Fostering Active Student Engagement in Flipped Classroom Teaching with Social Normative Feedback

Research Paper

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Abstract. Digital learning platforms have reshaped traditional education by enabling more flexible access to learning materials. Building on this foundation, the flipped classroom model facilitates independent knowledge acquisition while offering interactive support for knowledge application. However, students often struggle with timely completion of graded assignments and underutilize voluntary assignments, which impacts learning outcomes. This study examines the potential of social normative feedback in addressing these challenges. We conduct a randomized controlled trial (N = 140) in a Bachelor's course, providing students with social normative feedback on correct assignment completion. Our findings indicate that the intervention reduced late submissions of graded assignments by 8.4 percentage points (18.5 %), which correlates with higher performance. However, the intervention did not yield significant effects on engagement with voluntary assignments, leaving room for future research. This study contributes to digital interventions in education, offering insights into how behavioral interventions can optimize student participation in flipped classrooms.

Keywords: Flipped Classroom, Social Normative Feedback, Self Regulated Learning, Digital Interventions

1 Introduction

Digital learning platforms have become an integral part of higher education. They allow ubiquitous access to learning materials and enable the implementation of completely new learning concepts that place the learning process at the center and support students in continuous learning. One such concept is the *flipped classroom* (Bergmann & Sams 2012, Tucker 2012) in which students engage with lecture materials before class and use presence time for activities like discussions, problem-solving, and collaborative work. This allows for a combination of asynchronous online learning (e.g., provision of learning materials), with synchronous learning opportunities, in which teachers directly interact with students (Stöhr et al. 2020). The concept is associated with positive academic outcomes and other benefits for learners (e.g., greater flexibility), teachers (e.g., more time for active support), and institutions (e.g., increased scalability) (Akçayır & Akçayır

2018). Yet, compared to regular classroom teaching, the flipped classroom concept places greater responsibility on students to manage their own learning, which is a pain point for many students as they struggle with monitoring their learning process and planning their learning activities well in advance (Broadbent & Poon 2015, Barnard et al. 2009, Akçayır & Akçayır 2018). This leads to a phenomenon known as *student syndrome* (Steel 2007, Klassen et al. 2008), which means that students procrastinate and postpone their learning efforts until shortly before the exam. As a result, they may not have enough time left for proper exam preparation (van Eerde & Klingsieck 2018, Wolters 2003).

Recent research points to the important role of feedback in flipped classroom settings (Thai et al. 2020). Since feedback is an important facilitator in many teaching formats, and given that providing personal feedback is time-consuming, a growing field of research explores digital feedback interventions that help students better manage their own learning at scale, with promising effects (e.g., van Oldenbeek et al. 2019, Günther et al. 2020, Bernards et al. 2024). However, more research is necessary to develop and test digital feedback interventions in flipped classroom settings that allow to deliver feedback to many students at scale.

One promising approach in this context is social normative feedback. This type of feedback shows individuals how their behavior compares to that of their peers, prompting behavioral change through social influence. Its effectiveness has been proven in various fields of consumer behavior (Allcott 2011) and has also recently gained traction in higher education (Günther et al. 2020, Günther 2021). While these studies highlight its potential, empirical evidence regarding the effectiveness of social normative feedback in flipped classroom settings is still lacking. Therefore, we examine the following research question: *To what extent does social normative feedback in a flipped classroom setting influence submission timing and performance of graded assignments, as well as participation in voluntary assignments?*

To answer this question, we conduct a randomized controlled trial in a university course with N = 140 students. Students received email reminders before the deadlines of Graded Assignments (GAs) with feedback on their current progress, compared to other students in the course. We find that the intervention led students to submit GAs earlier, which correlates with better performance on these assignments. The intervention showed no significant effect on behavioral engagement with Voluntary Assignments (VAs) during the lecture period, revealing opportunities for future research. Understanding the effectiveness of such easy-to-implement interventions can assist educators in designing and improving flipped classroom courses as well as support the further development of digital learning platforms.

