Curb Your Procrastination: A Study of Academic Procrastination Behaviors vs. A Planning and Time Management App

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ABSTRACT

Procrastination is a major issue faced by students which can lead to negative impacts on their academic performance and mental health. Productivity tools aim to help individuals to alleviate this behavior by providing self-regulatory support. However, the processes of how these applications help students conquer academic procrastination are under-explored. Particularly, it is essential to understand what aspects of these applications help which kinds of students in accomplishing their academic tasks. In this paper, we address this gap by presenting an academic planning and time management app (Proccoli) and a study designed to understand the association between student procrastination modeling, in-app behaviors, and perceived performance with app evaluation. As the core of our study, we analyze student perceptions of Proccoli and its impact on their study tasks and time management skills. Then, we model student procrastination behaviors by Hawkes process mining, assess student in-app behaviors by specifying planning and performance-related measures and evaluate the relationship between student behaviors and the evaluation survey results. Our study shows a need for personalized self-regulation support in Proccoli, as students with different in-app studying behaviors are found to have different perceptions of the app functionalities and the association between the prompts for social accountability students received by using Proccoli and their procrastination behavior is significant.

CCS CONCEPTS

• **Applied computing** → **Education**.

KEYWORDS

Academic self-regulation, Procrastination, Time management, Student study behavior.

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1 INTRODUCTION

Academic procrastination, or voluntarily delaying academic tasks, is a common behavior among students that has been shown to negatively affect their academic performance [9, 13] and mental health [21, 22]. As a result, having models and tools to identify this behavior in students and help them curb it is essential for their success. While there are studies on apps to aid in addressing general procrastination [16, 24] and models to detect procrastination in students [1, 3, 5, 7, 12, 19, 26, 27], the process of how such tools can help students to hinder academic procrastination is underexplored. Particularly, the current apps lack supporting skills related to academic procrastination, such as self-regulated learning (SRL) skills [30]. Moreover, current studies don't address the helpfulness of these skills for different procrastination dynamics in students.

Self-regulated learning (SRL) skills are shown to be important factors in academic procrastination [23, 30]. These skills include forethought, performance, and self-reflection [30]. The forethought phase includes strategic planning and goal setting, the performance phase refers to self-control (e.g., deploying task strategies, time management) and self-observation (i.e., metacognitive monitoring), and the last phase (reflection) refers to self-evaluations and causal attributions. Based on this model, successful learning depends on students' effectively planning for their learning, executing their plans using appropriate strategies, and reflecting on their learning. Given the importance of these skills, the tool to help with academic procrastination should include functionalities to support SRL.

Given such an app, understanding in-app procrastination dynamics requires a model that can represent and identify student procrastination. Procrastination behavior demonstrates itself in irregular and bursty activity sessions. Accordingly, it is best represented using continuous temporal models that capture between-activity timings. The Hawkes process [11], which is a type of self-exciting temporal point process, has recently been adapted and proposed for effectively modeling student learning activities in large online course environments [10, 14, 26–29]. For example, it has been shown that the parameters learned according to Hawkes processes correlate with self-reported academic and general procrastination in students [26]. However, the association between an app to help with self-regulated skills with such student dynamics has not been studied.

In this study, we aim to shed a light on this gap. To achieve this, we first present a mobile application Proccoli that is designed to support self-regulated learning skills in students to curb their procrastination. Then, we design and run studies to answer the following research questions: **Q1.** Which functionalities and self-regulating support in Proccoli do the students find most beneficial in facilitating their studying, planning, and time management? **Q2.** Which functionalities and self-regulating support do students with different app-usage behaviors find most beneficial? **Q3.** Do the students with more or fewer procrastination behaviors, detected by student procrastination modeling, use the app differently? and **Q4.** Do the students with more or fewer procrastination behaviors, detected by student procrastination modeling, have a different perception of app usefulness?

More specifically, we present Proccoli which is designed to support students in planning and goal setting, enacting their plans and studying toward their goals, and monitoring their progress toward those goals, among SRL processes. We then present the results of a post-survey regarding students' perceptions of different features of Proccoli and their use of it. It is important to understand how students perceive the application, whether they use the functionalities as intended, and whether they find particular features helpful to their time management, planning, and overall self-regulation of learning. Next, we define and measure student in-app behaviors using 18 features and compare students' survey responses and their perceptions regarding the application with these features. Finally, we model student procrastination using Hawkes process modeling and evaluate the association between student perception of Proccoli, their usage of it, and their modeled procrastination.

2 PROCCOLI APPLICATION

We designed and developed Proccoli, a time management application to support students in self-regulating their learning, especially to effectively plan, track, and manage their academic tasks and the time spent on them. The functionalities of Proccoli include the following 10 items. Figure 1 shows screenshots of these functionalities.

(a) *Goals/subgoals setting* allows students to create study goals (e.g. completing a course project) and, if desired, divide these goals into smaller sub-goals (e.g. drafting a project report) to provide a clear and structured plan. Students can assign an estimated start time (when they anticipate to begin working on the goal/subgoal), a personal deadline (when they expect to finish the goal/subgoal), and a due date (the deadline set by the instructor) to each goal/subgoal.
(b) *Timer* is a built-in Pomodoro-style timer for the students to manage and record study time on goals or sub-goals.
(c) *Progress reporting* lets students self-report their past studying start and end time for working on each goal or sub-goal as another source for recording study time, in addition to using the built-in timer.
(d) *Individual wall and editing* displays detailed information about the goal, e.g., sub-goals, start date, and deadline. Students can edit and manage their goals on the individual wall to adjust their study plans, such as modifying goal start dates and deadlines or reporting their goal completion. Students are free to set, work on, and complete their goals without any support or intervention from the application.
(e) *Dashboard* displays the student's profile and their overall goal completion, current and expired goals, the student's respective progress towards goals, and the time remaining to complete them. The students can sort their goals and start working on them from the dashboard.
(f) *Progress chart* visually represents the progress for both overall goals and each specific goal, including proposed study duration, actual time studied, personal deadline, and due date.
(g) *Notification* is sent to students primarily to remind and encourage them to use Proccoli.
(h) *Performance reporting* allows the students to report the outcome of their performance on a goal (e.g. grade/score).
(i) *Self-evaluation* allows the students to assign a score on a scale of 1 – 5 (Not Very Well to Very Well) to their goals according to their perception of how well they performed on those goals.
(j) *Group goal* allows students to create group goals and invite their collaborators to use Proccoli and complete the group goals together. Each group goal has an individual wall. Students can subdivide the goal into smaller sub-goals, and members can claim one or more subgoals to work on.

