Engineering Education and Quantified Self: Utilizing a Student-Centered Learning Analytics Tool to Improve Student Success

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Abstract

This evidence-based practice paper assessed the implementation of a quantified-self learning analytics tool, called Pattern, and how it impacted study behaviors across multiple sections of engineering courses at Purdue University. The goals of the implementation of Pattern and subsequent research was to explore: (a) student study activities that correlated with success, (b) student study behavior change from exam-to-exam, and (c) whether the use of Pattern impacted study habits. Results indicated that simply studying longer does not correlate with success and that students spend the most amount of time doing activities they rate the lowest in effectiveness (e.g., reading). Additionally, while students do make behavioral changes from exam-to-exam, those changes are only moderate in size and scope. Gender differences were also found to be significant in how students studied. Based on the results of this study, recommendations for instructors are to 1) use technology that is familiar and facilitates peer comparison, 2) conduct analysis of recommended study strategies to assess effectiveness, and 3) stress to students that *how* they study is much more important than *how long* they study.

Introduction

In 2014, Purdue University released a report that detailed the DFW (grade D, F, or Withdrawal) rate of courses with over 500 students between 2011 and 2013.[1] In that report, multiple engineering courses were in the top five DFW rates, ranging from 25% all the way up to 42%. Due to these high DFW rates, identifying ways in which the engineering college could improve retention by helping students with their examinations became a focus. Previous research on studying, self-regulation, and the quantified self influenced the design of this study and use of Pattern[2] as a tool to collect data [1]. Specifically, the purpose of this study was to explore which study activities correlated with success, how students change (or do not) their behaviors from exam-to-exam, and what demographic differences exist between students, if any.

Studying

Studying is a foundational component of what it means to be a student, especially in college. It is likely that most students, upon entering college, have heard one of the many recommendations for how they should be studying in order to be successful. One common study recommendation is for students to study two to three hours per hour spent in class. Many colleges and universities even have calculations for the number of study hours needed outside of the classroom to be successful as a college student. However, research has repeatedly shown a weak correlation between total study time and performance [2], [3]. Much of the same research also suggests that how *long* students are studying matters less than specifically *how* students are studying. This research aims to dive deeper into the specific study activities that students employ when preparing for an exam and look at how those activities impact student success.

Self-Regulation

Zimmerman [4] describes self-regulated learning as a process that students use to acquire academic skills, an example of which is self-monitoring effectiveness. Self-monitoring is further defined by Zimmerman & Paulsen [5] as directing attention to specific activities and assessing the success or outcome of those activities. Pattern facilitates self-monitoring by giving students the tools to track, compare, and evaluate their study behaviors so they can then compare them to

[1] This report is no longer publically accessible, please contact first author for a copy.
[2] Pattern is a mobile and web application students used to log their study activities throughout the semester.

academic success. Pattern also functions similarly to reflective diaries used in previous research that helped promote self-regulation, where students are keeping track of goals, employing various strategies, and then monitoring the results [6]. Studies like these help to provide understanding and context for the results of student study logs.

The Quantified Self

The quantified self (QS) is generally described as the practice of tracking behaviors or activities over time, and analyzing or acting on the trends. While popular in health or fitness related applications (e.g., *Fitbit*), quantified self has taken longer to gain traction within higher education. There are many challenges when implementing quantified self in education, such as determining what data points students can or should track, and how those data points can or should be engaged with [7]. Ideally, quantified self in an educational setting would provide the same motivation as it does in the fitness world, but the research in this area seems to not exist yet. Research outside of education has identified a motivation to "optimize" a specific lifestyle issue like sleep quality or number of steps [8]. While this likely does not directly map to all student motivations in this study, the idea of improving or optimizing study behaviors and having a tool to quantify those is precisely the goal of the Pattern tool.

