

The Effect of Tracking and Reflecting on Study Habits on Study Behavior and Grades

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Abstract— Many college students struggle to adjust academically because they never learned how to study effectively. In our first study, we developed a web-based application that enabled students to record when and how long they were studying. 29 college undergraduates used this tracking application for two weeks, then reflected on how the app affected their self-awareness and/or behavior. Analyses of participant diaries and application logs indicate that tracking applications are far from accurate, but the act of tracking itself, paired with analysis of one's own data through reflection, enables students to have stronger self-awareness of their studying habits. Our second study, a 13-week long field experiment with 162 first-year students participating in 5 groups with varying combinations of tracking and reflection, showed that the tracking + self-reflection group scored significantly higher on their final exam than tracking with social reflection.

Keywords—self reflection, diary, education, study habits, tracking

I. INTRODUCTION

The transition from high school to college is a complex and difficult time for students [24]. Many are unable to successfully make this adjustment: in the U.S., despite a 40% increase in college enrollment between 1999 and 2009, college degree completion rates in that timeframe have remained the same [5]. While dropouts may occur at any stage in college, more than half of students who quit college do so in their first year [6]. The two main factors that contribute to retention problems are students' struggles related to academic adjustment and social adjustment [24, 29].

To address the problem of academic adjustment, we adopted the concepts of quantified self and technology-mediated reflection into the context of education—specifically studying behavior. Much of the work that has been done in the field of quantified self has focused on its use to maintain physical and mental health, i.e., in tracking eating, exercising, and mood [13, 15, 21, 27]. We aimed to apply the concept of self-tracking to the act of studying, which can be measured in terms of time and frequency. Studies in technology-mediated reflection have shown reminiscing can be effective in areas such as transitional adjustment crises, problem solving, acquisition of new knowledge, enhancing positivity, and gaining perspective [3, 9, 22]. Rarely, however, has tracking been paired with reflection in the context of learning.

We aimed to employ the concepts of technology-mediated reflection and self-tracking [18]—which have been widely used to support physical and mental health—into an academic context to help students develop better study habits. We wanted to explore how providing students with technology to compile and keep track of personal data related to their academic work would affect their ability to self-access and co-reflect on their behavior, and how that would relate to their academic efficacy, self-awareness, and academic performance.

In Study 1, we present a qualitative diary study where 29 students used a study-tracking app that we developed and wrote essays based on their reflection of their study behavior. In Study 2, we present a field quasi-experiment of computer science students and examine whether reflecting on their study habits on their own or as a group affects their performance in an introductory computer science class.

These two studies help understand how theoretical constructs of reflection—which have been mainly studied in health contexts—apply to other contexts, such as education, and add further knowledge of self- versus social- reflection. From a practical standpoint, the results of this study indicate that a relatively low-effort intervention of having students track their own studying behavior not only help increase self-awareness about their study habits, but also lead to higher grades.

II. APPLYING QUANTIFIED SELF TO EDUCATION

A. Reminiscence

Reminiscing is the act of recalling previous experiences and memories back to mind. It is often triggered spontaneously in an involuntary manner [26]. The concept of technology-mediated reflection aims to induce/enhance reminiscence by the use of digital media as a resource for reminiscence and reflection [9, 25]. Unlike reminiscence, which draws heavily upon sentimental and personal values of a memory, technology-mediated reflection allows one to access memories that are not necessarily surrounded by any sentiments but may contain information that is still of psychological importance or useful for personal growth and development [15].

The majority of work in the field of technology-mediated reflection has focused on its use to maintain physical and mental health, e.g., in tracking eating and exercising habits to keep fit and in the treatment of older adults with memory damage or loss

related ailments [15]. Numerous studies have shown immense health benefits of this phenomenon especially in the area of mental wellbeing [9, 15].

More recent studies have started exploring reminiscence in younger adults and have shown that reminiscence does not only transcend multiple age groups but also goes to serve just as many useful purposes in young adults as they do for older people in areas such as transitional adjustment crises, problem solving, acquisition of new knowledge, enhancing positivity, and gaining perspective among others [3, 22, 26].

The work of Habermas and Paha [14] presents a relatively different use of reminiscence as an adjustment mechanism for new college students to transition to university life. However, they discussed this in more of a social capacity than an academic one [3]. Our aim is to utilize this concept of technology-mediated reflection in a new light by exploring its use as an academic aid for college students.

