



Using a Planning Prompt Survey to Encourage Early Completion of Homework Assignments

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ABSTRACT

In an earlier study we showed that small amounts of extra credit offered for early progress on online homework assignments can reduce cramming behavior in introductory physics students. This work expands on the prior study by implementing a planning prompt intervention inspired by Yeomans and Reich's similar treatment. In the prompt we asked students to what degree they intended to earn extra credit offered for early work on the module sequence, and what their plan was to realize their intentions. The survey was assigned for ordinary course credit and due several days before the first extra credit deadline. We found that students who completed the prompt earned on average 0.6 more extra credit points and completed the modules an average of 1.1 days earlier compared to a previous semester. We detect the impact of the survey by creating a multilinear model based on data from students exposed to the intervention as well as students in a previous semester. Data from five homework sequences are included in the model to account for differences between the two semesters that cannot be attributed to the planning prompt intervention.

CCS CONCEPTS

- Applied computing-Education-E-learning
- Applied computing-Education-Computer-assisted instruction

KEYWORDS: self-regulated learning, SRL, planning prompt, extra credit, online learning

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1 INTRODUCTION

It is well documented that college students often procrastinate on assignments and, as a result of such procrastination, cram against due dates or before exams. Previous studies, as well as our own research, show that procrastination is associated with diminished academic performance [1,4,6,7]. A likely cause for this negative impact on academic performance is that students who cram due to procrastination do not have enough time to properly engage with the intended learning process. Accordingly, in this paper we focus on early work as the antithesis of procrastination.

In a previous paper, we showed that offering small amounts of extra credit to students who complete portions of assigned work in advance of the due date is associated with a small but measurable decrease in measured procrastination behavior. Yet a significant fraction of students did not take advantage of the extra credit opportunity [4].

In a study conducted on massive open online courses, Yeomans and Reich found that merely asking students to write a plan for how they would distribute their work dramatically increased the course completion rate, regardless of the contents of the plan. In the study, students were asked at the beginning of the course to indicate where and when they would work on the course material, and what they would do to ensure they would carry out their plan [9].

This work applies a similar intervention to a two-week sequence of online homework modules in a large, mixed mode, introductory physics course in addition to the extra credit we evaluated previously. We added Likert scale questions at the beginning of the planning prompt survey asking the student how strongly they intended to earn each extra credit reward for early completion of modules. We then asked them to write down their plan for completing the sequence of modules—and earning the extra credit if they intended on doing so.

We predicted that the intervention would prompt students to form concrete intent about whether they would seek the extra credit, and then create a plan for achieving their intentions. We hypothesize that the planning prompt thus will lead students to work on the module sequence earlier and as a result earn more of the extra credit offered.

One way to justify this hypothesis is through the framework of Zimmerman's Theory of Self-Regulated Learning. It posits that self-regulated learning occurs in a three-phase cycle. In the *forethought phase* a learner forms intentions and goals and creates a plan to realize them; in the *performance phase*, the learner puts their plan into action to the extent of their ability; and in the *self-reflection phase*, the learner forms opinions regarding learning and of their own self-efficacy that informs future forethought. Under this framework, we can view the planning prompt intervention as scaffolding for the forethought phase. The structure of the survey was chosen for this reason: we first ask students to form goal intentions about the extra credit, then prompt them to form a concrete plan to achieve their goals.

Because of the technical and pedagogical challenges of randomly assigning half of the class to receive this for-credit intervention, we exposed all students in the course to the prompt and compare their behavior to that of students in a previous semester. To control for any extraneous factors that could impact students' work distribution, we use the analysis method of *difference in differences*, initially used by John Snow in his famous efforts to pinpoint the source of London's cholera outbreaks and formalized by economists Ashenfelter, Card, and Krueger [3].

