On the Impact of Digital Boosts on Perceived Stress in a Self-Regulated Learning Experiment

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Abstract

Self-regulated learning (SRL) has been adopted as a successful strategy for promoting deeper learning and improving academic performance. In this context, digital boosts have been used to empower learners by expanding their competencies and helping them reach their objectives. However, existing literature has primarily focused on the academic performance-related outcomes of digital boosts, while their potential effects on emotional and psychological aspects like stress and well-being remain comparatively under-explored. In this study, we address this gap by studying the impact of digital boosts on perceived stress, in addition to study time. We have designed a digital SRL support system, through which we have delivered digital feedback boosts. To evaluate this system, we conducted a pilot study with 60 university students. Our digital boosts have helped students keep a steady study time. However, they have caused an increase in perceived stress, especially among students who did not attain their study time plans.

Keywords: Digital Boosts, Self-Regulated Learning, Feedback, Perceived Stress.

1. Introduction

Recent research has confirmed the effectiveness of self-regulated learning (SRL) on academic achievement in online or blended environments, for learners in K-12 education as well as learners in higher education (Xu et al., 2023). SRL is a process that involves a recursive cycle encompassing setting goals, monitoring progress, self-reflecting, and regulating learning (Järvelä et al., 2019). SRL assists learners in controlling, modifying, and directing their own experiences, promoting deeper learning approaches, and leading to improvements in adaptability and academic performance (Panadero, Alonso Tapia, et al., 2014).

In order to help students through their SLR process, *digital boosts* have been used as a successful strategy to promote goal achievement (Schlegel et al., 2023; Weijers et al., 2023). Boosts refer to interventions that aim at "empowering people by expanding (boosting) their competences and thus helping them to reach their objectives (without making undue assumptions about what those objectives are)" (Grüne-Yanoff & Hertwig, 2016, p. 156). A typical example of digital boosts is the use of personalized reminders or study tips sent to students via mobile applications or learning management systems (e.g., Castleman and Meyer, 2020). These digital notifications are tailored to individual learners to help them boost their educational outcomes. Indeed, digital boosts have been shown to have a positive impact on academic achievement (Pardo et al., 2019), course completion rates (Davis et al., 2017), and assignment adherence (Motz et al., 2021), among other performance indicators.

However, even if digital boosts can have these beneficial effects on learning, they can also have negative psychological consequences in some cases, such as increasing stress levels (Thuillard et al., 2022). In the context of SRL, much of the existing literature has primarily focused on behavior change and performance-related outcomes of digital boosts (e.g., Davis et al. (2017), Schlegel et al. (2023), and Terry and Doolittle (2008)). Nonetheless, the potential effects of digital boosts on emotional and psychological aspects like stress, anxiety, and well-being remain comparatively under-explored in SRL contexts.

This paper aims to address this gap by investigating the impact of digital boosts on perceived stress in the context of SRL. We specifically focus on using individual and social feedback as digital boosts to provide students with information that aims at boosting their efforts to reach their study goals, without making any assumptions about the adjustments they will make to achieve those goals. This aligns with the definition of boosts presented by Grüne-Yanoff and Hertwig (2016). We focus on these boosts since several literature reviews have identified feedback and social norm information as common ways used in previous studies to guide user behavior (Bergram et al., 2022; Caraban et al., 2019; Hummel & Maedche, 2019). While individual feedback involves delivering information that provides a direct assessment of a student's progress (Panadero & Romero, 2014), social feedback aims to leverage peer influence by providing information about the performance of peers (Gidley et al., 2010).

In this paper, we have designed a digital SRL support system, through which we have delivered digital feedback boosts to students. The main objective of this exploratory study is to assess the effect of these digital boosts on students' perceived stress levels in the context of SRL. To complement this, we have also explored the impact of these boosts on study time to capture how they influence behavior change in students. Finally, we have conducted an experimental study to evaluate our digital feedback boosts. The study took place during the so-called *fall reading week*, which is a one-week break students receive during the fall semester. We selected this timeframe because students need to engage in SRL during this period in order to catch up with their studies and prepare for their future exams (Poole et al., 2017).