Research shows reminiscing is easier when there are factors to preserve and aid the recall of memories such as memorabilia, pictures, notes and also other behavioral efforts such discussion of such experiences (with people that were part of the original event or not) or even the use of cognitive imagery to recreate events or certain pictures in the mind [3] as the recollection process in human memory has been shown to be incited by external cues [3, 16]. However, visual aids have been shown to be the most effective means for most detailed and accurate recollection [7].

From a psychological perspective, events are generally stored in the short term memory of the brain as episodic memories and time go, this information becomes less accessible and essentially deleted from memory as other new episodic memories replace them. Episodic memories only become integrated into long-term memory after repeated retrieval and rehearsal causing such episodic memories to become accessible in the long term memory [7].

B. Reflection and Self Tracking

Reflection, done individually or collaboratively has been shown to be essential for knowledge building [11]. Because it is time consuming and not always a natural process, reflection sometimes requires a reason or encouragement to happen [11].

The concept of technology mediated reflection aims to induce and/or enhance reflection by the use of digital media as a resource [30]. It is basically a system that encourages people to later revisit recordings of their lives and consequently reflect on these past activities [15].

However, some systems have combined tracking and reflection. Self-tracking technology helps individuals manage recorded information about ones' activities in order to improve self-knowledge and foster reflection [28], has been used to promote healthy behavior, and promotes greater self-awareness and management [11].

This idea has been vastly utilized in developing and promoting healthy behavior changes by promoting greater self-awareness and management through recording and self-tracking techniques. With the use of these technological aids, self-tracking, and consequently, reflection have become less

tedious [28]. Considering the significant benefits of reflection to cognition as well as the relative ease of self-tracking through technological mediation, we are utilizing this in the development of learning aids for college students by using a combination of tracking, recording, and reflection to instill better study habits.

C. Quantified Self

Most of our everyday lives revolve around data; including generating, collecting, consuming, analyzing them for tracking online behaviors of individuals by businesses and agencies or in driving our decision making as individuals among others [18]. For example, Amazon.com tracks everything we purchase to provide recommendations, and smartphones collect data about how many steps we take throughout the day.

The dominant ways people envision the use of data are: 1) unwittingly generated data as a result of using certain web services, and 2) Data analysts, statisticians, and scientists who are deliberately collecting and analyzing data for the purpose of finding information that may serve as a valuable resource for the body to which the results of such analysis is being provided [18].

The ubiquity of computers, mobile devices sensors, and cloud data storage now enable the aforementioned data garnering activities (generating, collecting, etc.) for the purpose of self-reflection [19]. People are now not only able to conveniently collect personally relevant data by simply going about their daily activities but also able to actively utilize this data to self-inspect/reflect [18, 19].

The awareness that comes from such data collections is very important in influencing behavior change [10, 19]. This rising phenomenon of automating personal data collection dubbed the quantified self by Gary Wolf and Kevin Kelly in 2007 [18] believes in the notion of self-knowledge through numbers [4].

There have been a several ways people have successfully used personal data to improve their lives and increase productivity [17]. For example, in the health domain, researchers/companies have developed technology for tracking physical fitness, sleep, diet, smoking, and stress [4, 19] to help users understand their habits.

Some researchers have conducted work in designing tools that tend to the questions and challenges that people have with understanding and interpreting their data by examining different stages of personal informatics and accounting for the resulting changes in people's information needs [19]. For example, a 90-day long trial of the health mash-up app with 60 participants showed that with a better understanding of the relationships and consequences of their data, the system helped increase self-understanding that led to focused behavior change [1].

Another example is Frost and Smith using visualizations to help diabetic patients explore the relationship between their blood glucose level and the types of food they consumed [12]. By providing visuals of things such as meals, exercises, work, play, and other factors that affect their health in addition to their medical data (blood sugar levels, etc.), patients were able to easily keep track of our their activities affected their health and consequently help them make healthier choices.

Even though the use of big data in learning is a large field of its own, quantified self at the individual, or student level, has yet

to gain momentum in the field of education. However, proponents of quantified self in education are excited about the possibilities for fully customizable learning technologies for each individual's needs [18].

An example of possible innovation using this technology is in K-12 schools, especially the STEM fields where students need to learn sophisticated ways of dealing with data that will be applicable at higher education levels as well as in the corporate world. Data collection in school activities such as science lab is tedious and repetitive, so quantified self-techniques offer a means of easily collecting data and focusing more on complex intellectual work [18].