2 METHODS

2.1 Experimental Setup

2.1.1 Implementation of Online Homework and Extra Credit. Homework assignments in the form of online learning module sequences are created on the Obojoko platform, developed by the Center for Distributed Learning at the University of Central Florida [2]. Each online learning module covers a single concept or one type of problem and consists of an instructional component containing text and practice problems, and an assessment component containing one or two problems. Several modules form a module sequence on a given topic; students must complete each module in the sequence in order. A module is complete when the student either answers the problems(s) correctly or exhausts their allowed five attempts to do so. Students have about two weeks to complete each sequence before the due date.

In this study we examine five sequences of 7–11 modules over two semesters: Fall 2020 and Fall 2021. Students in each semester enrolled in the same calculus-based introductory physics course taught in a similar mixed mode format by the same instructor. Each homework sequence is worth 3–4% of the total course grade. The 2020 semester had 226 and the 2021 semester had 114.

In both semesters, students were able to earn "Treasure Trove" extra credit points by completing some number of modules in advance of the due date. The extra credit was implemented in the form of quizzes on Canvas, which asked simply whether the student wanted extra credit. In the Energy sequence, students who completed the first 3 of the 10 modules 10 days before the due date could earn 2 points of extra credit. Similarly, if a student completed 6 of the 10 modules 7 days in advance of the due date,

they could earn 2 points of extra credit. Finally, those who completed 9 modules 2 days before the due date can access 3 points of extra credit. A total of 47 extra credit points were made available to students and are worth 5% of the total course grade. The other sequences had similarly structured extra credit which was the same across both semesters.

Submissions after the due date are graded with a 13-percentage-point deduction per day, rounded up to the nearest day. Thus, a student can earn partial credit as late as 7 days after the due date. The late submission penalty also applied to the extra credit, allowing students to obtain some credit for them later than intended. This impacts both semesters equally and does not jeopardize our analysis.

2.1.2 Planning Prompt Intervention. In Fall 2021, students were given a planning prompt survey before the Energy sequence of modules, the seventh sequence of the semester. It asked students to indicate on a Likert scale how strongly they intended to earn each extra credit Treasure Trove. It then informed the students that cramming leads to poorer academic performance and asked them to make and type a plan for when and where they would work on the modules of the sequence. Completion of the survey was mandatory (assigned for normal course credit) and worth 4 points—about 4% of the grade for the sequence. The survey is only graded for completion, so submitting it blank would still have earned the full 4 points. It was due 10 days before the Energy sequence due date, at the same time as the first extra credit deadline.

2.2 Data Analysis

2.2.1 Measures of Early Work. We use two different metrics for early work on modules in a sequence: Treasure Trove points earned and excess time per module. Treasure Trove points earned are extracted directly from the course gradebook. The more extra credit points earned, the earlier the modules are completed compared to the sequence due date. All sequences had 7 potential extra credit points except for 1D/2D Motion, which offered a maximum of 8. To make the sequences directly comparable, extra credit earned on that sequence is multiplied by 7/8 to make the maximum points 7 across the board.

Excess time per module for a sequence is the average amount of time between a student completing a module and the due date for the sequence. When calculating excess time, if a student does not finish a module within 7 days after the due date, we consider them to have completed it exactly 7 days after the due date. The 7-day cutoff corresponds to the time after which no partial credit can be earned due to late penalty. Modules completed after the due date contribute negative excess time.

2.2.2 Multilinear Fitting. Our analysis utilizes a linear fitting technique outlined in Cunningham's *Causal Inference* [3]. We assume that in the absence of intervention, both measures of early work will exhibit parallel trends in the two semesters. That is, the extraneous factors that impact students' work distribution, such as