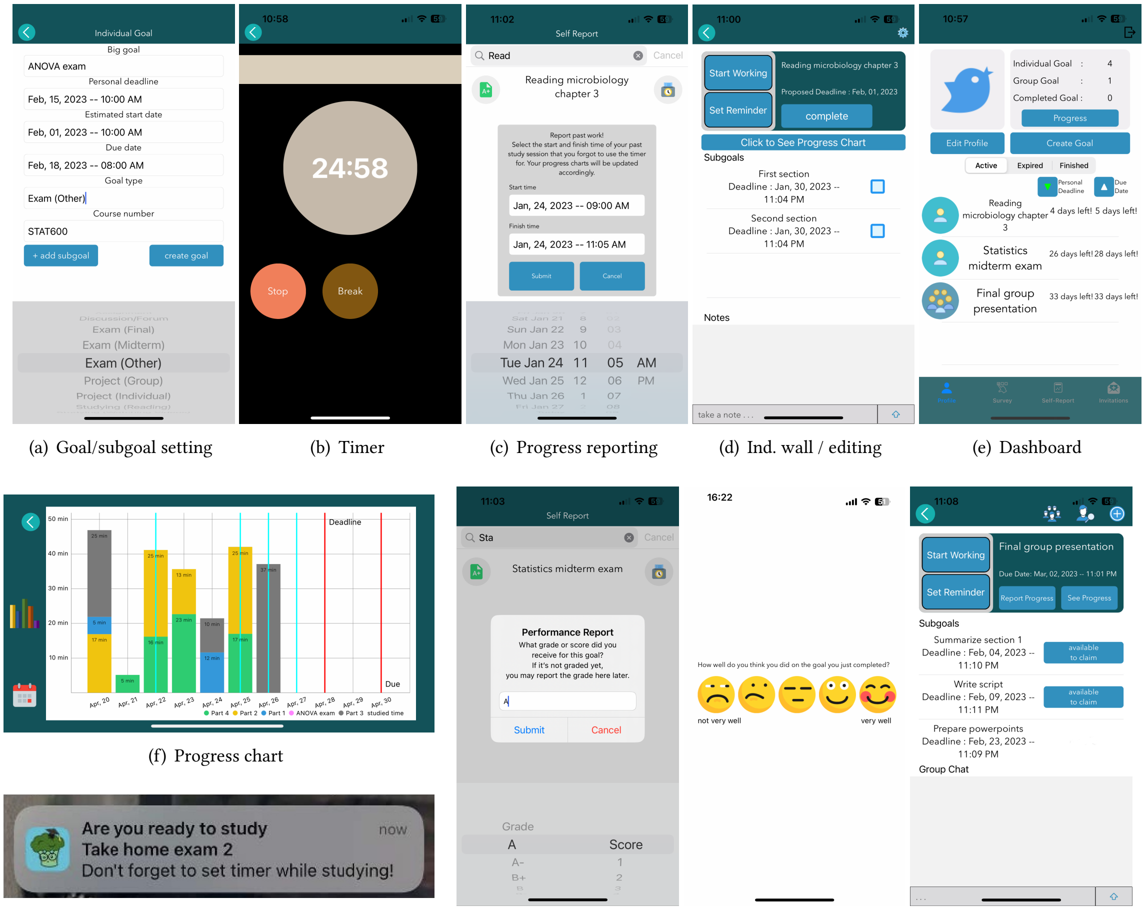
3 DATASET

Our study focuses on investigating the effectiveness of Proccoli in supporting self-regulated learning among students, as well as how it supports students with different studying and procrastination behaviors. To achieve this objective, we evaluate student satisfaction and experience in using Proccoli and the information that represent student behavior. Particularly, we use three sources of data that we introduce in the following.

3.1 Evaluation Survey

We designed and conducted an evaluation survey [18] to assess students' experience of Proccoli, specifically regarding its ability to support self-regulated learning [20]. The survey consisted of 38 questions, including 32 Likert scale questions, which were used to gauge agreement of Proccoli's evaluation on a scale of 1-5 (with 1 representing strongly disagree and 5 representing strongly agree), three multiple-choice questions, which offered 20 options for feelings students experienced while using Proccoli, such as "productive", "guilty", and "neutral", and three open-ended questions soliciting detailed feedback or suggestions. In this research, we only focus on Likert scale questions and multiple-choice questions. Each question was related to the overall Proccoli or the individual functionality introduced in section 2, with each question also focusing on an overall or a specific area of self-regulated learning support. The areas of self-regulated learning support that were evaluated include how much Proccoli: (a) *Time management awareness*: makes students mindful of their time management practices; (b) *Plan and execute*: helps students plan for, prioritize, and complete their goals; (c) *Motivation*: motivates students to plan for their studying and completing their tasks; (d) *Perceived accountability*: holds students accountable for their studying tasks; (e) *Perceived support*: helps students in improving their time management skills; and (f) *Social accountability*: how much seeing peer's progress in Proccoli holds students accountable when collaborating on particular group goals. Table 1 shows a sample of the survey questions. The complete survey is available on GitHub [1]. The survey was emailed to 201 undergraduate and graduate students in May 2022, who had participated in the studies involving Proccoli during Fall and Spring

[1] https://github.com/persai-lab/2023-UMAP-CurbYourProcrastination-SurveyAnalysis



(a) Goal/subgoal setting (b) Timer (c) Progress reporting (d) Ind. wall / editing (e) Dashboard

(f) Progress chart

(g) Notification

(h) Performance report (i) Self-evaluation (j) Group goal

Figure 1: Screenshots of Proccoli functionalities.

Table 1: A sample of the survey questions.

Q#	question	response options	functionality	self-regulation support
Q1	In general, using Proccoli was convenient for me.	Likert scale 1-5	overall application	overall Satisfaction
Q8	Creating a goal in the application makes me feel more motivated to complete that goal	Likert scale 1-5	goal/subgoal setting	motivation
Q26	Viewing the progress chart, which displayed proposed study time and actual time studied, did NOT help me to manage my time.	Likert scale 1-5	progress charts	time management awareness
Q32	Receiving notifications to use Proccoli made me feel (select any number of feelings that apply to you)	multiple-choice feeling	notification	perceived support

semesters of 2020 and 2021. While the students did not receive any additional rewards for filling out the usability survey, all the 201 students had received monetary incentives to use Proccoli when they used the app. We received a total of 38 completed survey responses.