Because much of the focus on quantified self in education is at a group analytic level, we wanted to apply the principle to the individual—the student—as quantified self in health is used by patients. By turning the spotlight onto the students rather than the educators, we thought it would be an interesting research question to see how generating data about one's own studying behavior would impact students.

Moreover, although the use of technology has greatly simplified data collection, organization, and retrieval, there are still a number of challenges associated with it. Being able to obtain the data is only one step in the process, it is equally as important to be able to decode and understand relationships and patterns in the data that can inform behavior change [1, 19].

D. Tools for Education

Although personalized data may provide useful information to an individual, this information does not have any merit if the user does not act upon it. Our work follows a long tradition of educational tools created to help individuals with their study habits. For example, Martin et al. [20] implemented a three-course invention (reflective writing assignments, schedule sheets, and e-mail alerts) into their computer science class to reduce procrastination. They found that those who did these tasks and submitted assignments earlier scored much higher on their assignments than those who submitted later.

Similarly, Corrin and de Barba found that students were adept at interpreting course feedback delivered through online dashboards, and that this feedback had a direct impact on both their motivation towards the subject as well as their ability to navigate through the course activities and assessments [8]. Our study complements these past studies, examining how more personalized, quantified self information, might affect students' study habits

III. STUDY 1: TRACKING STUDY HABITS & HOW IT AFFECTS ATTITUDES AND STUDY BEHAVIORS

In our first study, which was more exploratory, we wanted to understand how people interact with a study tracking application. We created a digital system similar to some of the technology-aided reflection apps such as Echo, Pensieve, etc. [15, 22], but with the aim of improving study habits, retention of academic material, and improved overall academic performance among college students using the method of reflective thinking by means of recording one's own behaviors and then taking time to reflect upon one's performance. While not about study habits per se, previous studies have found some

positive evidence for the effectiveness of tracking screen time in increasing productivity and disciplined device use [23]. We thus wanted to pair self-tracking with reflection to give students the opportunity to analyze their own data and to understand how they make sense of it and apply it to their own thoughts and behaviors. Our study was guided by a general research question:

RQ: How does a study time-tracking tool, paired with reflection, affect students' attitudes and behaviors about their study habits?

IV. STUDY 1 METHODS

A. Participants

Students from a mid-sized public university in the U. S. who were participating in a class to learn qualitative research methods participated in this study as part of their learning experience. There were 29 students (13 females and 16 males between the ages of 19-33 years old; median 22). Students' participation included tracking their studying behavior using an online time-tracking app that we developed for a minimum of two weeks. After using the time-tracking app for two weeks, each participant submitted a free-response essay individually reflecting on their use of the time-tracking app and whether they thought it helped them better understand their study habits. Participants also had to answer close-ended questions about whether or not they enjoyed using the app and if they remembered to use the app. They are also asked to rate from 1 (strongly disagree) to 5 (strongly agree) how much they thought the app helped them understand their study habits, how much they studied, and their study patterns.

B. The Time-Tracking App

The time-tracking app we developed is a web-based tool that is compatible with all modern desktop and mobile browsers (see Figure 1). We built the app to minimize the effort required by users to log their study habits. On their first use of the app, users enter their e-mail addresses for the system to log their individual data. Users do not have to re-enter their e-mail address on subsequent visits to the app (unless they log out).

The time-tracking tool's interface consists of three components: 1) A free text-box labeled "notes" with instructions for the user to provide any optional notes or comments about their activity; 2) one button that is labeled either "Start Timer" or "Stop Timer" depending on the current state of the logging process, and 3) a scrollable history log that displays a user's cumulative number of logged time, weekly cumulative logged time, and a reverse-chronologically ordered list of timestamped logged events. Hovering over a timestamp displays the user-provided comment if one exists. The system logged four things for each event: 1) the user's e-mail address, 2) the event type (i.e., "start" timer or "stop" timer), 3) the event timestamp, and 4) the user's freehand notes or comments, if any.

Identify applicable funding agency here. If none, delete this text box.