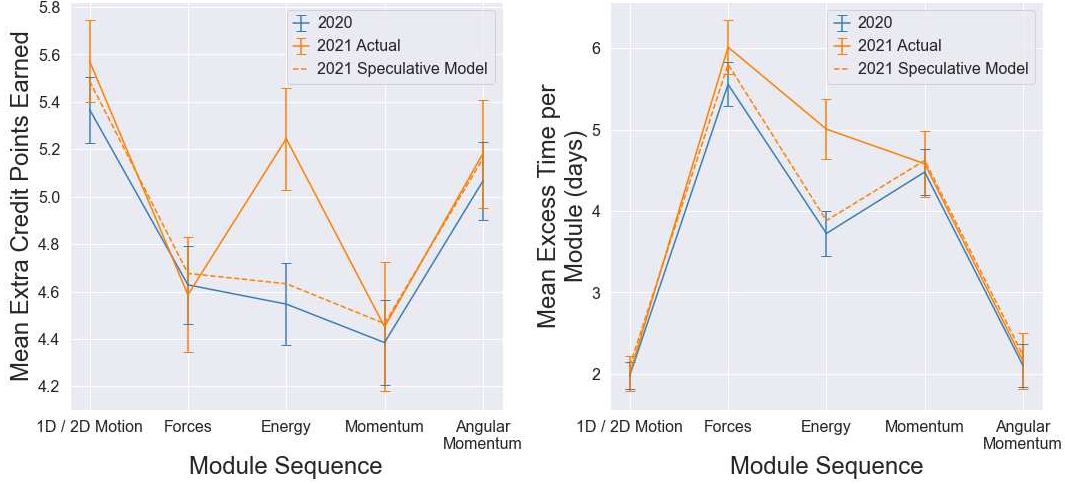


Figure 1: Mean extra credit points earned and mean excess time per module versus module sequence. Data for the 2020 semester is plotted in blue and shown with error bars. The actual 2021 data is plotted with a solid orange line with error bars. Error bars given correspond to one standard error for the mean. Plotted with an orange dashed line is a speculative model estimating what we would have seen in 2021 if we did not expose the students to the planning prompt intervention.

differences in instructional condition and student population, have mostly uniform impact on each sequence, whereas the impact of intervention will only be observed on certain module sequences. Under this assumption we can create the following linear model for each measure of early work:

$$\bar{x}_{est} = \beta_D D + \beta_F F + \beta_E E + \beta_M M + \beta_L L + \beta_Y Y + \beta_T T \quad (1)$$

Here $\bar{x}_{est}$ is the estimate for the mean of one of the two metrics on a certain module sequence in one of the two semesters. $D, F, E, M,$ and L are module sequence dummy variables for the five sequences included in our analysis; they are equal to 1 when the observation comes from the corresponding module sequence and 0 otherwise. Y is the semester dummy variable: it is 0 for 2020 and 1 for 2021. T is 1 only for the module sequence that received the planning prompt treatment (Energy 2021). Each β is a coefficient that remains the same for all sequences and both semesters. Values for β are determined using a least-squares multilinear regression algorithm.

We also created a “speculative model” to estimate what we would have seen had we not implemented the planning prompt survey, by removing the treatment (T) term from the equation. Since β_T is the estimated effect size of the treatment, removing it gives the expected result assuming that the intervention had no impact.

In our analysis we only include students from Fall 2021 who submitted the survey prior to its due date—86% of students. This includes those who submitted a blank survey. Students who were not exposed to the intervention for the Energy sequence (by failing to submit the survey on time) are discarded from the entire semester’s data, meaning any self-selection effect would manifest over all sequences in 2021. This means that while students who answered the survey could be less likely to procrastinate, this

effect would be the same for all sequences studied and be accounted for in the Y term of Equation 1.

3 RESULTS

In Figure 1 we plot the means of both measures of early work for both semesters. We also plot the speculative model estimating the hypothetical means of each measure in 2021 without the planning prompt intervention.

We find that the mean value of both measures are similar across the two semester on all sequences except for the Energy sequence, for which students in 2021 earned more Treasure Trove credits and had more access time prior to the due date. In addition, the speculative model also closely matches the observed 2021 data for all sequences except the Energy sequence. This further confirms that the assumption of parallel trends we used to make the model is indeed reasonable. If the assumption of parallel trends were unjustified, the model would be unable to closely estimate the means in either year.

Tables 1 and 2 give the coefficients associated with the multilinear model, as well as the p -value of a test for correlation. A sufficiently small p -value indicates that the measure of early work is correlated with the coefficient. The test is a t -test modified to be robust against heteroskedasticity—the case where variances of the dependent variable change with the independent variable(s) (HC1 standard error computation) [5]. The test used gives results identical to Student’s t when variance is constant.

