Engineering Time: Learning Analytics Initiative to Understand how First-year Engineering Students Spend their Time

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Abstract: This Complete Research paper describes a learning analytics (LA) informed initiative to collect a detailed account of how first-year engineering students spend their time. With a plethora of calls to increase the number of engineering graduates, it is imperative to set students up for success during their first year. While there are multiple strategies infused in students' first year of college, and as many focused towards engineering students, there are still gaps in our understanding of what students do with their time outside of the classroom. This paper presents a study that uses a learning analytics initiative to uncover what students are doing outside the classroom and how they spend their time. Specifically, this study addresses one research question: How do first-year engineering students manage their time? Time management is one of the most critical aspects of a student's success in college. Analyzing time management practices of students can provide valuable information about how they work and what helps them succeed. Our research details a pilot study of 14 first-year engineering students across two weeks during the Fall semester of 2017. Students used a shared Google Sheet to keep track of their activities in half-hour increments using a template created by the research team. The template includes six categories for students to fill-in: date, time, location, activity, course, and notes. Results of the study highlight the daily habits of first-year engineering students with sleep (36.94%), leisure (19.22%), other (11.04%), studying short- and long-term (8.93%), and class (7.89%) as the top four categories where students spend their time.

Introduction

Success of students in their engineering program has been shown to be shaped by a myriad of factors (Atman et al. 2010). From their high school GPA, prior knowledge in mathematics and physics, peer support, schedule of classes, pathways through the engineering curriculum, motivation, self-efficacy, to their resilience, a range of factors, both individual and institutional, have been shown to be important for student success in engineering. One of the factors reported to be crucial for new students entering the higher education environment is time management skills. Although seemingly a small component of students' overall experience, the ability to manage time is crucial as it affects numerous other aspects of student success. Being able to manage time means not only the ability to attend classes and complete homework but also having peer interactions that can be critical for developing a supportive network as well as learning out-of-class. For many students, the ability to manage their time might also mean the ability to finance their education. Therefore, it is important to understand better how time is managed by first-year students. Current literature in student time management notes the relationship between time management and stress, among other things, but does not delve into specific behaviors exhibited by students. If data on what students are explicitly doing with their time throughout the day was available, advances could be made in attempts to improve time management practices of students, and consequently, in their overall academic success.

Literature Review

Time Management

The ability to manage time has been shown to correlate to academic success (e.g., Karim & Kandy, 2011) especially as it related to managing stress. Macan, Shahani, Dipboye, & Phillips (1990) conducted one of the earlier studies to investigate the role of time management in coping with academic stress. They used the Time Management Behavior Scale to conduct a survey with 165 students. The scale measured the relationship between students' time management behaviors and attitudes, and their self-perception of stress, academic performance, and their grade point average. The primary finding of the study was that students who perceived control of their time reported significantly greater evaluations of their performance. Although other studies have found similar results, there is still a lack of clarity regarding the role of time management and academic performance. For instance, Nonis & Hudson (2006), examined the effect of both time spent studying and time spent working on academic performance but focused specifically on the interaction of motivation and ability with study time. They found that non-ability variables like motivation and study time significantly interact with the ability to influence academic performance. According to their findings, they argue that the amount of time spent studying or at work had no direct influence on academic performance. Van der Meer, Jansen, & Torenbeek (2010) examine the issue within the context of first-year experience in higher education. They found that a large proportion of students had realistic expectations about having to plan their work independently and having to spend significant time during the week on self-study. Yet, they found that students found it difficult to regulate their self-study and keep up with the work. In particular, they had difficulty in organizing their self-study time. They argue that universities need to play a more active role in assisting first-year students with time management.

Learning Analytics

The field of Learning Analytics (LA) is concerned with learners directly and includes as its purview "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs (Siemens et al. 2011, pg. 4)." Whereas learning analytics is largely concerned with improving learner success, the practitioners of LA differentiate academic analytics as "the improvement of organizational processes, workflows, resource allocation, and institutional measurement through the use of learner, academic, and institutional data. Academic analytics, akin to business analytics, are concerned with improving organizational effectiveness (Siemens et al. 2011, pg. 4)." Overall, an LA approach responds to the significant amount of data that is created through the digital devices and programs that are now a part of an educational institution (Lester, Klein, Rangwala, & Johri, 2017; Lester, Klein, Johri, & Rangwala, 2018). An LA approach aims to transform and link data points to gain deeper insights into a phenomena such as student trajectories in the program, retention, transfer in out of majors (Almatrafi, Johri, Rangwala, & Lester, 2016, 2017; Chen, Johri, & Rangwala, 2018), and, in our case, time practices of students. Consequently, this study proposes to answer one research question: What are the detailed activities and habits of first-year engineering students? We answer this question by recruiting students to log their daily activities in 30-minute increments for two weeks during a fall semester.