2. Theoretical Background and Research Questions

Digital Boosts aim at improving active decision-making capabilities by expanding the skills of individuals and supporting them in overcoming behavioral barriers and reaching their objectives (Damgaard & Nielsen, 2018). They are considered a subclass of nudging, a more general concept designating indirect incentives to change behavior (Thaler & Sunstein, 2008). While some nudges can be seen as manipulative because they might not be transparent, or might work on biases (Thaler, 2018), boosts are considered to be "nonfiscal, noncoercive digital intervention that facilitates people's choices by fostering their competencies" (Hertwig & Grüne-Yanoff, 2017). As such, digital boosts promote transparency and improve user choices by providing them with more information. Digital boosts have been used in education for various purposes, such as supporting autonomous and self-regulated learning behaviors (Schlegel et al., 2023; Weijers et al., 2023), improving learning performance (Franklin Jr et al., 2022; Motz et al., 2021; Van Lent & Souverijn, 2020) and increasing motivation (Damgaard & Nielsen, 2018).

Integrating digital boosts can support learners throughout the different phases of SRL. A typical SRL cycle comprises three phases: forethought, performance, and self-reflection (Zimmerman, 2002). During the forethought phase, which precedes the learning effort, learners engage in analyzing tasks and making plans. The incorporation of digital goal-setting boosts can be beneficial to learners during this phase, given their positive impact on performance and learning (Clark et al., 2020; Van Lent & Souverijn, 2020). During the performance phase of SRL, which includes processes that occur during behavioral implementation, learners apply strategic action and monitor their performance (Zimmerman, 2002). Finally, the self-reflection phase encapsulates processes that occur after each learning effort, such as evaluating the learning and adapting the effort based on outcomes.

During this self-reflection phase of the SRL cycle, feedback boosts can be particularly helpful to learners because they allow them to better reflect on their learning and take the necessary measures to improve their performance (Castleman & Meyer, 2020; Pardo et al., 2019). As such, feedback is perceived by students as an important part of the learning process (Besser & Newby, 2019). Individual feedback has long been identified as a powerful motivational factor that allows students to identify gaps between their current state and the desired outcome (Butler & Winne, 1995), leading to improved learning and performance (Kluger & DeNisi, 1996). At the same time, social feedback can provide norms that lead individuals to adapt or modify their behavior (Damgaard & Nielsen, 2018), leading to better self-regulated learning behaviors (Schlegel et al., 2023).

Several digital boosting and nudging interventions have been deployed to improve self-regulated learning processes in educational settings. Notably, Schlegel et al. (2023) explored the effectiveness of digital social nudges in supporting self-regulation in learning, with the aim of improving learning outcomes. They conducted an online between-subjects experiment and evaluated the impact of social nudges on the use of learning strategies and test scores. Their results indicate that the experimental group, which was exposed to social nudges, used the learning supportive features more frequently, and achieved higher test scores compared to the control group. These findings suggest that social nudges can positively impact learning outcomes in online learning environments. In another experiment, Terry and Doolittle (2008) investigated the use of a web-based tool designed to influence the self-efficacy of students by engaging them in goal-setting and time management strategies. They asked students to set goals about how they planned to spend their time, then report on how they actually spent it. The students received feedback on their goal attainment to make them more involved in the self-regulated learning process. Results from that experiment reported an increase in engagement with the learning tool, but no significant increases in students' self-efficacy. In contrast, Pardo et al. (2019) found a positive association between improved feedback and academic performance, in an experiment where they used learning analytics to improve the quality of personalized feedback provided to students, over three consecutive years. In a different context, Davis et al. (2017) explored how social comparison affects self-regulation and achievement in Massive Open Online Courses (MOOCs). The authors created a personalized social comparison system that uses interactive visualizations to compare a learner's behavior with that of previously successful learners. Results from that study show that social comparison cues increase completion rates, particularly among highly educated learners, with the cultural context of learners affecting their engagement and achievement. While some studies have shown that feedback could have a positive impact on study time (Jiménez et al., 2018), others indicate that assumptions about feedback could lead to maladaptive behaviors, such as procrastination (Jackman & Strober, 2003). As such, this paper aims to shed light on this issue through the following research question:

RQ1: How are digital feedback boosts associated with changes in study time in an SRL context?