Methods

At the beginning of the Spring 2017 semester, students from Thermodynamics I (ME200, five sections), Linear Circuit Analysis (ECE201), and Chemical Engineering Calculations (CHE205) were recruited to participate in a semester long study that would task them with logging their study habits in an online application, called Pattern, for one week leading up to each exam. In each course, there were 3 regular exams and one final exam, resulting in four weeks of recorded activities for students that participated. Students were offered 1-2% extra credit for their participation, independent of the number of entries that they created or the number of hours logged within Pattern, which was done to de-incentivize padding of entries. In total, 209 students (142 male, 67 female) participated in the study and generated 2,630 entries within the Pattern application, amassing 5,000 hours (over 200 days) of logged study activities over the four week data entry period.

Pattern

Pattern is a mobile and web application students used to log their study activities throughout the semester. It was developed and released in 2015 as a student success tool and is available for all students for free at Purdue University. Pattern enables the logging, tracking, and analyzing of student study behaviors. Specifically, students record their study activities within the application and the application provides: 1) a main dashboard (see Figure 1) that displays aggregate study statistics, like total time studied, and also productivity level for given days or activities (defined in Pattern as "based on the amount of work you complete and your level of Focus"), 2) data visualizations and automated feedback on their habits (see Figure 2), and 3) averages for the rest of the class so that students can compare themselves to their peers (but only if a student is in a course where there are others using Pattern).

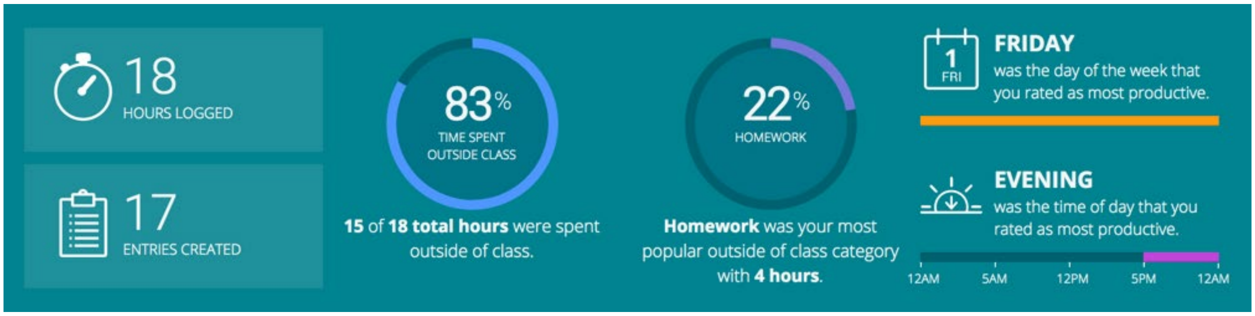

Figure 1 Main Dashboard in Pattern

The visual dashboards and automated feedback are based on four primary data points: 1) the activity, 2) the duration of the activity, 3) the productivity rating (five point Likert rating scale), and 4) comparison to peer data within the course if applicable. The automated feedback that students received from Pattern during the study included, but was not limited to, suggestions on the amount of time spent reading, reviewing notes, or other activities versus their peers. The activities that students could choose in Pattern was customized for the particular courses and use-case, so students could choose the following activities:

- Course Message Board
- Help Room
- Office Hours
- Read Book
- Review Notes
- Review Old Problems/Quizzes
- Review Videos
- Supplemental Instruction (SI)
- Tutoring
- Work New Problems/Quizzes

Figure 2 Additional Dashboard Data in Pattern

Students were also provided brief data digests (see Figure 3) from the instructor after each exam, showing how students at each grade point studied for the exam. The data digest information that was displayed was chosen based on the class and which study activities correlated the most or least with success. For example, Figure 3 displays Supplemental Instruction, Work New Problems/Quizzes, and Review Notes as the activities that correlated with that particular class and exam. Other sections and classes may have been shown different activities as they related respectively to their course. The digests were meant to be a way to show students how their study activities correlated with grades, and also to give them a sense of what others who were more or less successful were doing. Ideally, students would begin to identify which activities were more successful, rather than focus on how much time they were spending studying, and thus alter their behavior. For example, in Figure 3, students who received an A studied more, studied more often, and spent more time in supplemental instruction sessions.