2 Background and Hypotheses

Digital tools for higher education are central means of providing educational content, enabling digital learning activities, user communications, and notifications (Islam 2012). Alongside their core functions, they record high amounts of individual user data related to learning activities and outcomes (Ye & Pennisi 2022). Not only the design of digital learning systems (Leidner & Jarvenpaa 1995, Gupta & Bostrom 2009) but also the effective use of recorded data in learning analytics (Seufert et al. 2019, Nguyen et al.

2020) is an important part of the information systems discipline. Our study draws on theoretical foundations of self-regulated learning, the flipped classroom, and social normative feedback, which we review before formulating hypotheses for our experiment.

Self-Regulated Learning and the Flipped Classroom — Educational psychology defines self-regulated learning as the students' ability to actively manage their own learning. This entails a cyclical process of activities related to planning (e.g., setting goals, allocating time), monitoring (e.g., tracking progress, evaluating task difficulty), and control (e.g., adapting strategies, seeking help) (Zimmerman & Moylan 2009, Panadero 2017). The observable actions, strategies, and attitudes that learners exhibit in the process of acquiring knowledge and skills is referred to as *learning behavior* (Schunk & Zimmerman 2012). As students have great autonomy in digital environments and flipped classrooms, self-regulation becomes even more important. In the absence of direct teacher guidance, students are responsible for organizing and directing their learning (Vosniadou 2020).

There is a variety of designs to realize the flipped classroom concept that differ in aspects such as the technologies used, the types of in-class activities, and the level of structure provided (O'Flaherty & Phillips 2015). Yet, the core concept remains the same: Shifting knowledge acquisition outside the classroom to free up in-class time for more interactive learning activities (Bergmann & Sams 2012). The fact that students must engage with instructional content before class (in order to benefit from the in-class sessions), shifts much of the responsibility for content acquisition to students themselves (Broadbent & Poon 2015, Thai et al. 2020). Thereby, self-regulated learning strategies such as time management and self-monitoring, which are strongly associated with academic success in flexible learning environments (Hemmler & Ifenthaler 2024), are important antecedents for students' performance in flipped classrooms.

The online component of the flipped classroom concept is thereby particularly challenging for students due to the lack of support from both instructors and peers. Courses should, therefore, provide structures that support students' self-regulation (Yoon et al. 2021), which Hogan & Pressley (1997) describe as scaffolding. In digital flipped classroom settings, this can include staggered content releases, regular deadlines, and various assignments that guide students through the course. GAs (or mandatory ones) establish a foundational level of engagement, ensuring that all students interact with key content and actively participate during in-class sessions. They also serve as formative assessment, enabling both students and instructors to identify learning gaps and adjust teaching strategies (O'Flaherty & Phillips 2015). VAs offer students the opportunity to explore topics in greater depth and foster self-regulated learning without the pressure of formal assessments (Schwerter & Brahm 2024). Together, GAs and VAs contribute to a structured yet autonomous learning environment (Lo & Hew 2017).

Social Normative Feedback and Learning Behavior — Social normative feedback leverages the principle that individuals are influenced by their perceptions of how others behave and has its origin in social and behavioral psychology. Typically, it involves presenting individuals information on how their own behavior compares to that of others. This exerts a subtle but effective form of social influence on behavior (Cialdini et al. 1990). In fields like energy (Allcott 2011, Schultz et al. 2007) and medicine (Hallsworth et al. 2016), this type of feedback led individuals to comply with desired behaviors (e.g., using less energy, prescribing fewer unnecessary medications). Studies in higher education (Günther et al. 2020, Günther 2021) show that such feedback can support learners during the monitoring and control phases of their self-regulated learning. By making students aware of how their learning behavior compares to peers, it prompts reflection and encourages adjustments to their learning strategies (Steinherr 2023).