Whereas the literature above investigated the effect of digital boosting mechanisms on learner behavior, much less attention has been given to the effect of such mechanisms on psychological aspects, such as stress. While feedback boosts could potentially reduce learners' perceived stress by clarifying expectations and supporting self-efficacy (Kluger & DeNisi, 1996), there are also instances where individual and social feedback can lead to increased levels of stress and negative affect (Thuillard et al., 2022). Those findings suggest the potentially conflicting effects of digital boosts on learner stress levels. These observations lead to the second central research question addressed in this paper:

RQ2: How are digital feedback boosts associated with learners' perceived stress in an SRL context?

3. System Description

We designed an SRL support system to assist students in effectively structuring their study time. The system enables students to create schedules for their study sessions and obtain individual and social feedback boosts related to their study time and that of their peers (see Figure 1). The system is built around three features:

(a) *Goal-Setting*: Users initiate their experience by creating a schedule that details their planned study time, the courses they aim to study for, and the academic activities they plan to accomplish (see Figure 1a). The goal-setting feature is intended to help users organize their study period.

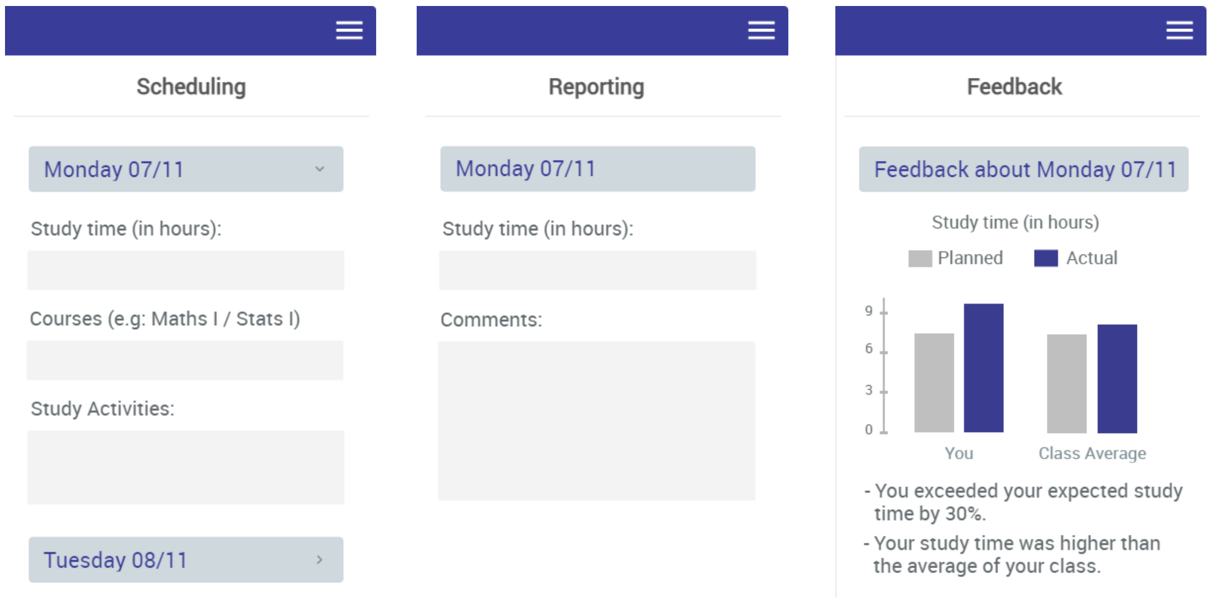
(b) *Reporting*: Using this feature, users can log their daily study time and provide any relevant comments about their experiences on a particular day (see Figure 1b). Users receive a daily notification that prompts them to complete their daily reports.

(c) *Boosting*: This feature allows users to receive a boost related to study time, based on the aggregation of data collected from scheduling and daily reporting of the previous day (see Figure 1c). The daily boost is two-fold. An individual feedback component compares a user's planned versus actual study time, while a social feedback component compares their study time to the class average. The feedback is represented in both a graphical and a textual format.

The individual and social feedback aim at informing students about their study time and that of their peers, so that they reflect on them and adjust their time planning behavior accordingly. The feedback is intended to boost them to reach their objectives without making assumptions about the adjustments they will make. Additionally, we made the feedback merely descriptive in the sense that it only revealed how much oneself and other users reportedly studied in relation to their plans. Previous studies suggest that descriptive social norms are more effective at changing behavior than injunctive social norms that prescribe certain behaviors based on some expectation (Melnyk et al., 2022).