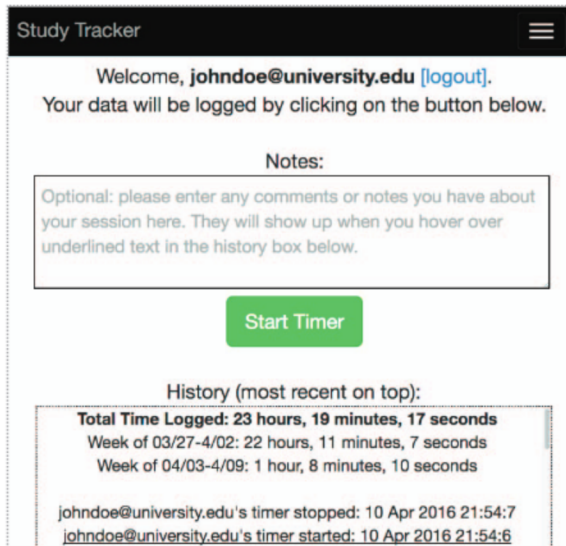


Figure 1. Screenshot of the study tracking app

V. STUDY 1 RESULTS

A. Time-Tracking App: Usage Data

Over a period of two weeks, participants logged a total cumulative time between 20 seconds to 98.91 hours (median 19.97 hours) using the time-tracking app. We removed any erroneous log entries that were missing either a paired start time or end time. Each person logged between 1-26 sessions (one session includes a paired start time and end time; median 8), averaging a median of 2.38 hours per session (see Figure 2). Most sessions took place on Sunday and Tuesdays (18.5% and 20.5% of the logs, respectively), with Mondays and Thursdays being the next popular choice (12.7% and 13.4%, respectively), and Wednesdays, Fridays, and Saturdays being the least popular days to study (11.6%, 12%, and 11.3% of the logs, respectively). There were no observable differences for any measure by gender or age.

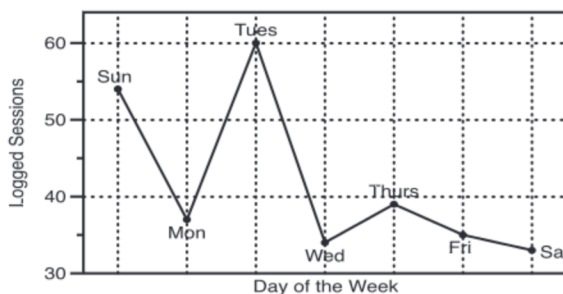


Figure 2. Frequency of sessions across days of the week

The time participants logged their data was normally distributed across the hours of the day, with 4pm being the peak time to start studying (see Figure 3), and the late evening and early morning hours being the least popular time to study. Figure 3 shows when participants started their sessions, with 83.9% of

the data falling between 11am to 11pm. The same time range between was also the most popular time range to stop studying (with 84.2% of the end times falling inside this range). There were no observable differences by gender or age for any of these measures.

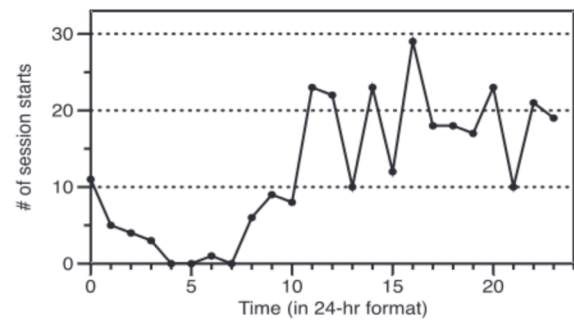


Figure 3. The time of day participants started their sessions.

B. Survey Data

Our post-study survey revealed that 60% did not enjoy using the app ($n=14$) and often forgot to use it to track their studying sessions ($n=17$). Participants were slightly more positive reporting that the app helped them understand their study habits (1 negative, 7 neutral, and 15 positive), how much they were studying (7 negative, 6 neutral, and 10 positive), and studying patterns (2 negative, 5 neutral, and 16 positive). There were no observable differences by gender or age for any of these results.

These results showed that most of our participants understood the importance of studying but might not have consistent study habits and may not start studying right away. The data also revealed that more participants did not like using the app overall but that it was slightly beneficial in helping them understand their studying habits. Contrary to these lukewarm results, the next section shows that students' reflections reveal a much deeper understanding of study habits by each individual.

C. Analyzing Students' Reflections

From the reflection papers, we discovered distinct themes regarding how participants used the app and how, if it all, the app influenced their thoughts and behaviors. The following observations and quotations from our participants are representative of our overall data (unless stated otherwise). Participants were given random names from consistent with gender to preserve their identity.

1) *Understanding One's Own Study Patterns*: Participants were able to use the time-tracking app to understand their own study patterns. When asked to reflect on their own data, some expressed that the data confirmed what they already knew about themselves while others were surprised to learn something new about themselves.