Hypothesis Development — While social normative feedback has shown promise in various online and blended learning environments, we apply this approach in a flipped classroom course. Thereby, we differentiate the effects related to GAs and VAs. Related to GAs, Nicholls (2023) finds a significant negative relationship between procrastination and grades. For the flipped classroom setting, we therefore want to confirm this relationship by examining the following hypothesis:

H1 *Earlier submissions of GAs lead to higher learning outcomes than submissions close to the deadline.*

Such a positive correlation motivates measures to help students towards earlier submissions. Günther et al. (2020) found that social norms related to online learning time led students to spend more time on coursework during the semester. We advance this line of reasoning to GAs in a flipped classroom course:

H2 *Social normative feedback leads to (a) earlier submissions of GAs and (b) improved performance.*

Related to VAs, studies indicate a relationship between students' participation in formative assessments and final learning outcomes (Kulasegaram & Rangachari 2018). Hence, the completion of VAs may serve as a predictor of overall academic performance:

H3 *The number of completed VAs in a flipped classroom course increases exam performance.*

Providing students with feedback on their learning activity relative to their peers can serve as an external motivator, encouraging them to increase their effort and participation in VAs during the lecture period (which is the focus of our study). Thus, we postulate:

H4 *Social normative feedback has a positive effect on the number of VAs completed during the lecture period.*

3 Experimental Setup

In order to investigate the hypotheses, we conducted a randomized controlled trial in an undergraduate university course on operations management at a business school in Europe. The course is compulsory for the bachelor program in business administration and enrolled approximately 600 students in the spring semester 2024.

3.1 Design of the Flipped Classroom Course

The course blends digital resources with in-person interactions, and fosters an application-oriented learning experience. Students independently acquire foundational knowledge online (e.g., through instructional videos) at their own pace. Subsequently, voluntary in-person coaching sessions are offered twice a week, designed to provide individual support and foster interactive problem-solving and peer discussion. This format reflects the core principle of the flipped classroom: Shifting knowledge acquisition outside the classroom to free up in-class time for more active learning activities.

The course is structured into five modules, each containing around 15 subsections. Each subsection includes a 10-12 minute instructional video that either introduces theoretical concepts or demonstrates practical calculations in spreadsheet software. Most videos are directly followed by short GAs, resulting in about 12 to 15 graded tasks per module. These tasks combine theoretical multiple-choice questions with spreadsheet-based computational tasks. The GAs collectively account for 10 % of the final course grade and can only be submitted once. Additionally, students have access to VAs, which allow unlimited practice on both theoretical and spreadsheet-based tasks.

While students have considerable flexibility regarding when to engage with the online content and whether or how frequently they attend the coaching sessions, the course provides scaffolding through staggered module releases and deadlines, as illustrated in Figure 1. The deadline for completing GAs in Module 1 occurs approximately two weeks after the official kick-off lecture, on a Sunday at 11:59 PM. Subsequent assignment deadlines for the remaining modules are scheduled at two-week intervals, consistently set for Sundays at 11:59 PM.