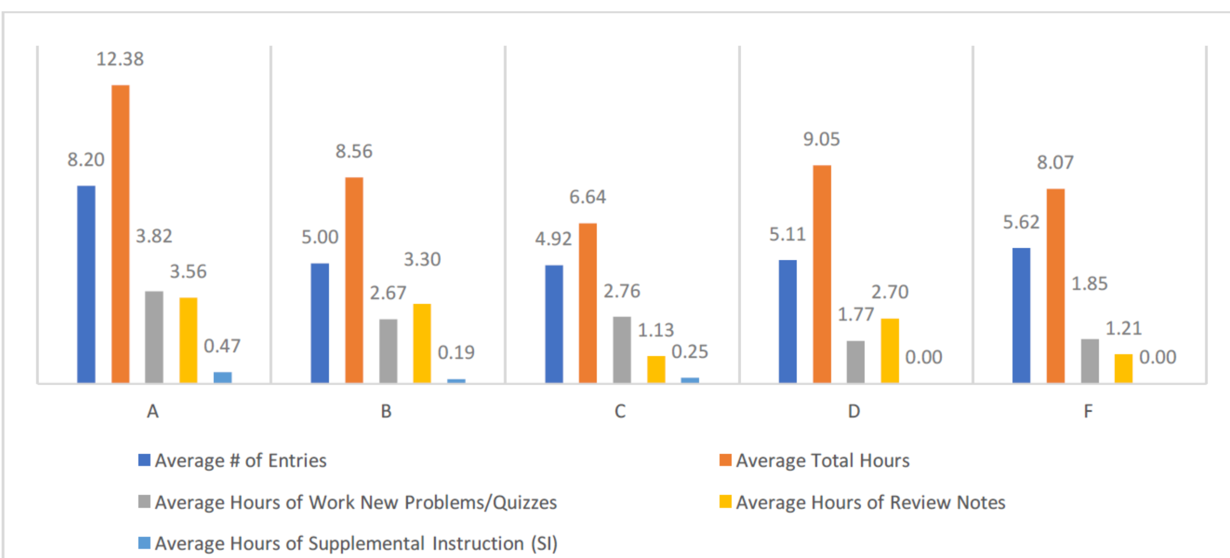

Figure 3 Data Digest Sample

Survey

A secondary focus for this study was to gather feedback on the use, implementation, and development of Pattern. More specifically, the survey sought to capture: 1) student perceptions of how helpful Pattern was in aiding or improving their study habits, 2) familiarity with the quantified self, and 3) feedback for future development in the Pattern application. Students were asked to complete the survey at the conclusion of the semester.

Data Analysis

Student exam scores were divided into three ranks for this study: top, middle, and bottom. To create these ranks, exam scores were summed and then ranked within each section. Next, the total number of students in each section was separated into thirds in order to create the group rankings. Due to the size and non-normality of the data, a series of nonparametric tests (Kruskal Wallis, Mann Whitney, Wilcoxon Signed Rank) were conducted, with post hoc analyses when needed, to examine exam score mobility and differences between the ranks (e.g., how often they studied, how long they studied, which activities were engaged in). Comparisons are made at the course level and across all participants, but results are largely driven by Thermodynamics I due to a larger sample size. Throughout this section, the four exams will be referred to in their respective order; exam 1, exam 2, exam 3, and the final, exam 4.

Results

The results for this research showed interesting differences between how often or for how long students study, the activities they employed while studying, and the behavioral changes from exam-to-exam. Gender differences were also present with regard to study time and frequency. All results in the following sections are statistically significant at the $p = 0.05$ level, unless otherwise stated.