3.2 In-App Usage Point Statistics

To understand how the students engage with Proccoli, we define 18 point measures that summarize each student's in-app studying behaviors that help us identify their usage patterns. These features include:

- *#goals*: the total number of goals created by the student.
- *finishRt*: the completion rate for the student, calculated as the percentage of completed goals out of all goals.
- *studiedTime*: the average time the student spent on studying each goal according to the *timer* and *progressReport*.
- *selfEvaluation*: the average of scores assigned by the student to their own learning behavior for their goals.
- *grades*: the average grade reported by the student for their goals, if available.
- *timerUsage*: the student's usage of the *timer*, as the ratio of timer activities to total number of learning activities.

Because Proccoli supports the creation of both individual and group goals, the above features are further arranged into statistics for individual and group goals, resulting in the following additional features:

- *#indGoals*, *indFinishRt*, *indStudiedTime*, *indGrades*, *indselfEvaluation*, *indtimerUsage* for individual goals.
- *#grpGoals*, *grpFinishRt*, *grpStudiedTime*, *grpGrades*, *grpSelfEvaluation*, *grpTimerUsage* for group goals.

Table 2: Summary statistics of In-app usage point statistics features and the number of students the features were calculated for.

features	#users available	mean	variance	median	features	#users available	mean	variance	median
#goals	33	18.0303	943.2178	9.0000	***selfEvaluation***	27	3.9240	0.7867	4.0714
#indGoals	33	17.3939	944.4337	9.0000	***indSelfEvaluation***	27	3.9240	0.7867	4.0714
#grpGoals	12	1.7500	0.7500	1.5000	***grpSelfEvaluation***	0	NaN	NaN	NaN
finishRt	33	0.6779	0.1753	0.9907	***grades***	13	11.1692	2.4708	12.0000
indFinishRt	33	0.6963	0.1742	1.0000	***indGrades***	13	11.1376	2.6073	12.0000
grpFinishRt	12	0.5000	0.2727	0.5000	***grpGrades***	4	10.2500	8.2500	11.5000
studiedTime	24	4.6025	143.9210	1.1942	***timerUsage***	31	0.2786	0.0748	0.2500
indStudiedTime	24	4.6025	143.9210	1.1942	***indTimerUsage***	31	0.2786	0.0748	0.2500
grpStudiedTime	0	NaN	NaN	NaN	***grpTimerUsage***	0	NaN	NaN	NaN

Summary statistics of these features are showed in Table 2. Due to data unavailability for *grpStudiedTime*, *grpSelfEvaluation*, and *grpTimerUsage*, they are not included in our study. The measurement unit for *studiedTime* is hours.

3.3 Timed Studying Activity Data

To gain a deeper understanding of procrastination dynamics in students, we looked at the data on the timing of students' studying activities while they used Proccoli, which were logged when these activities occurred. This timed data enables us to model the detailed dynamics of student procrastination behavior in continuous time, thereby providing a rich and nuanced understanding of how the use of Proccoli relates to procrastination behaviors in students. This data includes the following four activities with Unix timestamps: (1) Goal creation time, including the time when students create a goal or a sub-goal; (2) Time of student interactions with the built-in timer for studying, including start time, pause times for breaks, resume times, stop time, and the time when the timer automatically runs out; (3) Self-reported study time, including reported start and end time of the study session and the time when a self-reported study time is submitted; and (4) Goal completion time, which includes the time when students report that they have completed a goal. To ensure that Hawkes modeling is statistically feasible and meaningful, we only include active students, i.e., those who have more than five activities within a semester on Proccoli, in our analysis. Out of the students who responded to the evaluation survey, 31 meet this criterion, with 1850 activities.

4 ANALYSES

The present research aims to investigate the effectiveness of Proccoli in promoting self-regulated learning among students by helping them in planning and monitoring their learning and managing their academic tasks and time. To achieve this goal, we conduct four sets of experiments. First, to answer **Q1** and examine students' satisfaction with Proccoli, we perform an analysis of the student responses to the Proccoli evaluation survey (Section 4.1). Also, to explore the relationship among students' perceptions of the Proccoli in various areas, we study the associations of students' responses to the survey questions (Section 4.2). Third, to answer **Q2** and understand how Proccoli supports students with different studying behaviors, we examine the association between students' responses to the evaluation survey and their in-app usage point statistics(Section 4.3). Finally, to further investigate the relationship between students' procrastination and learning behaviors and the evaluation of Proccoli, we model student procrastination using the timed studying activity data and analyze their association with their in-app usage point statistics (**Q3**, Section 4.4.2) and responses to the survey questions (**Q4**, Section 4.4.3).

4.1 Proccoli Evaluation Survey Analysis

The focus of this analysis is to investigate student responses in two aspects: (1) to examine the specific functionalities of Proccoli that students find most beneficial in facilitating their studying and time management; (2) to analyze which self-regulated learning support the students feel is obtained through the use of Proccoli. By examining these two aspects, we aim to gain a deeper understanding of how Proccoli can be effectively utilized to enhance self-regulated learning in students. To provide a point estimate of student responses in each subcategory of questions, we first calculate the mean of each student's responses to all the questions within each subcategory. Then, we derive the basic statistical information over all students' mean data within each subcategory. The results are presented in Table 3 for the functionality questions and in Table 4 for the self-regulation support questions. In the following, we go over these results.

Functionality. As shown in Table 3, *overall application* received a median score of 3.5, with a mean of 3.2434, and a variance of 0.3496. This suggests that more than half of students assigned Proccoli an overall application score higher than 3.5, indicating a positive perception of Proccoli among the student population. Furthermore, the relatively low variance in *overall application* implies that, on average, students agreed on this positive perception of Proccoli's overall functionality. Additionally, all functionalities of Proccoli received mean and median scores greater than 3. This is consistent with the positive overall score. However, notably some functionalities, such as *performance reporting* and *timer* received higher scores compared to others, e.g., *progress reporting*. Equally important, the variance of students' responses to two functionalities, i.e., *timer* and *progress reporting*, is large (greater than or equal to one). This means that not all students agree about their satisfaction with these functionalities. But, many students agreed on functionalities like *progress chart* and *goals/subgoal setting*.