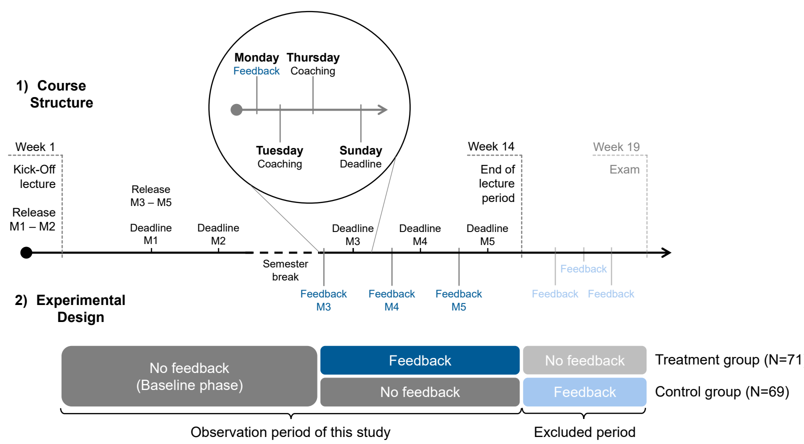

Figure 1. Course structure and experimental design

3.2 Experimental Design and Intervention

To comply with ethics requirements, all participants had to receive the same number of feedback interventions. We therefore designed the study so that one experimental group received the feedback during the lecture period, while the other group received it only after the lecture period had ended. To measure the actual effects of the intervention, *the analysis of this paper focuses exclusively on data collected during the lecture period*, when only one group received feedback. This setup allows us to treat that group as the *treatment group* and the other as the *control group*. Group allocation was done randomly, considering the activity in the baseline phase, and the responses in the pre-survey (see next section).

For each of the Modules 3, 4, and 5, students in the treatment group received an email on Monday afternoon before the respective deadline on Sunday. We chose email as the delivery channel because it is the most straightforward way to reach all students, given that feedback displayed online is only visible to those who actively access the Learning Management System (LMS). The key component of each intervention email was a graphic that illustrated the student's combined progress in both GAs and VAs for the respective module—an example is shown in Figure 2. The graphic included a progress bar showing the total number of correctly completed assignments (graded and voluntary), along with indicators highlighting how many peers performed better and how many performed worse. Additionally, the progress bar displayed benchmarks representing the median and the top 10 %. However, due to a weak descriptive norm (more than 50 % of students had not yet started the module) these benchmarks were calculated exclusively from students who were already active. Accompanying the graphic, the email also provided students with a summary of their individual progress in GAs and VAs, as well as a direct link to the course platform.

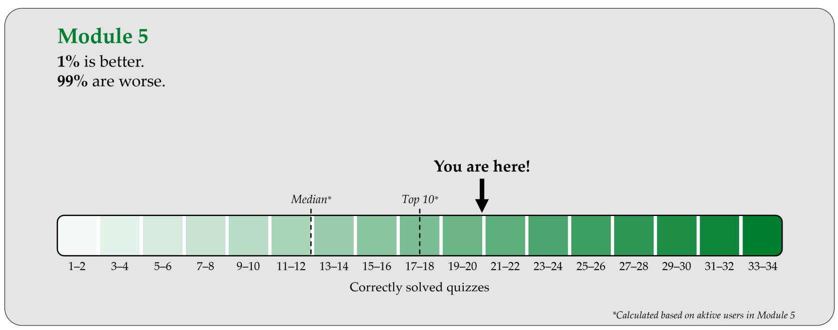

Figure 2. Example of the intervention

For H1 and H2, we consider submissions as *timely* when they were made $\geq 48h$ before the deadline, and as *late* if made $< 48h$ before the deadline. The reason for this threshold is that students had multiple weeks to complete the GAs and the deadline was on a Sunday evening. Given that the final opportunity for support (via the coaching session) ended on Thursdays at 6:00 PM, we classify submissions made during the final weekend (i.e., the last 48 hours before the deadline) as late.

3.3 Participants and Data Collection

Six weeks after the start of the semester, students received an online invitation to join the study. The announcement clarified that participation was voluntary, how their personal data would be collected and processed, and that their decision whether to participate or not would have no influence on grades or other academic outcomes. Students had about one week to enroll, and 140 ultimately consented to participate.

During enrollment, participants were asked to complete a voluntary survey that collected demographic information (e.g., age, gender), academic goals (e.g., intended final grade), and responses to established scientific scales measuring procrastination (Svartdal et al. 2016), social comparison (Schneider & Schupp 2011), and the Big Five personality traits (Rammstedt 2014). From the total sample of 140 participants, 74 fully completed the survey (response rate: 52.9 %). Table 1 summarizes an excerpt of the survey responses by presenting the means, standard deviations, p-values, and the number of respondents for both the treatment and control group.