Study Time and Frequency

First, we examined the amount of time (hours) and the frequency (Pattern entries) in which students studied in preparation for their exams. An encompassing look at the combination of exams across participants in all courses shows the mean hours spent studying was around 7.5 hours, regardless of rank. However, delving down to the course level reveals more separation between performance rank and time spent studying, although not statistically significant. In particular, students within Chemical Engineering Calculations had a non-statically significant, χ^2 (2, n=52) =2.72, p=.256 inverse relationship between study time and performance, where the top performers (n=18, mean=6.27 hrs) studied for less time on average than the middle (n= 17, mean=6.88 hrs) or bottom performers (n=17, mean=7.42 hrs). Individual sections of the Thermodynamics I course were also variable in terms of mean study hours spent per ranking, without statistical significance. These differences in mean study time across courses and performance support the notion that simply studying more does not result in success. When instructors delivered the data digests to students after each exam, this result was communicated to students often. In most courses, on an exam-to-exam basis, the students who scored the highest did not always study the most, but studied in ways that were hypothesized by faculty to be more effective. These included working new/unsolved problems, or demonstrating help seeking behaviors like attending supplemental instruction.

Second, we examined gender differences in study time and frequency. As shown in Figure 4, there were significant gender differences. Across all participants, female students studied more often (n=67, mean=4.28 entries) than their male counterparts (n=142, mean=3.77 entries) with a small effect size (U=3842, z=-2.25, $p = 0.025$, r=.16), but there was no statistically significant difference (U=4075, z=-1.67, p=.095) in the amount of time spent studying. However, female students studied about one hour more than their male counterparts. These gender differences are magnified within the Chemical Engineering Calculations course, where the female students (n=22) studied nearly two hours longer (U=210, z=-2.22, p=0.026, r=.31) *and* more often (U=209, z=-2.26, p=0.024, r=.31) than their male counterparts (n=30), with medium effect sizes.