Self-regulation support. Looking at Table 4, the mean and median scores larger than three for students' *overall satisfaction* suggests that, on average, students think that Proccoli could be effective in supporting them in managing their time and planning for tasks. However, the high variance indicates that there is a significant degree of variation in student perceptions. Particularly, for specific self-regulated learning skills, the subcategories *perceived support*

Table 3: Basic statistical information of the students' responses regarding app functionality.

Category	*# of questions included in*	*# of students responded*	*response mean*	*response variance*	*response median*
Overall application	5	38	3.2434	0.3496	3.5000
Goals/subgoal setting	8	36	3.2897	0.1195	3.2857
Individual wall and editing	4	31	3.2594	0.2166	3.1667
Timer	2	33	3.8788	1.4848	4.0000
Progress reporting	1	32	3.0625	1.5444	3.0000
Dashboard	4	37	3.2793	0.2007	3.3333
Progress chart	4	26	3.2564	0.0916	3.3333
Performance reporting	2	32	3.7358	0.9791	4.0833
Notification	2	26	3.4438	0.7536	3.5000
Group goal	3	23	3.2174	0.9733	3.0000

Table 4: Basic statistical information of the students' responses related to self-regulation support.

Category	*# of questions included in*	*# of students responded*	*response mean*	*response variance*	*response median*
Overall satisfaction	3	38	3.5175	0.8210	3.6667
Time management awareness	6	22	2.8712	0.1294	2.8333
Plan and execute	12	14	3.3690	0.1749	3.3750
Motivation	4	34	3.0147	0.2119	3.0000
Perceived accountability	4	23	3.2826	0.2915	3.2500
Perceived support	4	24	3.5069	1.0053	3.7292
Social accountability	2	17	3.2647	0.9099	3.0000

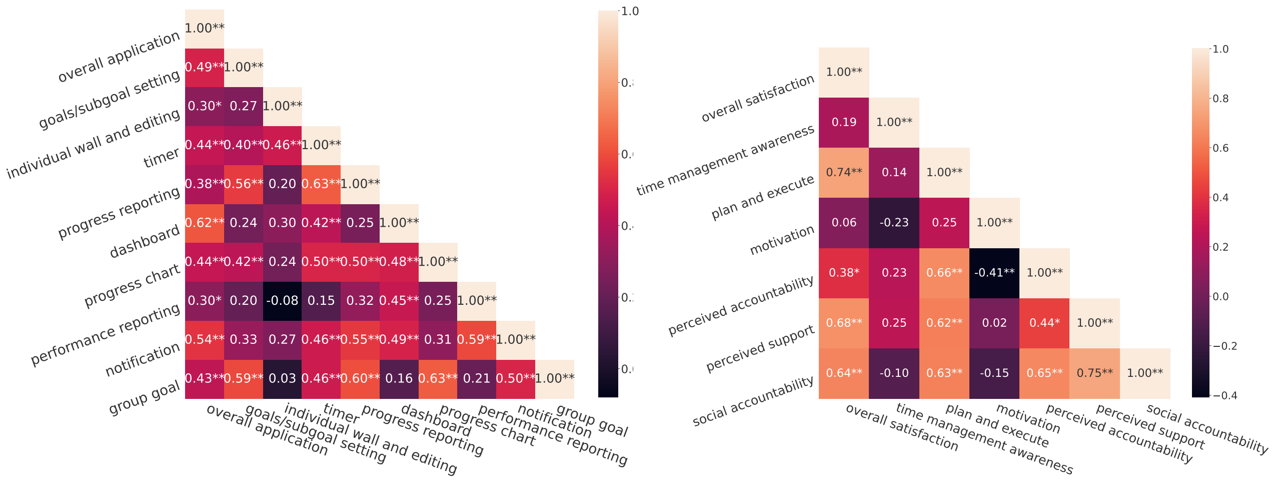
and *social accountability* had a high variance among student responses. This suggests that student perceptions regarding how Proccoli supported their self-regulated learning and how seeing their peer's progress affected their accountability are not consistent. Along with the fact that *perceived support* received the highest mean and median scores among all subcategories, this suggests a negatively skewed bimodal distribution in student perception of this subcategory. In other words, more students had a high perception of how Proccoli supports them in managing their time and planning for tasks, but some had a very low perception of it.

Another interesting observation is the difference between students' perception of *time management awareness* and *plan and execute* subcategories of Proccoli. The median and mean scores for *time management awareness* are both less than three, while *plan and execute* receives the second-highest mean and median scores among the specialized subcategories. This shows that while the students feel that Proccoli helps them in planning for their goals, they do not feel the same support in being mindful of managing their time. This suggests that Proccoli can improve *time management awareness* by introducing functionalities that can help students be more aware of their timelines, like *calendar*, and *notifications* that remind them of their timelines, particularly, since the *notification* functionality was highly valued by the students (Table 3). In addition to the need for functionalities that can provide better *time management awareness* support, We hypothesize two possible reasons for the low *time management awareness* scores: (1) that some students might already have sufficient awareness of their time management and do not value the extra support; (2) that students who rated time-management support features of the application lower might have used these features ineffectively, or might not have known how to use these features to aid in managing their time. Nonetheless, these results imply that the current version of Proccoli is effective in assisting students in some, but not all self-regulation support areas.

4.2 Association within Evaluation Survey

To delve further into students' perceptions of Proccoli, we study the relationship between different subcategories in each of the two functionality and self-regulating support aspects. Specifically, we calculate Pearson correlation coefficients [4] between students' responses to each pair of categories to quantify the degree of association. The correlation coefficients with significance level are presented in the top and bottom parts of Figure 2 for the functionality and self-regulation support aspects, respectively. A significance level of 0.1 is used to determine significant correlations in this study, unless otherwise is noted.