Table 1. Randomization checks for baseline variables (T = Treatment, C = Control)

Variable	Full sample	Control group	Treatment group	Respondents (T / C)	F-Statistics (p-value)
Total submissions - Baseline	21.35 (1.38)	21.22 (1.76)	21.48 (0.84)	-	1.26 (0.26)
Correct answers - Baseline	39.91 (5.03)	39.71 (4.63)	40.11 (5.41)	-	0.22 (0.64)
Total time to deadline (hours) - Baseline	5426.2 (3401.1)	5593.7 (3480.5)	5263.4 (3338.8)	-	0.33 (0.57)
Target grade	5.4 (0.42)	5.36 (0.47)	5.43 (0.37)	85 (46 / 39)	0.69 (0.41)
Procrastination	36.94 (18.68)	38.97 (18.46)	35.18 (18.89)	78 (41 / 37)	0.86 (0.36)
Social comparison	2.58 (0.74)	2.58 (0.79)	2.59 (0.71)	76 (40 / 36)	0.01 (0.94)
Big Five: Extraversion	3.47 (0.86)	3.32 (0.96)	3.6 (0.74)	81 (43 / 38)	2.33 (0.13)
Big Five: Conscientiousness	3.92 (0.73)	3.75 (0.7)	4.07 (0.73)	81 (43 / 38)	4.01 (0.05)
Big Five: Neuroticism	2.78 (1.01)	2.67 (1.05)	2.87 (0.98)	81 (43 / 38)	0.8 (0.38)
N	140	71	69		

The questionnaire remained open until the end of the semester to provide every student with enough time to complete it. The survey submissions that were made after the randomization led to slightly different group means in the final sample (compared to the baseline sample at the time of randomization). We repeated the same randomization checks with the final dataset, examining key baseline variables, including assignment submission metrics, demographic characteristics, academic targets, and the survey results from the scales described earlier. Although most variables were still balanced between the groups, a slight imbalance was observed for *conscientiousness* (N = 81). To account for this difference, we include *conscientiousness* as a control variable in the regression analyses for H2b and H3. This ensures that the observed intervention effect can be attributed primarily to the feedback rather than to pre-existing group differences.

In addition to the survey data, we measure learning behavior in the form of observable indicators (Hsiao et al. 2019). Similar to earlier studies (Günther 2021, Haag et al. 2023), we obtained data from the university's LMS, which provided detailed logs for each submission (both GAs and VAs) including the student identifier, assignment ID, timestamp, attempt number, student's responses to each question, and counts of correct and incorrect answers. Key metrics derived from these records were correctness rates, completion rates, and submission timing. Although these indicators may not capture all dimensions of self-regulated learning, they serve as useful proxies for students' learning strategies (Broadbent & Poon 2015).

4 Results

4.1 Effects Related to Graded Assignments (GAs)

As a first analysis, we examine the *relationship between submission time and learning outcome* among the GAs. To avoid confounding effects from the feedback intervention, we limit our analysis to submissions from the control group ($N = 69$), which did not receive feedback until after the deadline of the final GAs. Figure 3 illustrates that submissions made within the last 48 hours before the deadline had a correctness rate of 79.4 %, while submissions made earlier than 48 hours before the deadline had a correctness rate of 88.2 %. This difference is statistically significant in each individual module, as well as in the combined analysis with $t(2163.3) = 9.42$, $p < 0.001$. While the absolute difference is only a few percentage points, the effect size can be considered small to medium with Cohen's $d = 0.35$ (95 % CI [0.28, 0.42]) (Cohen 1988). That is because the assignments intentionally have high completion rates. Thus, we find support for H1.