4. Evaluation Setup

In order to validate the impact of using our SRL system on students, we conducted a between-subjects field experiment, using a pretest-posttest experimental design. We measured the effect of using our system on perceived stress and study time, during the fall



(a) Goal-Setting (b) Reporting (c) Boosting

Figure 1: Mockups illustrating the SRL system's main features of goal-setting, reporting, and feedback boosts

reading week. Participation in our experiment was on a voluntary basis. The experiment was conducted in a completely anonymous manner to motivate students to answer the surveys as honestly as possible. Students were randomly assigned a pseudonym that they used as their identifier along all the steps of the study. The pilot study was conducted at our university between November 2nd and November 16th, 2022.

4.1. Participants

Our participants were first-year undergraduate students that we recruited from a Mathematics class at our university. 90 students subscribed to the experiment. After the end of the reading week, 60 students (n = 60) completed all the required tasks. Their ages ranged from 18 to 35 (M = 19.68), and 66.6% of them identified as male. Students were compensated for their participation with an amount equivalent to 40 USD.

Students were assigned randomly to one of two groups. First, a control group used features (a) and (b) of our system to perform goal-setting and daily reporting. Second, an experimental group used these two features, and additionally had access to feature (c) which allowed them to receive daily feedback throughout the week.

4.2. Measurements

In this study, we employed the following quantitative measures to assess the impact of our SRL system:

Perceived Stress Scale (PSS). The PSS is a widely-used psychological instrument for measuring the perception of stress in individuals (Cohen et al., 1994). This 10-item scale evaluates the degree to which an individual appraises situations in their life as stressful. Students are asked to respond to each item on a 5-point Likert scale ranging from 0 (never) to 4 (very often). Total scores range from 0 to 40, with higher scores indicating greater perceived stress. The PSS has demonstrated good internal consistency and reliability, making it a valid and reliable tool for measuring stress levels (Nielsen et al., 2016).

Study Time. We used two measures related to study time: planned and actual study time. The planned study time was calculated from the students' schedules based on the number of hours they planned to allocate for their studies. For the actual study time, we asked students to self-report the total amount of hours they spent studying every day. It is important to note that self-reported measures may be subject to potential biases, such as recall bias (Chan, 2010). However, self-reported study time has been commonly used in educational research as an acceptable proxy for actual study time (e.g., (Persky & Hogg, 2017), (Agarwal et al., 2014), (Gyllen et al., 2019)). To minimize potential biases, students were encouraged to be as accurate and honest as possible.

4.3. Procedure

The evaluation experiment involved a pretest-posttest design, daily reporting and feedback on study time, as well as collecting general comments from students. It took place during the reading week. The following steps outline the study procedure.

Pretest. Before the reading week, students were asked to complete a pretest consisting of the PSS questions. This pretest aimed to establish a baseline for students' perceived stress levels. In addition, students were instructed to create a schedule for their reading week using feature (a) of the system. This schedule gave students an opportunity to plan their study time and activities, promoting a more structured and organized approach to their learning during the reading week.

Daily Reporting and Feedback. The second step of the experiment was conducted throughout the reading week, spanning five days from Monday to Friday. Students used feature (b) of the system on a daily basis to report the time they spent studying, and provide any general comments or observations about their experience using the system. This daily reporting allowed us to monitor study habits and gather qualitative data regarding perceptions of the system. At the same time, students in the experimental group had access to feature (c) of the system where they received daily feedback about their study time and the average study time of their class, based on data from the previous day.

Posttest. After the reading week, students completed a posttest where they responded to a PSS questionnaire again. This posttest allowed for evaluating changes in perceived stress levels after using the system during the reading week. Students were also asked to answer a series of questions related to their appreciation of the study and their experience with the system. This feedback helped to gain insights into the student's overall satisfaction with the intervention and identify potential areas for improvement.

5. Evaluation Results

This section presents our analysis results of the impact of our system on the perceived stress and study time of the 60 students in our sample. We start by presenting descriptive statistics for the main measurements used in this study, as seen in Table 1.

5.1. Digital feedback boosts and study time in an SRL context (RQ1)

We assessed the evolution of study time during the reading week. Since students in the experimental group started receiving feedback at the end of the second day of the week, we consider the first two days as the baseline period (pre-intervention), and the last three days of the week to be the intervention period.