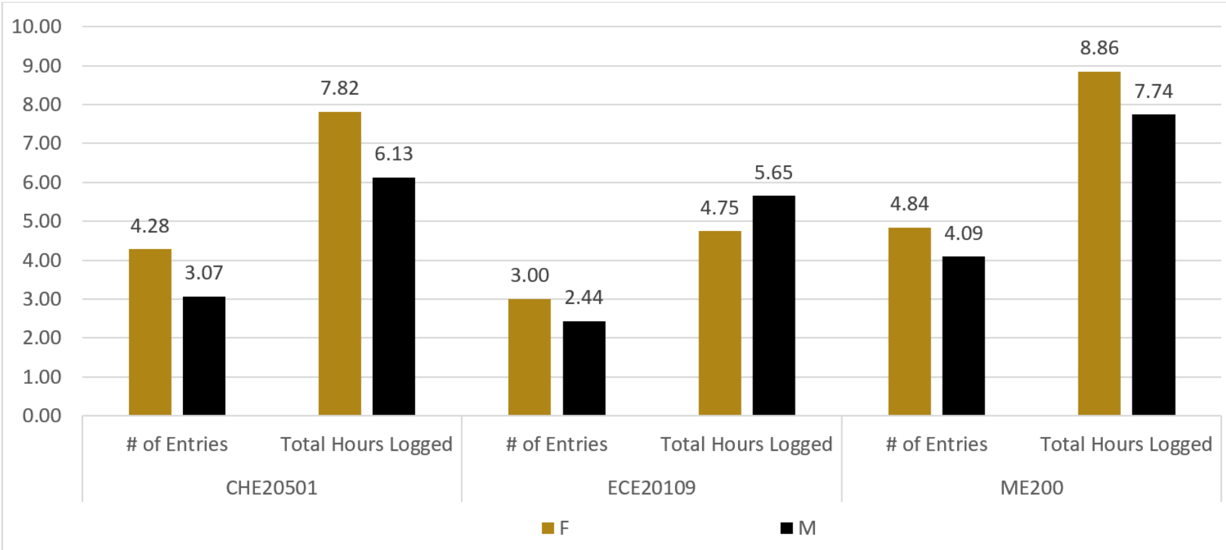

Figure 4 Male vs. Female Study Habits

Study Activities

The second way this study analyzed study habits is by activity. Previous research using Pattern identified discrepancies between how much time students were spending on activities they rated less productive versus those they found to be the most productive [9]. This study observed the same discrepancy. Not only did students spend the most time doing things they rank lowest in productivity (e.g., review notes, read book), they also spent the least amount of time demonstrating help-seeking behaviors that they rate the highest in productivity (e.g., attending office hours, Help Room, tutoring). For example, top performing students in Thermodynamics I (n=55) rate the Help Room (mean=0.54 hours, avg 3.9 productivity) and supplemental instruction (mean=0.43 hours, avg productivity=4.4) very high in terms of productivity, but spend little time on those activities. Conversely, those same students spent upwards of five times longer reviewing notes (mean=1.64 hours, avg productivity=3.6) or working new problems/quizzes (mean=2.34 hours, avg productivity=3.7). Students who demonstrate help seeking behaviors indicated within Pattern that the activity was more productive, but the reasons why more students did not take advantage of them is unknown.

A Kruskal-Wallis Test revealed the only activity that students differed significantly in was attending the Help Room, χ^2 (2, n=209) =9.52, p=0.009, with post hoc tests showing the top (mean=.40 hrs) and middle ranks (mean=.26 hrs) spend more time in Help Rooms than the bottom group (mean=.10 hrs) with medium (r=.26) and small (r=.23) effect sizes respectively.

Exam to Exam Changes

The final way in which this project explored student studying is the behavior changes students made from exam-to-exam. More specifically, this research sought to understand which changes resulted in positive or negative performance and which activities were associated with that change.

Overall, a lack of student mobility among performance ranks indicates that students had some difficulty improving their scores and jumping to a higher tier, and that students who were successful were likely to continue to be successful. Figure 5 shows the number of students and their movement among performance tiers from one exam to the next. For example, 15 students scored in the middle tertile on exam 1, but in the top tertile for exam 2. Similarly, 17 students scored in the middle tertile on exam 1 and remained there for exam 2. In each comparison, roughly 40% of students who scored in the bottom tier repeated that performance in the subsequent exam. Alternatively, students who scored in the top tier were increasingly likely to score in the top on each subsequent exam. For example, students repeated a top tier performance 54.3%, 60.5%, and 77.8% of the time respectively. Comparison of students who were able to make the jump from bottom to top tier versus those that scored in the bottom both times revealed no significant differences. Also, while not statistically significant, students that performed in the top tier averaged more time spent on help seeking behaviors - office hours, Help Room, supplemental instruction.

		Exam 2		
		Top	Middle	Bottom
Exam 1	Top	**25**	15	6
	Middle	15	**17**	13
	Bottom	7	12	**17**

		Exam 3		
		Top	Middle	Bottom
Exam 2	Top	**26**	13	4
	Middle	21	**15**	10
	Bottom	7	12	**13**

		Exam 4		
		Top	Middle	Bottom
Exam 3	Top	**21**	5	1
	Middle	13	**13**	2
	Bottom	3	7	**8**

Figure 5 Student Mobility in Performance from Exam to Exam

Survey

The end of the semester survey provided feedback on Pattern primarily, but also insight into student familiarity with study logging or logging behaviors at all. As previously noted, the quantified self is a movement that has garnered traction within health and wellness, but less than half of students (48%) in this study had ever logged activities before. This number, while lower than expected, may explain some variability in how students used Pattern. The distinction between those who are familiar with the quantified self versus those that are not and how they interact with Pattern is something that should be explored before further research is done. A result from the survey that was less surprising is what students valued the most during this study, namely, peer comparisons. Students overwhelmingly valued these comparisons (73%) over all other aspects of Pattern (e.g., having a place to visualize study habits, getting automated feedback). This type of comparison is data that is not normally available to students and the strong feedback suggests that any application of quantified self and education should feature this functionality.