Methods and Results

Subjects

During the Fall of 2017, we recruited participants from the First-Year Engineering Program (total student population of 227) to be a part of our study and offered a $50 Amazon gift card in return for logging their activities over a two-week timespan late in the semester. The final sample of participants consisted of 14 first-year engineering students in their first semester of college, of which four identified as commuter students. Students participated in an initial informational focus group to understand how to record their data and gain their initial thoughts on participating.

Procedure

The data collection method used was similar to the use of *diaries* in social psychology research (Duck, 1991). The diary study is a method of understanding participant behavior and intent *in situ* such that the effect of observers on participant is minimized. It also helps collect data which would be difficult for researchers to collect in person. Diary studies differ from other field study methods in that researchers are remote from participants and participants control the timing and means of capture.

For this study, we asked students to record their activities within 13 different categories as shown in Table 1. We created a shared Google Sheet for each participant to record their data in 30-minute increments each day. For every increment, a student would select from one of the 13 categories that described their activity for that 30-minute time block. Additionally, students were asked to also include what class an activity was associated with, the location of the activity, and any additional notes they could provide. Figure 1 shows a sample screenshot of the Google Sheet students were asked to fill out each day. Each shared workbook included 14 identical sheets, one for each day students were asked to record their data. For the categories column, a dropdown menu was used for students to select from one of the 13 activity categories for ease of use.

Descriptive Statistics

Participants logged their activity data each day for 14 days totaling 672 30-minute entries per participant. Each of the 14 participant's data was aggregated together to detail the percentage of each day and total hours per day for each of the 13 categories, as shown in Table 2. Weekdays and weekends were considered the same and thus reducing the overall percentage of the class category as there were no classes on weekends. The color scale green to red indicates larger to smaller proportions of activity. For example, sleep is shown in green indicating the highest proportion category and co-curricular and health/fitness are in red indicating the lowest proportion of activity on average for each student. In addition to the percentage of time for each category, hours per day is shown. Participants on average slept 8.85 hours per day and participated in health/fitness activities 0.24 hours per day.

In addition to the overall activity percentages table, we separated participants by commuter status (n=4) and on-campus residential status (n=10). Table 3 shows the percent time for each activity category between residential and commuters. A series of z-scores were calculated for each activity category to determine if there were any significant differences between how residential and commuter students spend their time. As expected from the very low sample sizes there were no statistically significant differences between any of the 13 activity categories. However, there are three activity categories worth mentioning with large differences between residential and commuter students. On average, residential students recorded they had twice as much leisure time, 5.39 vs. 2.68 hours per day, than commuter students. Moreover, as expected, commuter students were in transit—driving five times as much as residential students, 1.64 vs. 0.33 hours per day. And lastly, commuter students on average worked a paying job four times as much per day than residential students, 1.18 vs. 0.30 hours per day.

Table 1. Categories for each 30-minute Log Entry

Categories	Description	Examples
Sleep	For when you are sleeping.	Sleeping
Leisure	Activities that are fun and meant to keep you sharp. Anything outside of your academic life to sustain yourself and/or have fun.	Playing video games, partying, etc.
Homework/projects (short term)	Homework that is due tomorrow.	Homework due tomorrow.
Homework/projects (long term)	Homework that is not due tomorrow. This is for homework getting done ahead of time.	Homework due a week from now.
Study (short term)	Studying for something that is happening soon.	Cramming for a test.
Study (long term)	Studying for something that is not happening tomorrow.	Studying for a test that is in a week.
Work	Working a job. Specify on/off campus	Working at the REC, working at a pizza place
Class	Put this category if you are in class. If you skip class, please specify in your entry (You won't get in trouble with us).	Put the class in the column next to the drop-down menu
Health/fitness	Similar to leisure but we want to know if you are exercising. Examples: going to the REC, sports practice, etc.	Going to the REC, sports practice, etc.
Co-Curricular	Any activity related to school and your discipline, but not required for a class.	Club meeting, Honors Co-Curricular, Volunteer Work
Transit--Walking	Use this category for when you are walking to class.	
Transit--Driving	Use this category for when you are driving to campus, home, or work. Describe more in the notes section.	
Other	Anything that does not fall into one of the above categories. Keep notes on these.	Getting ready for the day, eating, etc.

