extensions, and Extenuating Circumstances) when using bootstrap to construct a 95% confidence interval. These differences are within the standard deviation (13.10) of the overall final scores. This suggests that while the exam means are significantly different, the observed discrepancies between each group from the control are relatively small compared to the expected variability in final scores, which we define as the standard deviation. Each subgroup appears to encompass a heterogeneous distribution of scores, reflecting a diverse range of academic performance levels. Thus, membership in a subgroup does not dictate a specific percentile of final performance; instead, a mix of high-performing and lower-performing individuals exists within each subgroup. This indicates that using the flexible extension policy in a certain way does not preclude individuals from achieving any score on the final assessment. Additionally, between the three groups that utilize the flexible extension policy, the lower bound of each interval is at most 1.2 points, meaning that the difference is negligible for policy users.

TABLE III
THE FINAL MEAN OF EACH SUBPOPULATION DIFFERS SIGNIFICANTLY FROM THE ON-TIME GROUP.

Group	Average final score (std err)	Observed difference from Group 1	95% confidence interval
On-Time	61.98 (12.58)	-	-
Grace Period	55.40 (12.18)	6.58	[4.22, 9.00]
Extension	56.68 (12.57)	5.31	[3.42, 7.22]
Extenuating	52.39 (13.79)	9.60	[6.75, 12.42]

VI. CONCLUSION & FUTURE WORK

Our findings demonstrate that while usage of flexible extension policies can improve assignment completion—thus contributing to student ability to keep pace with the course—it is correlated with lower exam performance—perhaps revealing a larger barrier to learning. Our analysis reveals a significant difference in final exam means between students who utilize the policy and those who do not; however, regardless of usage, students still have the potential to attain scores across the entire distribution.

We have acknowledged the limitations of the variables as defined in this early work. Our next step is to extend the definitions of learning experience and academic learning goals to capture more factors that more holistically a student's experience in a higher education, large STEM course. We also plan to explore the relationship between additional variables identified in the pre-semester survey. We aim to address whether the findings are consistent across different course sizes and demographics by conducting similar classes to other data science and computer science classes at the institution so that we can understand the impact of course content and course structure on the student learning experience.

By addressing these limitations, in future work, we aim to provide a more comprehensive understanding of the factors influencing extension requests and their implications for student learning and success. We aim to design flexible extension policies that allow students to engage with every learning opportunity without disadvantages on academic exams. This understanding, when shared across instructors from a variety of courses and institutions, can help foster a fair and equitable learning environment for all students.

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