Discussion

The purpose of this study was to examine study habits in engineering courses and how a learning analytics tool, Pattern, influences them. Key findings for this study were related to the study activities that correlated with success, how students changed their behaviors from exam-to-exam, and gender differences. This section will outline key findings, limitations of the study, and recommendations based on the results.

Key Findings

While this research does not offer explicit answers as to why gender differences were present, previous research examining performance and motivation within engineering education might provide some insights into these findings. One possible explanation may be stereotype threat, which Steele and Aronson [10] first described as being at risk of conforming to negative stereotypes within one's own group (e.g., men are better engineers, boys are better at math). Stereotype threat has been shown to inhibit performance and self-efficacy, which is interdependent on self-regulated learning [11], [12]. However, research has also found that female engineers can experience a "stereotype boost", where they are motivated by the presence of unfavorable stereotypes [13]. Female students in this study could be motivated by stereotype threat to overcome negative stereotypes, especially since they were able to compare themselves with peers, largely male, within Pattern. Further research is needed to explore the relationships between gender, study habits, and performance in engineering courses.

At the beginning of this study, one of the major research interests revolved around understanding which activities were associated with success in engineering. Instructors within the engineering program postulated that solving the new and unsolved problems would lead students towards success. While students did put an emphasis on this activity, likely at the direction of their instructor, the activity itself did not correlate with success. Students who were among the top performers across the four exams averaged more time spent solving these new and unsolved problems, but the difference was negligible. The lack of relationship between success and solving these new and unsolved problems could be related to instructor bias or differences in messaging. Each instructor was free to communicate his or her own messaging as it related to the data digests they were given. If students in one course were pushed towards any given study activity but not in another, variation is likely to occur in the study habits students elect to engage in. In order to come to a meaningful conclusion on the efficacy of the study activities in this research, more data is needed. Certainly, not all study activities are equally connected with success, and with more data over multiple semesters, trends should become more visible.

Identifying activities or behavior changes that correlated with students improving performance from exam-to-exam proved to be difficult. Students who performed in the top tertile were increasingly likely to perform well, but no statistically significant finding was found. This suggests that the necessary changes were not accurately captured within Pattern, or that those changes failed to result in a positive outcome. A cursory look at student performance, study activities, and mobility among tiers indicates that students make the most changes between the first two exams, but then largely do not modify study habits, and as a result, performance. Students who performed at the top tertile do exhibit more help seeking behaviors and indicate that the time spent on those activities is productive, but additional intergroup comparison needs to be conducted to determine the exact impact those activities had on performance. As Zimmerman [14] notes, students who demonstrate high levels of self-efficacy are more likely to choose difficult tasks, be more persistent, and give a higher level of effort. This would seem to coincide with the notion that students who are seeking out these additional help resources have higher levels of self-efficacy, and by extension, self-regulation. The relationship between self-regulation, self-efficacy, studying, and performance need to be further researched in order to understand how they impact one another.

Limitations

One limitation of this study is the method of data collection and the ability for students to freely create and evaluate their own data. Pattern is designed to collect and visualize data that shows how students are studying outside of class, which is information that instructors typically do not have access to. The data used in this analysis is all self-reported from within the Pattern application, and thus is prone to the same inaccuracies as is any survey measure. Students were given an in class demonstration for how to use Pattern correctly, a definition sheet for what each type of activity meant, and were told that more entries or time logged would not result in additional credit. Students were also assured that instructors could not see their individual data, only an aggregate view of their class. All of these measures were done to ensure that, when logging activities, students are accurate and forthcoming. Some entries were ultimately scrubbed from the data, as reading notes for over one thousand hours straight is clearly an entry mistake.