Functionality: First, we observe that all individual app functionalities have a significant positive correlation with the overall application. This indicates that students who have a more positive experience with the various functionalities of the app also tend to rate the overall application with high scores. Among all functionalities, this relationship is stronger for *dashboard* and *notification*, with the highest correlation and p-value < 0.01. Looking at the correlations between every other subcategory of functionalities, we do not find any significant negative correlations. *Individual wall and editing* in particular is not significantly correlated with any other functionalities except *timer*. The rest of the functionality correlations are positive, with some of them being significant. For instance, there are significant positive correlations between *timer* and *progress reporting*, *performance reporting* and *notifications*, and *progress chart* and *dashboard*. These positive correlations show that students' perceptions of the evaluation of app functionalities are usually consistent between different functionalities. Especially, we can see that students' perception of *timer*, *goals/subgoal setting*, and *notifications* have the most number of significant correlations (p-value ≤ 0.05) with other app functionalities, which shows their importance. Typically, it appears that students tend to have a consistent perception of different functionalities, either believing that all these functionalities as helpful for supporting their self-regulated learning or as not meeting their expectations.



(a) functionality (b) self-regulation support

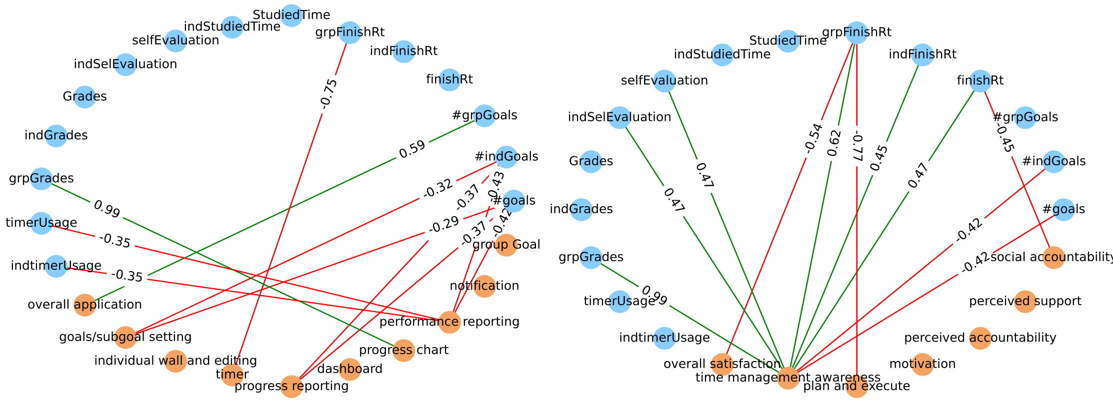
Figure 2: Correlation coefficients of evaluation survey questions. $**$ and $*$ indicate $p-value < 0.05$ and $p-value < 0.1$ for correlation coefficients, respectively.

Self-regulated support: Unlike our results in the functionality aspect, our study of self-regulation support suggests that there is not always a significant correlation between the overall satisfaction of Proccoli and all other self-regulation support subcategories. Specifically, all self-regulation support subcategories except *time management awareness* and *motivation* have a significant positive correlation with *overall satisfaction*. However, the *time management awareness* and *motivation* subcategories do not have a significant correlation with *overall satisfaction*. This suggests that students' perception of the overall effectiveness of Proccoli in supporting their self-regulation skills aligns with their perceptions of Proccoli helping them in most of their individual studying tasks, but not with their awareness of current time management practices or their motivation to plan and manage their time. In fact, *time management awareness* does not have a significant correlation with any other self-regulation support subcategories, and *motivation* has only one significant negative correlation with *perceived accountability*. Also, the students who think that Proccoli helps them in having a higher accountability do not see Proccoli helping them in their *motivation* and vice versa. This might be because they already have a higher level of accountability, self-regulation, and motivation, and do not receive motivation support from the app. The students' opinions of *Motivation* and *time management awareness* have the least significant correlations with other self-regulation support subcategories. Coupled with the observation of students' low scores for these two skills, it may suggest that Proccoli does not provide enough support for these two self-regulation skills as much as it does for the other ones. Among other self-regulated support subcategories, *perceived accountability* has the most number of significant correlations with the rest, having the maximum correlation with *plan and execute*. This suggests the importance of the *perceived accountability* skill in students' opinions of Proccoli. Also, the students who feel that Proccoli helps them in planning for their study goals also feel that using Proccoli holds them accountable for achieving their goals and vice versa. Overall, our study suggests that Proccoli can support students in some self-regulation skills, such as *plan and execute* and *perceived accountability* and the students have similar perspectives on most of the provided skills. However, Proccoli needs to improve in some other self-regulation support categories, such as *time management awareness*, where student perceptions are not similar to the other categories.

4.3 Association between Evaluation Survey and In-app Usage Point Statistics

This set of experiments aim to explore the connection between students' in-app usage behavior and their perception of Proccoli's functionalities and self-regulation support (**Q2**). We use the Pearson correlation coefficient between the variables introduced in Section 3.2 and the students' survey responses in the two support aspects. The results are presented in Figure 3(a) for functionality categorization and Figure 3(b) for self-regulation support. In these figures, each blue node represents one in-app usage point statistic, and each orange node represents one subcategory of the evaluation survey from the two survey aspects. We show the correlation coefficient value on each edge and only show the edges that correspond to significant correlations (p-value < 0.1). A green [red] edge indicates a positive [negative] correlation. In the following, we discuss the results for each of the two evaluation survey aspects separately.

Functionality: The results of our analysis reveal several negative correlations and two positive correlations between the in-app usage point statistics and survey categories. First, we observe negative correlations between *#goals*, and *#indGoals* and survey categories of *goals/subgoal setting*, *progress reporting*, and *performance reporting*. These suggest that the more goals (especially individual goals) students created in Proccoli, the less they perceived the functionalities to create and edit goals and subgoals (*goal/subgoal setting*), manually enter the time for past studies (*progress report*), and reporting the performance/outcome of a goal (*performance report*) to be effective in supporting them. We have four potential explanations for this observation. One potential explanation for the negative correlation with *progress report* could be that these students primarily use Proccoli's *timer* functionality rather than reporting their study time later. Although there is no significant correlation between *#goals*



(a) Functionality (b) Self-regulation Support

Figure 3: Significant correlations (p-value ≤ 0.1) between evaluation survey and student behavior. Left hand side (a) for functionality and right hand side (b) for self-regulation support. Green (red) lines indicate the correlation is positive (negative), values between lines are the corresponding correlation coefficients.