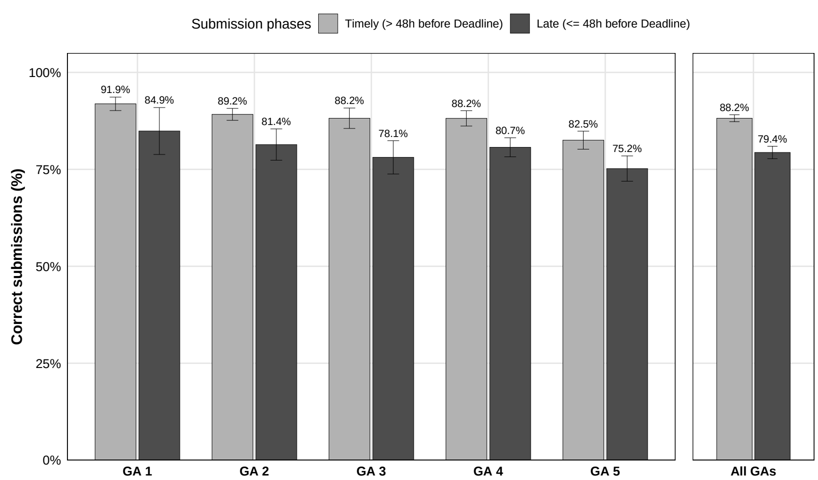

Figure 3. Percentage of correctly answered questions by submission timing across modules

To evaluate *whether social normative feedback influenced submission behavior*, we compare the number of submissions across the two different phases for each group. During the intervention phase, the treatment group submitted 8.4 percentage points (18.5 %) fewer assignments late than the control group, as shown in Figure 4. During the baseline phase, a χ^2 test of independence indicated that the treatment group had a slightly higher share of late submissions $\chi^2(1, N = 2903) = 8.35, p = .004, \omega = .05$. During the intervention phase, this pattern reversed and the treatment group submitted significantly fewer assignments late than the control group $\chi^2(1, N = 4626) = 33.75, p < .001, \omega = .09$. These results support H2a: While the control group increased late submissions by 25.4 percentage points, the increase in the treatment group was only 12.5 percentage points.

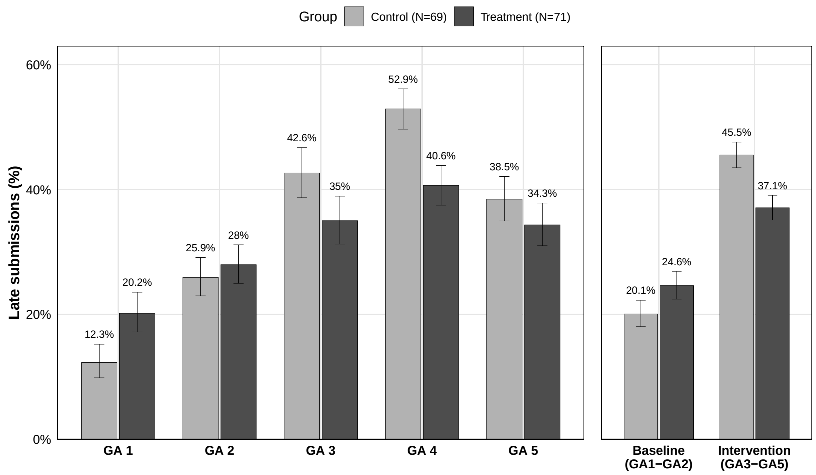

Figure 4. Share of late submissions across modules with 95 % CI

To examine whether the intervention also had a *direct influence on submission quality*, we conducted a difference-in-differences (DiD) analysis using an Ordinary Least Squares (OLS) regression model, following the general formula:

$$y_i = \beta_0 + \beta_1\, phase_i + \beta_2\, group_i + \beta_3\, (phase_i \times group_i) + \beta_4\, control_i + \varepsilon_i. \quad (1)$$

where y_i represents the correctness rate of a single submission i made by a student. The binary variable $phase_i$ is 0 for submissions made during the baseline phase and 1 for submissions made during the intervention phase. The binary variable $group_i$ is 0 for submissions from the control group and 1 for those from the treatment group. Additionally, we included the variable $control_i$, representing the student's *conscientiousness*, as our randomization check indicated a slight imbalance for this variable between the groups, leading to a reduced sample size of 81. Table 2 shows the results.