As shown in Table 1, the average study time of the control group dropped over the reading week, while the study time of the experimental group remained steady. We conducted a repeated measures analysis of variance (ANOVA) to examine the effect of time (before/during the intervention) and the interaction between time and the study group (control/experimental) on study time. The analysis revealed no significant main effect of time ($F(1, 58) = 1.49, p = 0.23$), indicating that there was no statistically significant change in study time from before to during the intervention, considering both groups in our sample. Furthermore, there was no significant interaction between time and the study group ($F(1, 58) = 2.15, p = 0.15$), suggesting that the change in study time did not differ significantly between the control and experimental groups over time.

However, a separate paired-samples t-test comparing study times before and during the intervention only for the control group revealed a statistically significant change in study time ($t(30) = 2.15$, $p = 0.04$). This finding suggests that although the overall interaction effect was not significant, there was a significant drop in study time within the control group.

Table 1: Descriptive statistics for the main measurements used in the study

	Control			**Experimental**		
Variable	n	M	SD	n	M	SD
PSS before read. week	31	16.71	6.92	29	14.86	5.96
PSS after read. week	31	16.71	7.32	29	17.00	5.75
Daily study time pre-inter.	31	4.04	2.16	29	4.28	2.06
Daily study time during inter.	31	3.48	1.67	29	4.34	1.86

5.2. Digital feedback boosts and perceived stress in an SRL context (RQ2)

We evaluated the evolution of the perceived stress levels of students (measured using PSS) before and after the reading week. As seen in Table 1, the average perceived stress level of the control group is exactly the same before and after the reading week; even if individual stress rates evolved in different directions. However, the average perceived stress rate of the experimental group is observed to be higher after the reading week. Figure 2 shows a distribution of the change in perceived stress for the two study groups using a raincloud plot (Allen et al., 2019). This change was calculated as the PSS score after the reading week minus the initial PSS score preceding the reading week. The raincloud plot comprises a distribution curve of the perceived stress change, a boxplot summary of the data, along with the jittered raw data where each point represents one participant. It visualizes the overall increase in perceived stress for the experimental group, compared to the control group for which the average perceived stress remained unchanged overall.

We conducted a repeated measures ANOVA to examine the effect of time (before/after the reading week) and the interaction between time and the study group (control/experimental) on the PSS scores. The analysis revealed a marginally significant main effect of time ($F(1,58) = 3.7, p = 0.059$), suggesting that there might be a change in PSS scores from before to after the intervention. Furthermore, there was a marginally significant interaction between time and the study group ($F(1,58) = 3.7, p = 0.059$), suggesting that the change in PSS scores over time might differ between the control and experimental groups.

In addition, a separate t-test revealed a statistically significant change in perceived stress in the experimental group ($t(28) = -2.77, p = 0.01$). This finding suggests that, while the overall interaction effect was not significant, there was a significant increase in perceived stress in the experimental group.

In order to gain more understanding of perceived stress, we investigated the relationship between students' perceived stress and the attainment of their planned study time, across our study groups. Existing literature points to a correlation between stress and goal attainment, especially in goal-directed tasks that require monitoring one's current state and discrepancy in goal pursuit (Duckworth et al., 2013; Maier et al., 2015; Oaten & Cheng, 2005). We examined the discrepancy between the actual and planned study time of our students to assess whether they achieved their planned study time or not. This discrepancy was measured as the

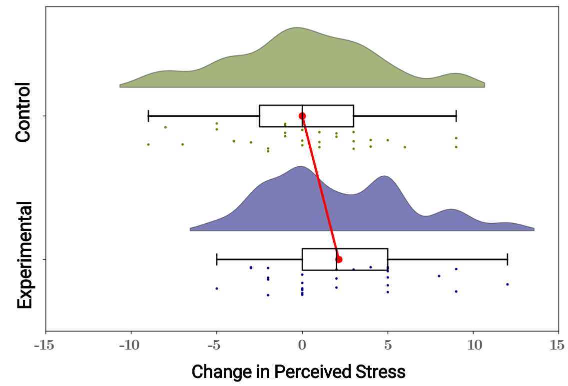


Figure 2: Raincloud plot (Allen et al., 2019) showing the distribution of the change in perceived stress among students in the control and experimental groups

sum of actual study time minus the sum of planned study time in hours. Then, we used a median split ($Median = -1.50$) on this measure to divide our students into two groups. This yielded two balanced groups: a group that over-studied (exceeded their planned study time) ($n = 30$) and a group that under-studied (did not reach their planned study time) ($n = 30$). The discrepancy between actual and planned study time for the over-studying group was ($M = 3.75, SD = 4.35$), meaning that these students on average exceeded their planned study time by almost 4 hours.