	A	B	C	D	E	F
1	Morning or afternoon	Time period	What category does student's activity fall under?	What is the associated class with what they are doing?	Where is the student doing this? Specify on/off campus and if it is in their living space or not	Any additional information
2	AM/PM	10/23/2017	Category	Class	Location	Notes
5	AM	1:00-1:30	Sleep			
6	AM	1:30-2:00	Sleep			
7	AM	2:00-2:30	Sleep			
8	AM	2:30-3:00	Sleep			
9	AM	3:00-3:30	Sleep			
10	AM	3:30-4:00	Sleep			
11	AM	4:00-4:30	Sleep			
12	AM	4:30-5:00	Sleep			
13	AM	5:00-5:30	Sleep			
14	AM	5:30-6:00	Sleep			
15	AM	6:00-6:30	Other			Getting ready
16	AM	6:30-7:00	Other			Eating
17	AM	7:00-7:30	Transit--Driving			To YSU
18	AM	7:30-8:00	Transit--Walking			
19	AM	8:00-8:30	Class			
20	AM	8:30-9:00	Class			
21	AM	9:00-9:30	Class			
22	AM	9:30-10:00	Class			
23	AM	10:00-10:30	Leisure			
24	AM	10:30-11:00	Leisure			

Figure 1. Sample Google Sheet for Recording Time Data

Table 2. Mean Activity Log Data for All Participants

Category	% Time	STDV	Hours/day
Class	7.89%	0.97%	1.89
Co-Curricular	1.03%	1.39%	0.25
Health/Fitness	0.98%	1.42%	0.24
HW/Projs (Long-term)	2.55%	2.17%	0.61
HW/Projs (Short-term)	4.74%	2.73%	1.14
Leisure	19.22%	8.18%	4.61
Sleep	36.94%	3.64%	8.87
Study (Long-term)	3.62%	3.66%	0.87
Study (Short-term)	5.31%	2.60%	1.27
Transit--Driving	2.94%	3.23%	0.71
Transit--Walking	1.42%	1.23%	0.34
Work	2.31%	3.30%	0.55
Other	11.04%	5.09%	2.65

Table 3. Mean Activity Log Data for by Living Status

Activity Category	Residential (n=10)			Commuters (n=4)		
	%	STDV	Hrs/day	%	STDV	Hrs/day
Class	8.08%	1.16%	1.94	8.15%	0.47%	1.96
Co-Curricular	1.01%	1.47%	0.24	1.08%	1.61%	0.26
Health/fitness	1.21%	1.68%	0.29	0.41%	0.56%	0.10
HW/Projs (Long-term)	2.47%	2.27%	0.59	2.75%	2.55%	0.66
HW/Projs (Short-term)	4.29%	2.50%	1.03	5.88%	3.09%	1.41
Leisure	22.44%	7.30%	5.39	11.16%	5.27%	2.68
Sleep	35.83%	3.79%	8.60	39.47%	2.58%	9.47
Study (long term)	3.27%	3.85%	0.79	4.50%	4.08%	1.08
Study (short term)	5.86%	3.10%	1.41	3.87%	1.77%	0.93
Transit--Driving	1.38%	1.86%	0.33	6.85%	4.00%	1.64
Transit--Walking	1.74%	1.32%	0.42	0.63%	0.79%	0.15
Work	1.26%	2.66%	0.30	4.91%	4.20%	1.18
Other	10.89%	5.82%	2.61	10.34%	4.30%	2.48

Correlation and Regression Output

Next, we sought to determine if the activity category variables are a predictor of GPA. First, to reduce the number of independent variables we grouped long-term and short-term homework/projects into one category entitled homework/projects, long-term and short-term studying into one category entitled study, and transit—driving and transit—walking into one category transit. Combining those categories, not including 'other,' adding on a dummy-variable for commuter status, and including credits taken, there were 11 total independent variables included within the model to predict overall GPA, as shown in Table 4. Additionally, a correlation matrix was calculated as shown in Table 5 to determine how each activity category related to another. Below we show the model equation and output along with the corresponding independent variables.