"Based on my diary, I had a very inconsistent study schedule, with days in which I did not study at all and days where I studied a net total of seven hours! Although I know that I am a procrastinator the data can prove that it is true," Aaron¹ said.

¹We use randomly assigned, gender-consistent pseudonyms for our participants in this paper.

"I rarely study unless it is for a big exam. I knew this going into the study. However, what I didn't know is the actual time I spend when I actually do study. It's a little startling to see the stats," Brian said.

Some participants also believed that they would not have any observable study habits (before using the study tracker), but realized that their weekly patterns were actually quite regular:

"I assumed that my schedule would look rather erratic but with[in] two weeks, patterns begin to emerge. I found that my time is equally split between afternoon and night, which is interesting because I don't consider myself a morning person. But maybe I could shift my schedule ahead a few hours and try to get more stuff done in the morning," said Carl.

Participants discussed how they could utilize the insights from their own data "analysis" to change their behavior. This was a more prominent theme among students who felt like they could do better academically. Most participants who were already doing well in school said that the tracker was neither a motivator nor a deterrent for studying and that they were already highly aware of their studying patterns without the app. However, Steve, a well-performing student, was willing to continue using the app in the future:

"The timer study was cool and I really enjoyed using it. It really helped me focus in on study patterns I've had for 7 years, in 2 weeks. This has allowed me to become more efficient and as soon as I have time this summer I will download the repository and implement it on my own site so that I can use it in the future."

Daniel, who worked a full-time job in addition to school, realized that he had limited time left in the day to study, which was not apparent to him until he actually saw his data:

"Understanding the raw data allows me to see visually how I use my time to study. In my retrospect I understand that I need to double my time in studying, study at proper times, to not cram late at night, and to use my time wisely."

Participants were also able to observe and reflect on the times that were most effective for them. Alicia said:

"Being able to track the times that I study made me realize that I actually retain more of the information if I study either at campus on my down time not around anyone, or when I am home right before bed. These were the times that I was more focused with fewer distractions."

Most of the students who were surprised by their data were the ones who noticed how little they studied. Several participants noticed that they did not study unless there was an upcoming exam. Students also differentiated between studying and doing assignments, saying that they did not consider certain assignments to be studying. Raj said:

"After using this application and tracking the time I have been studying I realized things I had put a blind eye to. I saw that I do not study that much as I should, based on the classes I am taking."

D. Changing Attitude

Most participants did not have any emotional responses to the app, but some reported feeling better or worse from tracking

their own behavior. Hernandez said that using the app gave him a feeling of satisfaction:

"Prior to this application I was not tracking information about how long and how much I studied. [...] by having this timer, I felt as if I was productive and accomplished."

On the other hand, Sara did not like the idea of being timed: "I like to go on my own pace while studying. I don't like the feeling of something timing me. Timing also made my breaks less enjoyable."

This feeling of pressure was also reported by two others, saying that they felt they were being "watched" by the app. Even though we had assured them that the researchers did not care about how much they did or did not study, these participants said that they felt pressured to study more. Rosa said:

"I had the sensation of feeling observed by the time tracker. Since I was aware the time tracker was running on the background I constantly went back to it to make sure it was running appropriately. Likewise, during the days where I did not study the most I would double think it before stopping the timer as I saw it as something wanting me to study more."

E. Changing Behavior

While all students reported learning something about their behavior by using the app, only a small group of participants said that the app made them actually change their behavior. Most participants said that the app did not impact the way they study because their studying behavior is influenced by external factors they cannot control, like having a job. Chris said:

"I will continue to study for assignments or tests at random times or whenever I can make time. With other priorities like work and family obligations it's sometimes hard to set time aside to study for a test until the night before or perhaps even the day of."

Prior habits also had an impact on whether or not participants were willing to change their behavior. Ned said that in high school he was used to "winging it" and that his studying habits didn't change much in college. On the other hand, some participants discussed how using the app itself made them more aware of studying and thus studied more than normal. Even though studying more was not associated with any grade, they were more cognizant about studying in general. One participant said that he wished there were inspirational quotes or pictures that would remind him of the importance of studying. Two participants used the app to set goals for themselves. Fernando used the app to track his breaks:

"This enabled me to be more conscious about time and made sure not to waste so much time taking breaks and to focus more on returning to study. This timer application can also aid in setting goals. For instance, I wanted to study three chapters in a day. I was able to pace myself with the timer."