and student perception of the *timer*, we further checked the correlation between *#goals* and *#timerUsage*. Our results indicate that these two in-app usage point statistics are correlated with a coefficient $r = 0.49$ and $p-value = 0.01$. This shows that the students who create more goals and subgoals primarily use the timer functionality of Proccoli and accordingly the *progress report* functionality is not as useful to them. Additionally, we note that for the students planning their learning effectively by breaking down large goals into smaller subgoals and monitoring and checking their progress by looking at progress charts are more important processes, as compared to creating numerous goals. Another explanation could be that students might find it onerous to report any missed study session where they forgot to use the in-app timer, report their performance on each and every goal/subgoal, or go through steps in the app to set goals and break down their goals into subgoals, especially when managing numerous goals and subgoals. This could have negatively affected their perceptions of these application features. The third potential explanation comes from the variability in the *#goals* and *#indGoals* statistics. As shown in Section 3.2, these two variables have a high variance, with a mean that is much larger than the median. While most of the students only created a few goals, we observe a few students with numerous goals. Because of this skew in *#goals* and *#indGoals*, the perceptions of these few students may have a bigger effect on the correlation results and may have skewed them too. Finally, this finding may suggest that as students create more goals (especially individual ones) within the app, they gain enough expertise in the self-regulation strategies that are related to these functionalities and do not see the need for using these functionalities in the app.

Second, our analysis also revealed a negative correlation between *grpFinishRt* and *Timer* functionality within Proccoli. This finding suggests that as students engage in more collaborative tasks with their peers, they perceive the *timer* functionality as less effective in supporting their self-regulated learning during group tasks. This may indicate that the timer functionality is not well-suited for the specific needs and dynamics of collaborative learning, or that students are using alternative strategies for regulating their group work. Another explanation for this correlation could be that students might prefer studying on their own, without using the in-app timer, and then manually report their progress in the app. On the other hand, our analysis revealed positive correlations between *groupGrades* behavior variable and *progress chart* functionality, as well as between *#groupGoals* and *overall application*. These findings suggest that students who perform well on group tasks perceive visualizing their peer progress on goals as beneficial, and that students who are more satisfied with the overall use of Proccoli are inclined to create more group goals. This could indicate that students who are engaged and satisfied with the app find value in the progress visualization and goal-setting features, particularly in the context of group work. The features these students have found useful are designed to facilitate how groups plan, set goals, or claim goals among themselves, and view their own and other members' progress. Interestingly, that these features have been found useful in the context of group work, but not as well in the context of individual goals. Further research is needed to fully understand the relationship between group tasks and effectiveness of Proccoli and its features in supporting co- and shared-regulation of learning.

Self-regulated support: In contrast to the functionality aspect, our analysis of the relationship between in-app usage point statistics and self-regulation support reveals a mixed pattern of results, with half of the correlations being positive and half being negative. In particular, we observe that all the positive correlations happen between the *time management awareness* variable and six self-regulation support subcategories, i.e., *finishRt*, *indFinishRt*, *grpFinishRt*, *selfEvaluation*, *groupGrades*, and *indSelfEvaluation*. This suggests that students who are more proficient at finishing goals and have higher self-evaluation, regardless of whether the goals were for individual or group tasks, perceive Proccoli's self-regulation support as effective and feel that Proccoli makes them aware of their current time management practices. Particularly, given that the median and mean scores of these in-app usage point statistics are relatively high, their median is larger than the mean, and that the mean student score of *time management awareness* is relatively low, we can conclude that the few students who have lower self-evaluation estimates and finish rates need much better support for the *time* *management awareness* self-regulation skill. On the other hand, we see a negative correlation between the *#goals* and *#indGoals* behavioral variables with the *time management awareness* self-regulation support. Similar to the negative correlations between these two behavioral variables and the app functionalities, this result can be attributed to the students' usage of Proccoli, the need for an improved *time management awareness* support in Proccoli, the skew that the few students with a high number of goals have on the correlation results, or the reduced need of the students to this support as they use the app. Combined with the positive correlations, this result potentially indicates that personalized time management awareness support is crucial for Proccoli to support the self-regulation skills of students with different learning behaviors.

Additionally, our analysis reveals negative correlations between the *overall satisfaction* and *plan and execute* self-regulation support with the *groupFinishRt* behavioral statistic. These findings suggest that students who have a higher group goal finish rate may not be as satisfied with the overall experience of Proccoli in supporting their self-regulation skills, and may find Proccoli less effective in planning and achieving their goals. A potential reason could be Proccoli's design which is more focused on helping students in planning their individual tasks. In particular, all team members should be users of Proccoli for effective planning of group goals and executing them. This was not the case for many of the group goals. This result, in combination with the positive correlation that *time management awareness* had with *groupFinishRt*, may suggest that the students who adopted and finished the group goals in Proccoli used it efficiently to manage their time rather than planning as they were not satisfied with Proccoli's group planning functionalities. There is also a negative correlation between *social accountability* and *finishRt*. This indicates that the students with a low rate of finishing their goals, whether group or individual, find Proccoli and its display of their teammate's progress effective in the accountability they feel toward their goals. One potential explanation for this observation could be the relationship between the students' goal orientation [8] and goal-completion performance. In other words, students with higher intrinsic motivation and mastery orientation who finish goals at a higher rate are not affected by (or do not need) the social accountability self-regulation support in Proccoli as much as those with lower levels of intrinsic motivation, who finish goals at a lower rate. These results imply that while time management awareness is important, other factors such as planning for studying and executing these plans and holding the students accountable for collaborating with their peers also play a role in determining the effectiveness of self-regulation support within Proccoli, especially during group tasks. Particularly, the students' behavioral statistics, such as how often they finish their planned goals or the number of goals and subgoals they define for their tasks, can be an indicator of how they perceive the effectiveness of Proccoli in supporting different self-regulation skills, and vice versa.

4.4 Association of Evaluation Survey and In-app Usage Point Statistics with Procrastination Behavior

Here, we aim to investigate the relationship between the student in-app usage behaviors and perception of how Proccoli helps them in planning and managing their goals with their procrastination-like behaviors (**Q3** and **Q4**). We first give a brief introduction to procrastination modeling by Hawkes processes and then present our results.