The quality of the model is acceptable (F(4, 4432) = 20.57, p < 0.001) and for our analysis, the low explained variance (Adjusted R^2 = 0.0187) is reasonable, as non of the independent variables are strong predictors of academic success (see Molnár & Ádám Kocsis 2024, for factors that explain academic success). The *constant* confirms our initial observation that all submissions have a relatively high correctness score. The dummy $group$ confirms our assumption that there were no significant differences between the groups during the baseline phase. The coefficient for the dummy $phase$

shows that the control group had lower correctness scores in the intervention phase ($\beta_1 = -0.074$, p < 0.001), indicating that overall submission correctness declined in later modules. Our main interest lies in the interaction effect $phase \times group$, which is significant ($\beta_3 = 0.031$, p = 0.031) and suggests that the decrease in correctness was less pronounced in the treatment group compared to the control group, supporting H2b.

Table 2. Difference-in-differences analysis of the intervention on the correctness of GAs

	Dependent variable: Correctness		
Constant	0.830	***	(0.020)
Phase	−0.074	***	(0.010)
Group	−0.012		(0.010)
Phase × Group	0.035	**	(0.014)
Conscientiousness	0.017	***	(0.005)
Observations	4,437		
R^2	0.018		
F Statistic	20.565*** (df = 4; 4432)		
Note:	*p<0.1; **p<0.05; ***p<0.01		

4.2 Effects Related to Voluntary Assignments (VAs)

Since the control group also received feedback after the lecture period, our experimental setup does not allow estimating a direct effect of the intervention on final grades. Therefore, we first establish a *relationship between the completion of VAs and academic performance* and then examine to what extent the feedback intervention helped increase the number of VAs completed during the lecture period. In doing so, we estimated an OLS regression model explaining the final exam points $points_i$ of each student i:

$$points_i = \beta_0 + \beta_1 \, \mathrm{VA}_i + \beta_2 \, control_i + \varepsilon_i. \tag{2}$$

As an independent variable, we consider VA_i, the total number of unique VAs each student i submitted (each assignment is counted only once to account for the breadth of exercises offered). Similar to the previous analysis, we include *conscientiousness* as a control variable, reducing the sample to 81 students. Since not all students took the final exam, the effective sample size for this regression is 67. Table 3 presents the results.

Table 3. Regression results: Voluntary assignments and exam performance

	Dependent variable: Exam Performance		
Constant	8.395		(11.016)
Voluntary Exercises	0.983	***	(0.199)
Conscientiousness	4.079	*	(2.160)
Observations	67		
R^2	0.336		
F Statistic	16.185*** (df = 2; 64)		

The model shows an appropriate fit (F(2, 64) = 16.19, p < 0.001) and explains approximately one third of the variance in exam performance (Adjusted R^2 = 0.336). The coefficient β_2 indicates that each VA completed at least once is associated with an increase of 0.983 exam points, which is a considerable and significant effect (p < 0.001). The control variable *conscientiousness* shows a marginally significant effect (p = 0.064). With this analysis, we also find support for H3.

Finally, we examine whether *social normative feedback influenced students' behavioral engagement with VAs during the lecture period*. To this end, we estimated the DiD model analogously to Equation 1, using the number of VA submissions per student as the dependent variable y_i. In contrast to our expectations, the model did not yield significant results, and we cannot confirm H4.

To better understand this result, we conducted a short follow-up inquiry with ten students from previous semesters asking, how much of their learning time they spend during the lecture period and after. Almost all students reported that they had done most of their workload in the days or weeks before the exam. One student said "I only actively engaged with the videos and GAs in the first four weeks or so and after that, I didn't really do anything, except click through the quizzes. The rest, I did during the learning phase." Another said that he "did quite a lot in the semester due to the graded quizzes, but it was quite exhausting every time." Yet, also this student reported to have done around 60 % of his total workload after the lecture period, which is roughly consistent with the average among the 10 students. A plain comparison of the submission figures confirms this claim: Only 253 VA submissions were made during the lecture period, compared to 4595 during the exam preparation phase after the lecture period had ended.