Arguably the largest limitation of this study is the inability to infer that Pattern activity directly mirrors actual activity students engaged in. As previously noted, the number of Pattern entries leading up to any given exam cannot, without validity testing, be a trustworthy measure for the frequency of studying. Most quantified self applications log data automatically based on the actions of the user. Counting steps, measuring heartrate, or tracking movement are a few examples. Pattern relies on students inputting their own data, which is an inherent limitation to the application. Like sleep or fitness trackers, student study logs are prone to mistakes, and while the researchers made efforts to scrub obvious errors, the data may not be completely accurate. As noted previously, about half of students were unfamiliar with the idea of logging behaviors and this unfamiliarity likely impacted how, when, and how often students logged behaviors.

From exam-to-exam throughout the entire semester, students across all courses logged fewer study activities. Students simply logging less, adjusting how they logged their entries, or participation fatigue, can likely explain the decline in entries within Pattern. An important distinction to make is that this does not necessarily mean students studied less in terms of frequency. However, it could mean that students have a better understanding of what will be in their exams and how to prepare for them, and thus are more strategic in how they study. Additional research would need to be done to understand what this decline in entries actually means, whether it is an accurate depiction of study frequency, or simply a change in the way students are recording their activities as the semester progresses.

The final limitation is that of scale and scope. In the exploration of individual study behaviors, more than a single semester and a larger number of students is necessary to accurately identify any significant differences. Also, some study activities proved to be superfluous, like Watching Videos, since so few students engaged in that activity. It is difficult to identify the activities up front that so few students will engage in, but a pilot test in a previous semester would have identified these and is recommended for similar investigations. This study also only recorded data for the week leading up to each exam and may not accurately capture the study habits of students who consistently study between exams versus those that cram right before the exam.

Recommendations

Based on the results and potential implications of this study, recommendations are needed for instructors who are teaching engineering courses and want to improve study habits or student success for their students. It is also important to identify processes in this study that worked well and those that did not.

The first recommendation is to be cautious when using technology to track student study habits and focus on peer comparisons. Pattern is a very simple tool that allows students to record their data when using any mobile device or personal computer, but most students in this study were not familiar with logging activities for anything related to the quantified self. Students will also likely need at least minimal training to effectively self-monitor their behaviors and make informed, positive changes [5]. There are other options (e.g., paper, spreadsheet, blog) to log personal study habits, but most are more cumbersome and not specifically designed to easily visualize data. Finding the right balance of student familiarity and simplicity is key. Students were also incredibly interested in comparison to their peers, even more so than visualizing their own data. Facilitating peer comparisons for study data will likely motivate students, but the data needs to be connected to performance.

The second recommendation is to analyze promoted study habits or materials and how they correlate to success. Most instructors were convinced that solving new, unsolved problems was the key to success in the courses for this study. However, there was little evidence to support that claim, which is similar to the findings of Gurung, who noted that common study suggestions lacked empirical evidence to suggest they were superior strategies [3]. It is certainly possible that some students benefited more from solving certain types of problems, but instructors should be cognizant of the recommendations they are making and whether or not those activities *actually* correlate with success.

The final recommendation is to stress to students that focusing on how *long* they study, rather than *how* they study, is antithetical to what research says about studying. The results in this study clearly align with previously published research that shows 1) total study time poorly correlates with success, 2) students spend the most time on the least effective study strategies, and 3) students spend the least time on the most effective study strategies [2], [3], [9]. Focusing on offering resources like the Help Room, which correlated with top and middle performers, can direct students to more productive and effective uses of their time when studying. These efforts should be aligned with the previous recommendation to actually analyze the impact that suggested study habits are having on student performance.

Conclusion

The results of this study support previous research in showing that there is only a weak correlation between total study time and performance, that gender differences in study habits are significant, and that it is difficult for students to make the necessary changes in order to improve performance. Each of these findings warrant further investigation, but the differences between study habits and gender were the most compelling.

Ultimately, there is still a wealth of knowledge to be gained from using a tool like Pattern, examining how students study, and finding insights as to how, when, or if behavior changes are made. This research provides an initial step in trying to tie together these challenges in an application, and the results are promising.

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