There were also two distinct cases where students used the app to "compete" with themselves. Dylan, a college athlete, said that he used the app to motivate himself to study more each time by attempting to log at least a few more minutes than his

last session. Similarly, Gary said that seeing the metrics pushed him to try to log more often:

“Seeing a decline in how much time I spent in each week makes me challenge myself to put in more hours towards studying which is like a reward or positive reinforcement. During the 2 weeks’ time frame of using this application, I would force myself to study just to log in more hours into the application, even though I didn’t need to study.”

This motivation to self-improve, however, was quite distinct from most other participants’ usage, suggesting that competitive metrics, such as badges and virtual rewards, would only be meaningful for certain types of people.

Tracking, however, could backfire in specific scenarios. There was one unique case of a student who thought they had studied enough, based on their tracking information, and thus refrained from studying further. “I saw I already studied seven hours the previous day so I didn’t see a need to study the following day,” said Phan. This exemplifies that students who are not intrinsically motivated could use the metrics as an “excuse” to not study beyond what they deemed to be an adequate amount.

F. Design Reflections

Participants liked the simplicity of the app and the ease of use but requested that there be more graphical elements of data visualization.

1) *Inaccurate Data*: One of the major flaws of the app was that participants forgot to use it when they were studying or forgot to turn it off when they were not studying. This generated a lot of inaccurate data (e.g., we removed any log entries that were missing either a paired start time or end time in reporting our results for this paper). A few participants noted that they have many programs and browser tabs open simultaneously, which means that the study tracker got buried and forgotten. “The study tracker became buried in a list of tabs, quickly fading from my mind. That window with many tabs would then become buried under many other windows,” Bruce said. Forgetting to stop the timer was also a prevalent issue, especially among late-night studiers. One participant suggested that having a way for the browser to detect when the computer is asleep would automatically stop the timer.

Participants suggested that one way to deal with inaccurate data would be for retroactive data editing or data entry. However, that would not solve the issue of a non-continuous study session. For example, Britney said that during studying, she would often check Facebook, email, or answer text messages. “Sometimes not all the time is actually dedicated to studying. Although, these things or ‘distractions’ did not take much time away from my studying but at the same time it does not give an accurate time for that session,” she explained. Another participant said that he watches television without the volume on when he is studying, making it difficult to tell how much of the time spent is studying versus watching TV.

As a way of addressing short distractions within study sessions, a few participants suggested having a “pause” button rather than having to start and stop new sessions. This means that students were using the data to consider frequency in their

own behavioral analyses, since the study tracker only provided aggregate statistics related to time.

2) *Internet-dependent*: Although most participants studied in a place that had an Internet connection, several pointed out that the browser-based app made it difficult for people who are not studying using a computer or are in an area with no Internet connection. Participants who did not study using their computer thought that a mobile app would be more convenient “because I always have my phone on me.”

The tracking was also difficult when people were not engaging in continuous behavior and had intermittent connectivity. Jeremy, a commuter student, said that he often studies in short bursts on the train, which often cuts off connectivity when underground or passing through tunnels:

“These sessions were the most difficult to log because I was in environments that were loud and busy. When at home using a desktop computer in a familiar environment, I remember to log my studying.”

3) *Context*: Several participants noted that they liked the ability to add short notes. “You can also just add random thoughts like, ‘I’m sick’ or ‘I’m tired because I did this [...] today,’ these can be important things to note be that may explain why you didn’t study for long or properly that day,” Brian explained.

Andrea mentioned that she liked the annotation function because it would help her remember the circumstances that led to her specific behavior, such as why she studied more on a particular day, or why she skipped studying on certain days.

4) *Suggested Features*: Several participants wanted additional features in the app, or to integrate the app with existing applications, such as the ability to block social media websites during the study period, or being able to interface with task management apps. One participant said that the app could have features to help the user take mandatory breaks that will help them retain more information. Jane mentioned that she wanted more granular tracking, so that she could monitor how much time she spent on different study projects. At the same time, some participants felt that additional features would complicate the app and distract from the main purpose of tracking study times.

VI. STUDY 1 DISCUSSION

The participants in our study would most likely have not used this application of their own volition. In other words, many had low or no motivation for improving or learning their study habits. We saw, however, that most students reported that they learned something from using the app and doing the reflection even if they never intended to use the app again.