The other group ($M = -8.41, SD = 5.32$) studied for around 8 hours on average less than they planned to. Table 2 shows descriptive statistics for the study time discrepancy and final perceived stress of four subgroups, representing the students who under/over-studied in the control group, and students who under/over-studied in the experimental group.

Then we assessed the impact of the interaction between this under/over-study condition across study groups on the final perceived stress of students (PSS score after the reading week). Figure 3 visualizes this interaction. The figure shows that low-studying students in the control group reported lower perceived stress levels, while the over-studying students in the same group reported higher levels of perceived stress. This trend is more equalized across the experimental group where the stress levels are less discrepant, suggesting that study plan attainment may have a moderating effect on the relationship between digital feedback boosts and perceived stress levels. The results are further discussed in the discussion section.

A two-way ANOVA revealed the statistical significance of this interaction effect between the group (control/experimental) and study time condition (under/over-study) on final perceived stress levels

Table 2: Descriptive statistics on the four subgroups based on students' study time discrepancy.

		Study time discrep.		Final PSS	
Sub-group	***n***	M	SD	M	SD
Control (under-studied)	18	-6.45	4.39	14.33	7.86
Control (over-studied)	13	3.81	3.90	20.00	5.12
Experimental (under-studied)	12	-11.35	5.66	17.67	6.79
Experimental (over-studied)	17	3.75	4.78	16.53	5.06

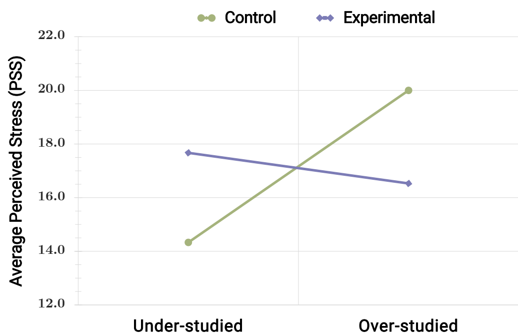


Figure 3: Interaction of under/over-study condition and study group (control/experimental) on PSS

($F(1, 56) = 4.14, p = 0.046$). It is worth noting that the main effects of group ($F(1, 56) = 0.04, p = 0.95$) and study condition ($F(1, 56) = 2.03, p = 0.16$)) on perceived stress were not statistically significant, meaning that neither the group nor the study condition individually had a statistically significant impact on the PSS scores of the students.

5.3. Participant perception of digital boosts

We manually analyzed the comments of students in the experimental group in order to understand their perceptions of the feedback they received. We first extracted all the comments they noted in the open-ended sections related to the feedback and social boosts. Then, we carefully read through each comment and assigned a code based on the sentiment expressed (positive or negative) and the specific aspect of the boost being discussed. Out of a total of 40 comments, we identified 12 comments that expressed either a positive or negative perception about these boosts. Among these, comments about the individual feedback boost were mainly positive overall, while comments about social feedback conveyed a rather mixed perspective.

For the individual feedback boost, 6 comments mentioned that they perceived it positively, and no comment pointed out a negative perception. For instance, one of the students highlighted: "Feedback managed to motivate me to reach my objectives, in comparison to myself". Another participant stated: "I am completely within my schedule, so everything works well for me". However, students were more mitigated about social feedback. There were 4 comments depicting a positive perception, and 2 comments showing a rather negative perception about it. On the positive side, one participant stated: "I am relieved to see that I am within the average, so my study time must be enough". Another highlighted: "I am satisfied to discover that I am within the norm". On the negative side, one participant stated: "Knowing how long the other students studied was completely uninteresting". Another one pointed out: "I care about my objectives, and do not care about what others do".

