No Benefit for High-Dosage Time Management Interventions in Online Courses

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ABSTRACT

In past work, time management interventions involving prompts, alerts, and planning tools have successfully nudged students in online courses, leading to higher engagement and improved performance. However, few studies have investigated the effectiveness of these interventions over time, understanding if the effectiveness maintains or changes based on dosage (i.e., how often an intervention is provided). In the current study, we conducted a randomized controlled trial to test if the effect of a time management intervention changes over repeated use. Students at an online computer science course were randomly assigned to receive interventions based on two schedules (i.e., high-dosage vs. low-dosage). We ran a two-way mixed ANOVA, comparing students' assignment start time and performance across several weeks. Unexpectedly, we did not find a significant main effect from the use of the intervention, nor was there an interaction effect between the use of the intervention and week of the course.

CCS CONCEPTS

• Applied computing→ Education → E-learning

• Human-Centered computing → Human computer interaction (HCI) → Empirical studies in HCI

KEYWORDS

Time management, Behavioral interventions, Diminishing effect

1 INTRODUCTION

Behavioral interventions are frequently used in online courses to influence student behaviors [4]. For example, time management interventions have been successful at improving student assignment completion rate and performance [11]. However, most past studies have investigated aggregated effects or the effectiveness of a single dose of interventions. As such, little is known about how the effectiveness of such interventions changes over time when they are administered repeatedly, a common case in their real-world use. One study has found that the effectiveness of an intervention that initially leads to better time management diminishes over time [1]

indicating that it is important to examine interventions across a longer time span, in order to understand how their effectiveness is impacted by dosage.

Therefore, in the current study, we seek to understand how the dosage of a time management intervention influences its effectiveness over time. To investigate this, we conducted a randomized controlled trial experiment and randomly assigned students within an introductory computer science class to receive intervention based on two levels of dosages (i.e., receiving messages every week vs. every three weeks). By examining subsequent student time management (specifically, how early they start the next homework assignment) and their performance on the assignment each week, we hope to understand how the effectiveness of the intervention is influenced by the dosage.

2 RELATED WORK

2.1 Time management

Time management reflects a person's ability to use time effectively and efficiently to accomplish goals [3]. During this process, relying on self-regulation, learners estimate, plan, and organize the time needed on various tasks to maximize productivity and achieve goals [15].

In the context of online learning, where the class schedule is more flexible, which allows learners to learn and practice at their own pace, the ability to manage time efficiently becomes even more critical to the success of learning [2, 10] . By surveying students who dropped out of Massive Open Online Courses (MOOCs), time related reasons, such as poor time management, were repeatedly found as the main cause for the discontinuation in learning [9, 12]. Additionally, less effective time management strategies, such as procrastination, have also been found to be negatively associated with learning outcomes [8].

In Wolters and Brady [15], time management was examined through the lens of self-regulated learning. Grounded the analysis in the three phases of problem-solving (i.e., forethought, performance, and post-performance; [18]), Wolters and Brady explained how self-regulation can be

applied at each phase to help learners manage time more efficiently. For example, in the forethought phase, through monitoring and planning, learners analyze the time needed to complete a task and then set goals on when to execute the task and when to complete it.

However, as noted in Kelly [7], people rarely give an accurate estimation; instead, they tend to underestimate or overestimate how long it takes to complete a task. In the context of online learning where students have greater flexibility in deciding when to start working on an assignment, students may underestimate the time needed to complete an assignment and start working on it too late. And this late start may lead to negative consequences, such as missing the deadline or a subpar performance on the assignment. Thus, having a correct estimation helps students to budget time wisely and prevent situations where they start working too late [16]. To this end, Nawrot and Doucet [12] recommends that courses in MOOCs should include a time estimation for tasks, as this feature would help students have a more accurate estimation on the amount of time needed to complete a task, which allows them to plan and allocate their time more wisely and efficiently.

2.2 Time management interventions

With the goal of helping students to manage time efficiently, behavioral interventions, such as the use of prompts, alerts, and planning tools, have been used in online courses. For example, in [11], email alerts were sent to students who were missing submissions for assignments with imminent deadlines. Compared to students who did not receive the alerts, students in the experimental group were less likely to miss the assignment and were more likely to obtain better course grades. Furthermore, planning tools have also been shown to be beneficial. In particular, Yeomans and Reich [17] introduced planning prompts in three MOOCs and found that students who were assigned to use the prompts and planned their study at the beginning of the course were more likely to complete the course. Similarly, Baker et al [1] found students who were asked to schedule lecture watching time in the first two weeks of a semester scored higher on the first quiz. However, the effectiveness diminished over time, with a marginal negative effect found on the last week's quiz.

Pérez-Álvarez et al. [14] used dashboards to visualize the time a student has spent on each learning activity and the time required to complete them. Similarly, Learning Tracker [5], was implemented to help students monitor the time spent on each learning topic and compare it to successful learners from the past. As a result, more students who used Learning Tracker submitted graded quizzes and were more likely to submit these quizzes earlier, compared to students who did not use the tool.

In the studies that evaluate the effectiveness of time management interventions, most of them investigate aggregated effects of interventions, such as the likelihood of course completion or the overall course grades, while others examine the effectiveness of a single dose of interventions. That is, few of them investigated the effectiveness of these interventions over time, raising questions as to whether the effectiveness will continue if the interventions are used repeatedly, a common case in their real-world use.