Participants were split in terms of their perceived usefulness of the time-tracking app to follow their study habits. Participants who were already self-aware of their behavior did not see any incentive in using the app, and participants who felt like they were already doing well, or did not care about studying at all, did not feel a need for the app.

Conversely, most participants reported the study tracking as a useful exercise, even if they did not want to use it again. They

thought that even when forced, it was a good learning experience. While it may be difficult to get users with no motivation to engage in quantified self for health, these results suggest that in the context of education, quantified self exercises could be used by instructors and built into the curriculum as an educational tool. Our study was conducted in the context of a university, but if such a tool were used in high school, students may be able to develop a better sense of awareness about time management early on.

VII. STUDY 2: EFFECT OF STUDY TRACKING ON ACADEMIC PERFORMANCE (GRADES)

Based on our findings from the first study, we refined our research questions and explored them in a new field study. Because the first study, being qualitative, did not distinguish the effects of tracking and reflection, we were unable to determine whether it was the tracking, reflection, or their combination that led to what we saw as students' insights into their own behavior. We also wanted to explore if students would benefit more from reflecting on their own, or as a group. Most of the previous studies on technology-mediated reflection were in the context of the individual [9, 22], but much research in education documents the benefits of peer learning [2].

We also took into consideration some design suggestions that were made by the study participants; the text field for notes was expanded so participants could add more comments or meta-data about their study sessions. Since the first study examined students' attitudes and study behaviors, we decided to look at an alternative measure of objective academic performance: grades. This decision came from the fact that most students did not particularly enjoy using the app but found it useful, making us wonder if the app usage could lead to actual performance.

RQ1: What is the effect of tracking and reflecting on academic performance?

RQ2: Are there differences between social reflection and self reflection?

VIII. STUDY 2 METHODS

The field study was a quasi-experiment that took place over the course of a single semester. A total of 162 Computer Science majors enrolled in a one-credit, mandatory, introductory-level seminar course that covered the soft skills associated with college success (e.g., how to utilize the library, how to find internships, time management, etc.) participated in the experiment. Participants were also concurrently enrolled in a three-credit, mandatory, introductory programming course. The sample was disproportionately male.

Using 10 sections of the seminar course, we had five conditions randomly assigned to the sections with approximately 30 participants in each condition. Although the conditions were randomly assigned, we could not randomly assign students to the sections, which is why the design was quasi-experimental. We later discovered that honors students were all in the same section that was part of Group A, thus we could not conceptualize Group A as a control group, as it would

be expected that honors students have high academic performance:

Group A: Honors students (3 females, 25 males, 4 opt-out²)

Group B: Tracking (3 females, 21 males, 2 opt-out)

Group C: Tracking and self reflection (1 female, 30 males, 2 opt-out)

Group D: Tracking and social reflection (6 females, 27 males, 3 opt-out)

Group E: Tracking, self reflection, and social reflection (3 females, 25 males, 7 opt-out)

Tracking (Groups B, C, D, and E) students recorded their studying activities relating to the introductory course through a web form that asked about when, how much time they spent studying, and a brief description of what they were studying. We chose the introductory course because it included course material related to things that required studying and had graded exams. The students were informed of this tracking technology and encouraged to use it. They were also told that participation was strictly optional, and that no aspect of their participation (or non-participation) with the tracking application would be associated with their grade.

Self-reflection (Groups C and E) students wrote a journal entry once every two weeks reflecting on their: tracking data, performance in class, and general study habits. This activity was performed at home on the student's own time.

Social reflection students (Groups D and E) shared their reflections with a small peer group during the seminar class every two weeks. These group reflections were completely unstructured, where students were given time to discuss their study activities in the past two weeks. Aside from the social reflections, which were conducted in class as an in-class activity, tracking and self reflection activities were completely voluntary; students did not receive any evaluation or incentive for participating in these activities, although it was recommended by the seminar instructor(s).

IX. STUDY 2 RESULTS

To answer our research questions, we examined students' grades on their midterm and final exams in an intro-level first-year class and compared performance across the five groups. Throughout the analyses in this section, we used non-parametric Chi-Squared and Wilcoxon Rank Sums tests with $\alpha=0.05$ confidence, as our data (i.e., exam scores) were not normally distributed. For post-hoc analyses, we used the Bonferroni correction for five comparisons: ($\alpha/5 = 0.01$).