$$\boldsymbol{Y = -14.38 + 16.14x_1 + 11.70x_2 - 0.76x_3 + 12.62x_4 + 7.37x_5 + 16.52x_6 + 9.82x_7 + 3.01x_8 - 8.25x_9 - 0.98x_{10} + 0.48x_{11}}$$

Where,

$\boldsymbol{Y: GPA\ predictor}$

$\boldsymbol{x_1: Time\ percentage\ spent\ in\ class}$

$\boldsymbol{x_2: Time\ percentage\ spent\ in\ Co-Curricular\ activities}$

$\boldsymbol{x_3: Time\ percentage\ spent\ in\ Health/Fitness}$

$\boldsymbol{x_4: Time\ percentage\ spent\ in\ Homework/projects}$

$\boldsymbol{x_5: Time\ percentage\ spent\ in\ Leisure}$

x_6: *Time percentage spent in Sleep*

x_7: *Time percentage spent in Study*

x_8: *Time spent percentage in Transit*

x_9: *Time percentage spent in Work*

x_{10}: *Commuter status*(**1** *if commuter*, *otherwisw* **0**)

x_{11}: *Number of Credits*

Table 4. Detailed Activity Log Data for Each Participant

	Class	Co-Curricular	Health/ Fitness	Homework /projects	Leisure	Sleep	Study	Transit	Work	Commuter =1	# Credits	GPA	Predicted GPA
P1	8.78%	0.15%	0.00%	1.64%	34.52%	38.24%	5.80%	3.87%	0.00%	0	15	4	3.31
P2	7.29%	0.00%	0.74%	4.61%	31.99%	35.27%	4.02%	2.23%	0.00%	0	14	2.35	4.04
P3	8.63%	1.19%	5.21%	6.70%	23.51%	35.57%	5.80%	1.04%	6.10%	0	17	4	3.78
P4	8.33%	0.00%	0.00%	11.16%	13.39%	35.86%	13.84%	4.61%	7.89%	1	16	3	3.07
P5	5.65%	1.64%	1.79%	5.21%	22.77%	36.90%	16.07%	2.23%	0.00%	0	14	3.57	4.40
P6	7.59%	0.00%	0.30%	9.08%	25.74%	39.14%	6.99%	4.02%	6.55%	0	15	4	3.75
P8	8.63%	3.42%	1.34%	8.04%	16.07%	26.79%	20.98%	3.72%	0.00%	0	15	3.6	3.27
P9	7.44%	0.89%	1.19%	9.67%	7.29%	41.96%	3.72%	13.10%	0.00%	1	14	2.14	2.26
P10	8.48%	0.00%	0.00%	4.61%	17.56%	39.73%	3.72%	8.04%	8.93%	1	16	1.75	2.06
P11	8.33%	3.42%	0.45%	9.08%	6.40%	40.33%	12.20%	4.17%	2.83%	1	16	3.75	3.61
P12	9.52%	3.72%	0.00%	11.16%	13.10%	33.18%	8.63%	2.68%	0.00%	0	16	3.75	3.89
P13	7.89%	0.00%	0.00%	5.21%	25.45%	36.90%	2.08%	4.32%	0.00%	0	15	4	3.48
P14	6.40%	0.00%	0.00%	8.33%	18.01%	40.33%	5.65%	4.91%	0.00%	0	16	4	3.95
P15	7.44%	0.00%	2.68%	7.59%	13.24%	36.90%	15.63%	2.23%	0.00%	0	16	4	3.77

Table 5. Correlation Matrix

	Class	*Co-Curricular*	*Health/Fitness*	*HW/Projects*	*Leisure*	*Sleep*	*Study*	*Transit*	*Work*
Class	1								
Co-Curricular	0.37	1							
Health/Fitness	-0.06	0.08	1						
HW/Projects	0.15	0.39	-0.05	1					
Leisure	-0.11	-0.47	0.00	-0.76	1				
Sleep	-0.36	-0.48	-0.19	-0.08	-0.11	1			
Study	-0.06	0.50	0.19	0.30	-0.35	-0.57	1		
Transit	-0.04	-0.16	-0.33	0.17	-0.43	0.50	-0.35	1	
Work	0.28	-0.25	0.05	0.16	-0.07	0.19	-0.12	0.08	1