4.4.1 Representing Procrastination by Hawke Process. We use the Hawkes point process [11] to represent the dynamics of student studying and procrastination behavior. The Hawkes process is a specific type of self-exciting point processes [11]. Unlike other point processes such as the Poisson point process that assume a constant rate for activity arrivals, the Hawkes process considers an adaptive activity arrival rate and assumes time-dependency between activities. The interpretation of this time-dependency assumption and the learned Hawkes parameters fits well with student activity modeling. Namely, it is assumed that students' learning activities are driven by both external and internal stimuli [11, 26]. External stimuli, such as deadlines, refer to factors other than prior activities that influence a student's behavior. For example, a deadline may prompt a student to start a study session. Internal stimuli, on the other hand, refer to a student's historical activities that can trigger subsequent activities, for example, taking the time to study for a sub-goal on Proccoli can subsequently trigger the student to work on other related sub-goals [26, 27]. In addition to the fit and interpretability of Hawkes, modeling student activities using the Hawkes process provides an efficient method to represent the continuous dynamics of activities using a finite set of parameters.

Individual Student Procrastination Modeling. Assume that there is a set of N students, with their respective learning activity sequences represented by $S = \{S^1, ..., S^u, ..., S^N\}$. Each S^u represents all learning activities of student u, and is denoted as $S^u = \{t_1^u, ...t_i^u, ..., t_{L^u}^u\}$, where t_i^u is a timestamp that represents the logged time at which the i^{th} activity took place and L^u represents the total number of activities that student u has engaged in. To model student u's procrastination behaviors as a Hawkes process, we model the number of activities of this student at time t as a function of time, using the Hawkes intensity function [15] in equation 1.

$$\lambda(t|S^u) = \mu^u + \sum_{t_i^u < t} \alpha^u \beta^u e^{-\beta^u (t - t_i^u)} \tag{1}$$

Where μ^u (external stimuli rate or base rate) represents the expected rate of activities for student u triggered by external stimuli, α^u (internal stimuli rate) denotes the individualized expected rate of activities self-excited by previous activities, and β^u (or decay rate) models the decaying influence of self-excitement by prior activities for student u. A higher value of μ^u indicates a higher rate of activities triggered by external stimuli for student u. For example, this can mean the student has frequent study sessions close to the deadline. A higher value of α^u indicates that student u's historical activities have a stronger influence on their future activities. For example, a student modeled with a high α^u value can have bursty study sessions with many activities happening one after the other with a short interval time. A larger value of decay rate β^u corresponds to a faster decay of self-excitement, meaning that for student u, the past activities have a shorter period of influence on future activities.

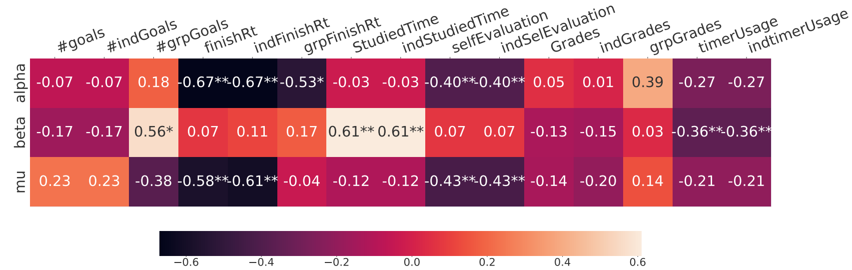


Figure 4: Correlation coefficients between in-app usage point statistics and learned Hawkes parameters, $**$ and $*$ indicate $p - value < 0.05$ and $p - value < 0.1$ for correlation coefficients, respectively.

For each student's learning activity sequence S^u, we learn the parameters of the Hawkes process by minimizing the negative log-likelihood built based on the intensity function of equation 1 for all observing historical activities t_i^u. Eventually, each student u's individually learned Hawkes-based procrastination parameters can be represented as $H^u = (\mu^u, \alpha^u, \beta^u)$. As a convention of traditional Hawkes process optimization [6, 25, 27, 28], we employ a grid search to select the optimal decay rate β^u and time-interval unit. Specifically, for each student activity sequence, the grid search for the decay rate is conducted within $[0.1 - 2000]$, with a step size of 0.1 when $\beta^u < 1$ and a step size of 1, otherwise. We conduct a grid search of the following time units for activity intervals: one-second, one-minute, five-minute, thirty-minute, one-hour, twelve-hour, one-day, two-day, and five-day. We found the twelve-hour time unit has the smallest negative log likelihood and the best fit to our data. Our code are available on GitHub [2]. To evaluate the fit of the learned Hawkes model to the observed activity sequences, we use the Point Process Residual Theorem with the Kolmogorov-Smirnov (KS) test [2, 17]. We obtained a p-value of 0.5381 from the KS test on all student sequences, providing evidence that the Hawkes model is an effective representation of our data.

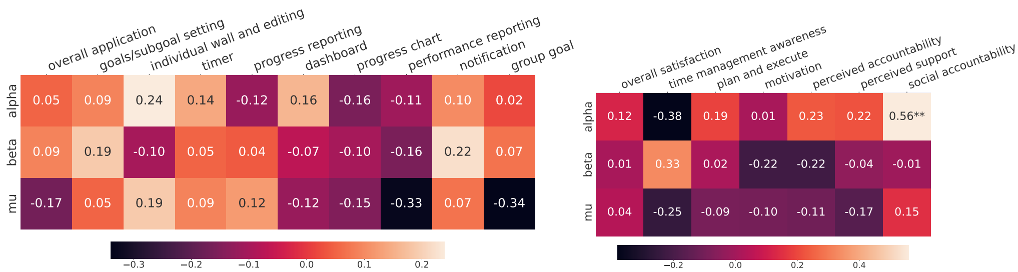
4.4.2 Association between In-app Usage Point Statistics and Hawkes Parameters. Here, we investigate the relationship between the dynamics of student procrastination behavior modeled by Hawkes and student in-app usage behaviors (**Q3**). Since our student activity model provides three parameters (i.e., α, μ, β) that are representative of students' continuous activity timings, we calculate the Pearson correlation coefficient between these parameters and student behavioral statistics. The correlation coefficients with significance level are presented in Figure 4. The parameter α has significant negative correlations with *finishRt*, *indFinishRt*, *grpFinishRt*, *selfEvaluation*, and *indSelfEvaluation*. This means that students who exhibit more "bursty" or procrastination-like patterns in their studying activities have a lower goal finish rate, for overall, individual, or group goals. Also, these students have a lower self evaluation and report lower self-assigned scores to their overall and individual goals. Interestingly, the parameter μ also has significant negative correlations with *finishRt*, *indFinishRt*, *selfEvaluation*, and *indSelfEvaluation*. This means that the students whose activities are more triggered by the external stimuli have lower overall and individual goal finish rates and report lower self-assigned scores to their goals. However, unlike α, there is no significant correlation between μ and *grpFinishRt*. This might hint about different kinds of motivation or goal orientation students feel about group goals, and their behaviors regarding these goals might differ from how they approach individual goals. The decay rate β shows significant positive correlations with *#grpGoals*, *studiedTime*, and *indStudiedTime*. This means that students whose prior activities have a long-lasting effect on creating follow-up activities have lower recorded average overall and individual study times per goal and a lower group finish rate. Conversely, as β has significant negative correlations with *timerUsage* and *indTimerUsage*, these students have a larger rate of using the timer functionality in Proccoli. Together, these two results show that these students use the timer functionality frequently to study in short time periods for their goals. A potential explanation for this behavior is the Pomodoro-style design of the timer in Proccoli which is by default set to give breaks to students after a 25-minute studying session. Another potential explanation could be related to how the *studiedTime*, and *indStudiedTime* statistics are calculated. These two include both the times reported by the student in *progress reporting* and the times calculated according to the *timer* functionality. So, this result could mean that the students, whose effect of prior activities on creating future activities last shorter, use *progress reporting* more to report their *studiedTime* after the study session, rather than using the *timer* during their studies. Overall, bursty and procrastination-like behaviors are shown to be related to lower task finishing rates, lower self-evaluations, and later progress reporting.