As shown in the tables, completion of the planning prompt intervention (β_T term) is significantly associated with earlier submissions and increased Treasure Trove points earned ($p < 0.05$).

Table 1: Model coefficients for extra credit points earned. The coefficients listed correspond to those in Equation 1. Given p -values come from significance test for difference from 0. The test used is a t -test with modification to make it robust against heteroskedasticity (unequal variances).

Model Coefficients for Extra Credit Points Earned		
Coefficient	Value (credit points)	p -value
β_T (Treatment)	0.6117	0.048
β_Y (Year)	0.0859	0.543
β_D (1D/2D Motion)	5.4025	0.000
β_F (Forces)	4.5905	0.000
β_E (Energy)	4.5470	0.000
β_M (Momentum)	4.3789	0.000
β_L (Angular Momentum)	5.0749	0.000

On average, students who submit the planning prompt complete modules 1.1 days sooner and earn 0.61 more extra credit points. This is in accordance with the observed gap between the observed data and speculative models for 2021 Energy sequence shown in Figure 1.

On the other hand, the year-to-year difference as captured by the β_Y coefficient is not significantly different from zero, which indicates that extraneous differences between the two semesters did not significantly impact students' completion of work, nor did selecting only those who completed the survey in 2021 significantly impact the observed difference.

4 CONCLUSIONS AND DISCUSSION

We assigned students a planning prompt survey asking whether they intended to earn extra credit for early progress on online homework and what their plan was for realizing that intention for one online learning module sequence. We find that for that sequence, students who submitted this survey on time completed work significantly earlier and earned more extra credit compared to peers in a previous semester. On sequences assigned either before or after the intervention, students' early work measures are almost identical across the two semesters. This evidence shows that such an intervention is promising as a tool to reduce cramming behavior for a short period, by influencing students' planning and execution of work. However, additional intervention is needed to change students' long term work habit.

One shortcoming of the analysis presented here is the inclusion of only students who completed the survey. While self-selection effects are ruled out by the difference in differences analysis technique, the choice still restricts our conclusions to those who turned in the survey on time. Work is underway to include different levels of compliance with the intervention into the linear

Table 2: Model coefficients for excess time per module. The coefficients listed correspond to those in Equation 1. Given p -values come from significance test for difference from 0. The test used is a t -test with modification to make it robust against heteroskedasticity (unequal variances).

Model Coefficients for Excess Time per Module		
Coefficient	Value (days)	p -value
β_T (Treatment)	1.1234	0.026
β_Y (Year)	0.1586	0.443
β_D (1D/2D Motion)	1.9389	0.000
β_F (Forces)	5.6442	0.000
β_E (Energy)	3.7248	0.000
β_M (Momentum)	4.4631	0.000
β_L (Angular Momentum)	2.0713	0.000

model. This will allow us to examine the impact of assigning the survey and the impact of students submitting it on time separately.

In a follow-up experiment currently in progress in the Spring 2022 semester, students in two parallel course sections taught by different instructors will receive the planning prompt intervention on two different sequences. This not only reduces the impact of differences between different semesters (especially the impact of the COVID pandemic) but will also double the total number of data subjects. A combined linear model can be created over three semesters and four class sections, which will enable us to measure the effect size of the intervention more precisely.

Finally, there are two important future directions that will follow from the current work. First, we will study the impact of early work on students' learning behavior to determine if reduction of cramming as a result of the planning prompt intervention also leads to a change in students' learning behavior. Students' learning behavior can be measured by analysis techniques developed by Zhang, Taub, Banzon and Chen [8,10]. We will also evaluate the impact of the planning prompt intervention on performance on subsequent exams and quizzes.

Second, we will investigate the impact of implementing more than one planning prompt activity on multiple sequences. We will measure whether the impact on students' early work wanes on the second or third activity, as well as whether repeated planning prompts can have lasting impact on reducing cramming behavior on subsequent homework sequences.

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