5 Discussion

Our study set out to examine the impact of social normative feedback on students' learning behavior in a flipped classroom setting. To this end, we developed a feedback intervention in which we sent emails to students containing a progress bar that visually summarized each student's combined progress on graded and voluntary assignments in comparison with benchmarks based on their peers. Drawing on insights from social and educational psychology, we evaluated four hypotheses in a randomized controlled trial, involving 140 undergraduate students enrolled in a flipped classroom course.

Most importantly, our findings confirm that social normative feedback can influence students' learning behavior in a flipped classroom setting. After establishing that late submissions are correlated with lower performance (H1), we demonstrated that the intervention significantly promoted earlier submissions of GAs (H2a). A DiD analysis further revealed that while submission correctness declined overall in the intervention phase, this decline was significantly less pronounced in the treatment group, suggesting a positive relationship between the intervention and improved academic outcomes (H2b).

In relation to VAs, our intervention during the lecture period did not have the expected effect, we had hoped for. Importantly, this result does not allow concluding that the type of intervention is ineffective for VAs in flipped classroom settings. Rather, we find possible reasons for these outcomes in the limitations of our study: First, our experiment was limited in that we could not use a control group until the point of the final exam, because we were required to provide all participants with the same number of feedback. Therefore, our analysis could not cover the whole learning behavior and might miss important aspects, especially for the VAs (which seem to have been solved mostly after the lecture period). Second, we could attract only a relatively small sample of students to participate in the experiment (140 of 600) and even less to complete the survey. This may lead to a quite homogeneous sample in terms of motivation and therefore to lower effects related to the tested intervention. Third, it was not possible to track whether or when students read the email. Future studies may benefit from combining multiple delivery channels (e.g., email and in-platform messages) to balance reach and traceability.

Considering the limitations of our study, we find two explanations of the missing effect related to VAs. On the one hand, students' procrastination behavior may be harder to counteract than expected using social normative feedback. With the insights gained in this experiment, we will improve the feedback intervention in the future. In addition, students may have a high workload during the semester. This may lead to the situation that the feedback arrives when students are not in a state of receptivity, in which they effectively process and respond to the feedback they receive. Receptivity, in this context, is defined as an individual's transient tendency to receive, process, and utilize the support provided (Nahum-Shani et al. 2015, 2016). In our study, students were receptive to the provided feedback, but only in relation to GAs. However, they showed no inclination to process the feedback concerning VAs. Reasons could be the semester workload and the immediacy of implications. Processing VAs primarily occurs after the lecture period, when students are no longer preoccupied with coursework and examinations are imminent. Subsequently, feedback could be leveraged more effectively in the post-lecture phase rather than during the lecture to encourage submission of VAs. Moreover, our results suggest that GAs are a more viable option than VAs for fostering behavioral engagement with assignments during the lecture period.

6 Conclusion

The findings of this study provide empirical support for the effectiveness of social normative feedback in influencing students' behavioral engagement within a flipped classroom setting. By leveraging peer comparison, the intervention successfully encouraged earlier submissions of GAs, contributing to improved academic performance. However, its impact on the submissions of VAs must be subject of further investigation and follow-up studies to better understand students' motivational triggers and learning behaviors.

Our research contributes to understanding self-regulated learning in digital environments by demonstrating how social normative feedback can compensate for reduced social cues in online or hybrid settings. From a practical standpoint, the relatively simple to implement intervention with visual progress indicators offers instructors a scalable approach to support students' behavioral engagement in flipped classroom environments. As higher education continues to embrace digital learning platforms and the flipped classroom concept, supporting students with their self-regulated learning becomes increasingly important. This study demonstrates that social normative feedback can enhance student engagement and performance when properly aligned with students' receptivity patterns and learning behaviors.

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