As noted above, Baker et al. [1] found that effectiveness of such an intervention diminished over time. In another such study, Maxim et al [13] examined the effectiveness of an email-based intervention over time and across repeated use on changing students' video watching behaviors. In their study, emails containing student progress were sent out every week. By comparing the minutes of videos watched between students who received and did not receive the email on the day after the email was sent out, they found that students who received the email watched videos for 20 minutes more in the first week of the experiment. However, the initially significant effect becomes negligible and reversed in direction over time.

3 METHODS

Students enrolled in an online introductory computer science course at a university in the northeastern U.S. participated in the study. At the beginning of the course, students were randomly assigned to one of two groups where they would receive intervention messages based on two schedules (see Table 1; Xs indicate weeks intervention messages were delivered). These two schedules enabled us to study the impacts of different dosage levels, while providing each student with the same overall dosage. In the first half of the semester, starting at week 2, students in group 1 received intervention messages every three weeks, whereas students in group 2 received the message every week. The schedule was flipped for the second half of the semester.

In these messages, information is provided regarding the level of difficulty of each week's assignment, including how early students from previous cohorts started the assignment (suggested to the students as a start time) and the average grade they obtained (see an example message below). This information was designed to help students to have a more accurate estimation of the amount of time needed to complete the assignment each week, enabling them to plan and allocate their time more efficiently [12] and avoid situations where they start working too late. These intervention messages were delivered two days before the suggested start time each week; a filler message that welcomed students to the week of study was sent to students on weeks when they did not receive the intervention messages.

Table 1: The schedule of delivering intervention messages

Week	2	3	4	5	6	7	8	9	10	11	12	13

Group 1	x			x			x	x	x	x	x	x
Group 2	x	x	x	x	x	x			x			x

Example message:

> Welcome to this week of the class. You can now access homework assignment 11 on the course platform. The assignment is due on 11/15/2021. On average, students in the last semester started working on this assignment **5** days before the due date and had an average score of **94%**.

For each homework assignment, we collected a measure, hours started before due, that reflects the number of hours between the time a student started the assignment and the due date. As such, the sooner a student starts the assignment, the higher the value is. Additionally, we collected homework grade, which was then transformed to ranks due to left skewness, and a binary variable indicating whether the intervention message was opened by the student that week. We narrowed the analysis to the first seven weeks to avoid carry-over effects, and excluded students who did not read the message in all weeks. Compared to intention-to-treat approach where all participants are included regardless of their compliances with the treatment, our criteria (per-protocol approach) excluding the noncompliant students is more able to identify treatment effects [6]. Since the goal of our analysis is to analyze the impact of reading the messages rather than being sent the messages, this approach is warranted.

To understand the effect of the intervention in relation to the repeated use of the intervention, we conducted a two-way mixed ANOVA with data collected from week 3, 4, 6, and 7, the weeks in which the treatment varied between the two groups. In total, 51 students in group 1 and 47 students in group 2 opened the email at each of the four weeks, and were included in the analysis.

4 RESULTS

In Table 2, we report the mean and standard deviation on the dependent variable, hours started before due, for the two groups of students in week 3, 4, 6, and 7. Unexpectedly, there was no main effect on start time depending on whether the intervention was present or absent, $F_{(1, 96)} = .005$, p=.95. There was a significant main effect for assignment (i.e., week of the course), $F_{(3,248)} = 4.48$, p=.007, indicating that students started different assignments at different times during these weeks. However, there was not a significant interaction between the use of intervention and which homework assignment it was (i.e. , week of the course) on assignment start time, $F_{(3, 248)} = .99$, p=.39.

Table 2: Mean and Standard Deviation of Hours Started before Due

	Week 3	Week 4	Week 6	Week 7
Group 1- no msg	121 (91)	102 (77)	106 (83)	101 (76)
Group 2- msg	118 (87)	93 (71)	111 (88)	111 (86)

In terms of grades, as shown in Table 3, the presence of an intervention was not associated with a difference in grade in weeks 3,4,6, and 7, $F_{(1,96)} = 1.56$, p=.21. In addition, no significant main effect was found for assignments (i.e., weeks), $F_{(3, 242)} = .35$, p=.76. The interaction between the two factors was also not significant, $F_{(3,242)}= .45$, p=.68.

Table 3: Mean and Standard Deviation of Ranks

	Week 3	Week 4	Week 6	Week 7
Group 1-no msg	80 (53)	80 (53)	85 (53)	84 (50)
Group 2-msg	98 (53)	88 (48)	91 (49)	93 (47)

5 DISCUSSION AND CONCLUSIONS

Although positive effects for time management intervention were found in prior work, the effect was not significant in the current study. The lack of such a main effect may have led to the lack of any effect of dosage. The unexpected null effect may reflect the intervention not working in this context, or it may be due to one of several limitations to this study. First, confounding factors were not fully considered. Very busy students may not have read the message early enough, attenuating its possible effects. It may also be possible to statistically control for how busy a student is overall, using a self-report measure. Selection biases, where over half of students did not read the messages, may have impacted results; delivering messages another way may have reduced this bias. Third, our findings do not necessarily indicate that a single dose of the intervention would be ineffective. Both groups received the intervention in week 2, and that single dose might have already achieved the intervention's maximum benefit for the semester.

Overall, it is important to continue investigating what conditions will lead to this type of intervention being effective, including investigating how to maintain effectiveness over time.

6 ACKNOWLEDGEMENTS

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