6. Discussion

Our results suggest that students who were exposed to digital boosts managed to maintain a steady study time until the end of the reading week. On the other hand, the study time of the control group decreased significantly over the week. The observed difference between the two study groups could be attributed to an improvement in self-regulation within the experimental group as a result of receiving feedback boosts. This is in line with existing literature related to behavior change in response to feedback mechanisms. For example, previous research suggests that effective feedback, particularly in educational contexts, can significantly impact learner behavior and enhance self-regulated learning strategies (Hattie & Timperley, 2007). In addition, Narciss (2008) argues that feedback that aids in self-regulation can improve learners' motivation and keep them engaged in their studies for longer periods. Nevertheless, future research could employ more direct measures of SRL to validate the interconnection between study time and self-regulation.

Despite the rather positive impact of digital feedback boosts on study time, our results also indicate that they might have increased the perceived stress levels of students overall. Indeed, when considered collectively, students who were exposed to digital boosts saw their perceived stress levels increase in contrast to the control group. However, looking at the results in more detail, we observed a more nuanced picture. Indeed, the perceived stress levels only increased for students who under-studied, i.e., who did not attain their intended study time goals. In contrast, the perceived stress levels for students who over-studied *decreased*. These results can be seen through the lens of negative feedback, where the negative aspect does not come from a third party that sets the standards for a given task, but from failure to achieve a self-assigned goal. As such, the heightened stress among under-studying students aligns with previous literature demonstrating that negative feedback can cause self-threatening reactions and lead to increased stress (Laudel & Narciss, 2023).

Our findings thus convey the fact that digital boosts can not only be seen as useful interventions to increase study time for students who perform well, but they also have the added effect of reducing their perceived stress. However, the picture is different for students who under-study, as they experience an increase in perceived stress levels. This is an important finding because the intervention can have a positive impact on a category of students, but might backfire for another category for which it should particularly be effective. Indeed, the increased perceived stress in the under-studying students could further exacerbate their condition, since stress can lead to memory impairment and underachievement in exams (Vogel & Schwabe, 2016) or lead to increased procrastination (Utami et al., 2020), This, in turn, would further prevent students from completing their learning tasks. Accordingly, future research should further investigate personalization strategies for digital boosts, in order to consolidate their positive outcomes by steering them toward students who would benefit most from them; in our case, the students who reach or exceed their study time plans. Alternatively, other digital boosts that would potentially generate less stress could be offered to students who do not manage to reach their study plans. Personalization can be achieved by taking into account the learner's self-perception and study habits for example (Baker et al., 2016; Zimmerman, 2002). In previous research, Bulut et al. (2019) successfully used personalized feedback to improve the overall performance of students. It is worth investigating to which extent the personalization of digital feedback boosts can also positively impact their perceived stress.

This study has some limitations that should be acknowledged. First, the self-reporting nature of the stress measurements may be subject to response bias (Chan, 2010), as students may have responded to the PSS questions in a way that does not accurately reflect their true stress levels. Employing more objective measures of stress, such as physiological markers, could make the assessment of stress less susceptible to self-report bias. Second, this study only explored the short-term impact of digital boosts, without considering the potential long-term effects. Previous literature indicates that the effect of nudges is reduced over time, especially for performance-related outcomes (Caraban et al., 2019), However, it is not clear if this would also be the case for stress. Capturing the perceived stress of students in different periods subsequent to our intervention could have revealed whether the stress-inducing effects of the boosts are short-lived, or whether they persist or even escalate over time. Finally, our feedback boost combines an individual and a social component. So we are unable to detect the impact of each component individually. Disentangling these two components could allow us to study the impact of each element individually on perceived stress. Our analysis of students' comments suggests that the individual feedback component of the boosts is typically viewed positively, while the social feedback component has received mixed reviews. Future research could benefit from exploring how each of these components influences stress in specific student categories.

7. Conclusion

In this article, we built an SRL support system and used it to deliver individual and social feedback boosts. We evaluated the impact of these digital boosts on perceived stress and study time, using a sample of 60 university students, during the fall reading week break. Our results suggest that digital boosts have helped students keep a steady study time throughout the reading week. However, they have caused a general increase in students' perceived stress, especially among those who did not attain their study time plans. Our findings suggest that study plan attainment may have a moderating effect on the impact of digital boosts on perceived stress. This implies that incorporating digital boosts might alleviate the perceived stress of students who reach or exceed their study time plans, while having an adverse impact on the ones who do not.

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