4.4.3 Association between Survey Response and Hawkes Parameters. To answer **Q4**, we study the relationship between the dynamics of student procrastination behavior and student evaluation survey results by calculating the Pearson correlation coefficient between the Hawkes model parameters and student perception of Proccoli functionalities and self-regulation support. The correlation coefficients with significance level are presented in Figure 5(a) for the functionality aspect, and in Figure 5(b) for the self-regulation support aspect.

Functionality: At a significance level of 0.1, there is no significant correlation between the Hawkes parameters and students' evaluations of the app's functionalities. This implies that how the students perceive Proccoli's functionalities is not directly and consistently related to their procrastination-like behaviors, although Section 4.4.2 shows that there is a difference between functionality usage in students with different procrastination-like behaviors.

Self-regulation support: In the context of self-regulation support, our analysis reveals a statistically significant positive correlation of 0.56 between the parameter α and the *social accountability* self-regulation support, with p-value ≤ 0.05. This correlation suggests that the dynamics of students' procrastination behavior, as triggered

[2]https://github.com/persai-lab/2023-UMAP-CurbYourProcrastination-SurveyAnalysis



(a) functionality (b) self-regulation support

Figure 5: Correlation coefficients between evaluation survey questions and learned Hawkes parameters. $**$ **and** $*$ **indicate** $p - value < 0.05$ **and** $p - value < 0.1$ **for correlation coefficients, respectively.**

by self-excitement, is positively related to their perceptions of the social accountability provided by the app in facilitating their self-regulated studying. Specifically, students who exhibit more "bursty" or procrastination-like patterns in their studying activities report that seeing the list of completed (or expired) goals by their peers in Proccoli motivates (or discourages) them to complete their goals on time. A potential explanation of this result could relate to student goal orientation [8]. Particularly, studies have shown that students with a performance-avoidance or performance-approach goal orientation, who focus on comparing their abilities and performance to others, show more procrastination-like and bursty studying behaviors [26]. We hypothesize that such students may be affected more by peer goal completion rates shown in Proccoli and display such "bursty" studying patterns as a result, rather than having steady and regular studying patterns. On the other hand, students who do not show procrastination-like behaviors do not perceive Proccoli affects them in social accountability, and seeing their peers' completion rates does not motivate or discourage them. These students might have more mastery-approach goal-orientations, where they study for the sake of their own learning, and not competing with other peers. Overall, our analyses suggest that different most self-regulation skills, except for social accountability, are perceived similarly in students with different procrastination behaviors.

5 CONCLUSIONS

In this paper, we presented a planning and time management app Proccoli to help students in self-regulated learning toward curbing their procrastination. We conducted and presented the results of a post-survey study, defined and measured student in-app usage behaviors using 18 features, and modeled student procrastination using Hawkes process modeling to answer four research questions on the relationship between Proccoli's self-regulation support, student in-app usage behaviors, and student procrastination behaviors. Our analyses to answer **Q1** revealed that although student perceptions of different functionalities were correlated, *timer* and *performance reporting* helped students better, with *timer* playing an important role in association with other functionalities. However, the students were not satisfied with how Proccoli made them aware of their *time-management* practices. Instead, they felt supported by the app in planning for their studies and helping them to complete their tasks (*plan and execute*). Thus, there is a need for a better designed timer and time-management support. Our study of in-app usage behaviors vs. evaluation survey results to answer **Q2** showed that students with different in-app usage behaviors have different perceptions of Proccoli's functionalities. Specifically, for the students who create more goals and subgoals, manually entering the time for past studies (progress report) and reporting the performance/outcome of goals (performance report) is cumbersome and leads to more use of the *timer* functionality. However, *timer* was not as useful for students with many group goals. Instead, seeing their own and peers' progress on *progress charts* provided better support for these students. In terms of self-regulation support, we concluded that devising personalized *time management awareness* support is essential in the app, as the students with different in-app usage behaviors had different perceptions of this critical skill. Especially since the students with lower goal finish rates and higher self-evaluation needed more *time management awareness* support. However, *time management awareness* is not the only essential skill that needs personalized support. For example, our studies reveal that students with a low goal completion rate, value *social accountability* support more. Thus, providing better *social accountability* support could potentially increase their goal completion rate. Our experiments to answer **Q3** unveiled that students with different procrastination behaviors use Proccoli differently. Specifically, students with bursty and procrastination-like behaviors report their progress later (after the study session) rather than using the timer, have lower task-finishing rates, and have lower self-evaluations. However, our results to answer **Q4** showed that the students' perceptions of Proccoli's functionalities were independent of their procrastination-like behaviors. Rather, their perception of self-regulation support was associated with these behaviors. In other words, the usefulness of different functionalities was invariant to student procrastination. Instead, students with procrastination-like behaviors were influenced by the *social accountability* support in the app. We hypothesize that this influence and the relationship between lower completion rates with *social accountability* in **Q2** can be explained by the students' goal orientation. Indeed, future studies are needed to study this hypothesis.

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