Our data from the classroom study revealed that there were no detectable statistical differences in midterm exam grades between groups ($X^2(4) = 4.3217, p = n.s.$). However, we found significant differences in final exam scores by group ($X^2(4) = 14.5045, p < .05/5$). Group C (Tracking + self reflection) participants did significantly better than their Group D (tracking + social reflection) counterparts ($W=1232, Z=-3.18, p<.05/5$). All other group pairings did not show statistically significant differences between scores (including those that were adjusted using Bonferroni correction).

²“opt-out” refers to students who did not wish to report a gender.

X. DISCUSSION

We found that all of Study 2's groups performed similarly for their midterm, but that the Group C (tracking + self reflection) did significantly better than Group D (tracking + social reflection) for the final exam. Table 1 reveals that this divergence in scores are starting to trend during the midterm exam, suggesting that the interventions do not show immediate effects, but take several weeks to become significant. This may be a bootstrapping problem since the early data available to users is sparse and disparate. As data accumulates over time, users may be able to better organize and see more meaningful patterns in their logs and reflect more deeply on their use. This could imply that introducing a study-tracking/reflection intervention early on could help students in the long-term. Even though our intervention was much longer than those used in typical 4- or 8- week interventions for behavioral change, it could very likely take more time to see performance improvements in an educational context.

The data suggests that even if students are not particularly keen about tracking and reflecting on their study habits, introducing this method early could help them in the future. The intervention is also a low-cost one—note that in Study 2 we did not analyze students' actual tracking behaviors.

Why was social reflection not helpful? Although we do not know what the students were actually discussing in their small group sessions, it could be a lowest common denominator phenomenon, where instead of being inspired to do better, participants could have felt they were studying less and doing better than others, or collectively realizing that others were not studying much either. Future studies may include more structured social reflection. Institutional culture and/or motivation may also have a large effect. We may have found different results with this intervention in a more competitive environment.

XI. STUDY 2 LIMITATIONS

In Study 2, we only looked at academic performance—students' introductory Computer Science grades—as our dependent variable of interest. We purposefully did not analyze their individual tracking activities to examine whether or not a low-involvement intervention would yield significant differences among groups and thus be a scalable intervention. Given the variance in study tracking behavior that we saw in Study 1, however, it is very likely that an analysis that takes into account individual engagement would yield more nuanced results. Future studies may want to try to control variance within groups when doing between-group analyses.

We only found a significant difference in final exam scores for some of the groups. However, our studies did not examine factors such as satisfaction, interest, enjoyment, and retention. Future studies should include these factors, as they might be important things to consider for students' self-tracking. We also did not take into consideration instructor effects. Although we coordinated with all the instructors for the CS107 classes to make sure the experiment was conducted properly, the classes were not all taught by the same instructor and the instructors were blind to this study.

Another limitation is that while we randomly assigned ten course sections to our five experimental conditions, the students themselves enrolled in their respective sections. Self-selection into particular sections may have introduced a selection bias, i.e., there may be fundamental differences between people who choose morning versus afternoon classes that may have affected our results.

XII. CONCLUSION

In Study 1, a group of 29 college students used a time-tracking app to help them follow their study habits and possibly change their behavior utilizing this information. Participants reported not enjoying using the app overall. However, they had many ideas about how to improve the app, and expressed that their usage information either helped them confirm what they already knew about their study patterns or revealed something new about their study habits. The act of using the tracking app, paired with the analysis of one's own data through reflection, enabled students to have stronger self-awareness of their studying habits.

Building on these results, in Study 2 we conducted a quasi-experiment where 162 students in ten sections were randomly assigned into five different conditions to examine group-level effects of different combinations of tracking and reflection on academic performance. The combination of tracking with self-reflection resulted in significantly higher final exam grades.

What is the role of technology? We believe that the simplicity and ease of use of the study tracking app made it optimal for most of the students who were not intrinsically motivated to engage in study tracking behavior. Even if the app data was not accurate—mostly due to human error—the data that was generated enabled students to take an objective stance on their own behavior.

On its own, however, we do not think technology is the solution. Most students were not interested in tracking their study habits because they were not interested in improving themselves academically. However, students experienced benefits when they used a tracking app in a structured educational setting. This brings into question how important agency is in the delivery of interventions purported to help the participant. While it is well-documented that those who are intrinsically motivated and have autonomy are those who benefit most from behavioral change interventions, the reality may be that many people just are not motivated enough. In the context of education, where it is understood that sometimes students need to do things that they do not enjoy, it could be that even without agency, the introduction of this type of technology could still yield positive results.

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