The regression output is shown in Tables 6 and 7. Although there is a high r-square value showing that 83% of the variance of GPA can be attributed to the predictor variables, the model as a whole is not significant (*p=.65*), which means our variables are not able to predict GPA accurately. With a very low population value of 14 total students, it is expected that the model, along with the coefficients would all not be significant at alpha less than 0.05. The ANOVA, or analysis of variance, output in Table 7 shows the degrees of freedom (df), sum or squares (SS), mean sum of squares (MS), F-ratio, and significance of the model. With the F-ratio less than 1 and not significant, the model overall for predicting GPA based on our variables is not a good fit, and thus we cannot conclude any statistical significance.

Table 6. Regression Output

Regression Statistics	
Multiple R	0.909
R Square	0.827
Adjusted R Square	-0.125
Standard Error	0.834
Observations	14

Table 7. ANOVA Statistics

ANOVA					
	df	*SS*	*MS*	*F*	*Significance F*
Regression	11	6.64818	0.60438	0.8687	0.64838578
Residual	2	1.39145	0.69573		
Total	13	8.03964			

Discussion and Conclusion

The detailed activities and habits of 14 first-year engineering students were recorded throughout two weeks during the Fall 2017 semester. Data logs from students indicate that students reported sleeping for over eight hours each day, engaging in leisure activities for over four hours a day, and attending classes for less than two hours each day. With this initial low participation pilot effort, there were no statistically significant findings. However, there are few takeaways from this effort to understand the activities of students outside the classroom.

First, first-year engineering students should not be all grouped into one category. As our data shows there are differences, although not statistically significant, in how residential and commuter students spend their time. For example, commuter students spend almost four times as many hours per day (1.18 hrs/day) as residential students (0.30 hrs/day) working. This has implications for how commuter students can participate in certain academic activities such as office hours or group projects. This finding is in line with other commuter student research such as in Brozina (2018) where the levels of academic integration (i.e., sufficient access to faculty and resources) were significantly less for those who were commuter students indicating a much-needed effort to ensure proper access to resources for all students.

Secondly, students do not report being overburdened by workload or stressed based on the amount of leisure time and sleep reported. The four students who received a 4.0 GPA for the semester reported spending 23.4% of their time on leisure activities and 37.8% of their time sleeping. This may be indicative of being able to manage their time effectively, not procrastinate, or it can indicate that they have a clear purpose for their career as found in work by Kearns & Gardiner (2007). Time management coupled with low stress are associated with higher academic achievement (Khatib, 2014) therefore these results can be shown to first-year students to help them understand that if they can effectively manage their time and focus on what matters, they will be able to perform better in their studies.

Lastly, in an informal focus group session after logging their data for two weeks, participants had positive feedback regarding tracking their time. Students mentioned they focused more of their attention on the task at hand and important items and less time on unfocused activities. One participant remarked on the benefits of logging their time, "I think it definitely helps in keeping yourself accountable. If you want to put in a certain amount of time studying or you want to get a certain amount of stuff done, looking at how you have been spending your time is beneficial." Even though this was a pilot study using a template within Google Sheets created by the research team, there were benefits found by using the system. If there was a streamlined app or dashboard which would allow students to track and better monitor their time spent on various activities it may be quite beneficial to the overall success of students (Knight, Brozina, Stauffer, Frisina, Abel, 2015) and potentially have faculty receive that data to know their students better would also be of help to the student (Knight, Brozina, & Novoselich, 2016). Of course, any system that can shape student experiences needs to be designed carefully taking into account student perspectives and how that system will integrate with the rest of their experiences (Klein, Lester, Rangwala, & Johri, 2019a, 2019b). Without proper user-centered design considerations the technology is less likely to be adopted (Johri, 2018, 2019; Knight et al., 2018).

In conclusion, this study uncovered several insightful findings related to first-year engineering students' use of time. Future work should look at collecting data on a larger scale to determine if any of the activity categories are significant predictors of success, such as GPA. Additionally, the development and use of a time tracking app and dashboard may allow for deeper findings into how students and potentially faculty can think about time spent outside the classroom.

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