
Assessing Mental Health Issues on College Campuses: Preliminary Findings from a Pilot Study

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Abstract

A significant fraction of college students suffer from serious mental health issues including depression, anxiety, self-harm and suicidal thought. The prevalence and severity of these issues among college students also appear to increase over time. However, most of these issues often remain undiagnosed, and as a result, untreated. One of the main reasons of this gap between illness and treatment results from the lack of reliable data over time. While health care services in college campuses have been focusing on detection of illness onset and appropriate interventions, their tools are mostly manual surveys which often fail to capture the granular details of contexts and behaviors which might provide important cues about illness onset. To overcome the limitations of these manual tools, we deployed a smartphone based tool or unobtrusive and continuous data collection from 22 students during an academic semester. In this paper, we present the preliminary findings from our study about assessing mental health on college campuses using passively sensed smartphone data.

Author Keywords

Mental Health; Mobile Sensing; Predictive Modeling; mHealth; Behavioral Intervention

ACM Classification Keywords

J.3 [Life and Medical Sciences]: Health

Introduction

In recent years, there has been a growing concern about the mental health issues on college campuses. The 2015 National College Health Assessment (ACHA-NCHA II) [3], based on 19,861 students over 40 schools, reported that 35.3% students “felt so depressed that it was difficult to function” and 9.6% students have seriously considered suicide at least once in last 12 months. Using data from 26 college campuses, Eisenberg et al. [14] reported that around 32% of students suffer from mental health issues including depression, anxiety, suicidal thought and self-injury.

Moreover, a number of studies have reported that the prevalence and severity of mental health issues among college students are on the rise. From the ACHA-NCHA national survey, the rate of students diagnosed with depression in last 12 months has increased by almost 40% from 2000 [2] to 2015 [3]. Treatment providers on college campuses have also reported an increasing trend towards higher number of students suffering from mental health issues over the years [16].

The prevalent and extent of these issues on college campuses has far-reaching consequences for overall health care policy and practice. More than 20 million students are enrolled in US colleges [15]. Moreover, for 75% of individuals with mental health problems, the age of onset is prior to 24 years [20]. Given that early intervention can significantly improve long-term prognosis for a wide range of mental health disorders [4], college campus based mental health care can provide a unique opportunity to prevent and treat mental health disorders.

However, most of these issues remain undiagnosed, and hence, untreated. Blanco et al. [5] reported that less than 20% of college students with mental health issues received any treatment in past 12 months. Health care service on

college campuses often seriously lack in resources required to address these mental health issues. Hunt et al. [17] reported that the overall ratio of students to psychological counselors to be 1900 : 1 indicating an overburdened and understaffed system.

Moreover, the tools for assessing students' mental health are mainly survey based, which have several disadvantages: i) they rely on students periodically filling out surveys, which can be burdensome, and hence students tend to stop doing self-report after a while, ii) since there might be a lag between the illness onset and survey completion, the self-reported data sometimes can be inaccurate, not exactly reflecting the change of their mental health status, iii) due to the difficulty of manual recording, the survey tools often fail to provide longitudinal data with high granularity. As a result, it is difficult for healthcare providers to pick up subtle behavioral changes associated with students' mental health status and provide early intervention using existing tools. In addition, the early signs of mental health illness vary from person to person, and many people who suffer from mental health issues are unaware of these early signs and do not actively reach out for help until the symptoms get severe.

As such, there is a need for new tools that can better monitor students' daily activity and assess their mental health status continuously and unobtrusively. Recently, there has been a lot of work focusing on using smartphones as a tool to keep track of mental health issues [1, 8]. Smartphones are equipped with various types of sensors that enable us to acquire information on users' behaviors in different contexts. Moreover, the college students tend to be habituated and heavy smartphone users. Indeed, around 86% of US college students regularly use a smartphone [12]. As a result, the information collected from smartphone's multi-

modal sensors could potentially help us gain more insights on both students' behavioral and mental health changes.

In this work, we deployed a smartphone based tool over 22 college students over the duration of an academic semester (4 months). Our app can unobtrusively and continuously track behavioral and contextual cues. We also collected self-assessed survey data related to mental health status throughout the duration of the study. In this paper, we described the preliminary findings from the collected data discussing the effectiveness of using mobile sensing in this context.

Methods

Enrollment Process

We announced the study at the beginning of the Spring term to the students of a class taught by one of the co-authors. Students were free to not participate in this study. Institutional Review Board (IRB) of Cornell University approved the study protocol. During the enrollment process, we described the overall research goal of this project and how it relates to the student wellness and productivity. The university health care service was also involved during the announcement of the study. We allowed students to use their data for the final class project. To further encourage participation, we handed out rewards to the students throughout the study (one iPad mini and 2 Android phones). Rewards were given based on adherence to the data collection protocol. After initial announcements we held a series of three orientation and enrollment sessions in the following week.

In total, 24 students initially enrolled in our study. But, 2 participants did not comply with the protocol. So, we used the data from the rest of the 22 participants in our analysis (12 Female and 10 male). All of the students were within

20–25 years age range.

Data Collection

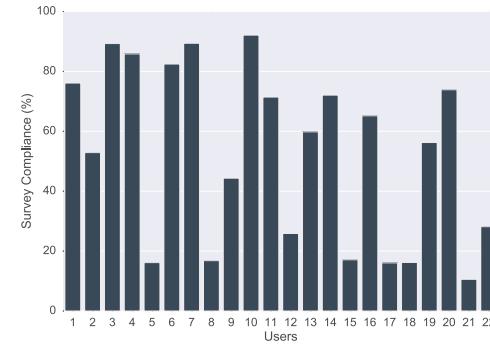


Figure 1: Compliance rate across the study duration.

Throughout the study, we collected both self-assessment survey and passive sensing data. To better understand the trajectory of mental health status and overall well-being, we conducted surveys at the beginning of the term, after mid-term and at the end of the term as shown in Table 2. We recorded academic performance (weekly assignment grade and overall GPA at the end of the term).

Participants also installed our app in their phones. It passively and unobtrusively collected a wide range of behavioral and contextual data as shown in Table 1. Due to architectural disparity, the data collected from iOS and Android devices can be slightly different. For example, Android allows collecting information about running applications while it is not permitted under iOS architecture.

Using the app, the participants also completed a number of daily surveys. The app notified the participants to complete the sleep journal and PAM survey [24] at 10:30AM. It also prompted them to complete the stress and PAM survey at

4:30pm. The stress survey was in 0-4 Likert scale (0=Feeling Great, 4=Stressed Out).

Sensor Data Type	Description
Location	Latitude and longitude data
Activity	Current motion activity (e.g., walking, biking, driving)
Step Count [†]	Pedestrian data including step counts and distance traveled
Audio	Audio information and features collected from microphone (i.e., if someone having a conversation)
Accelerometer ⁺	Motion features from smartphone accelerometer
Device Usage	Duration and frequency of smartphone usage
Charging Event	The timing, frequency and duration of charging
Battery	Status of phone battery
Light*	Illuminance of nearby environment
SMS*	Log of SMS sent and received
Call*	Log of incoming and outgoing call
Currently running apps*	List of currently running apps and corresponding processes and services

Table 1: Sensor data collected from Smartphone. †: iOS only, *: Android devices only.

Data Analysis

Compliance rate

Based on daily survey responses, the compliance rate varies across different participants as shown in Figure 1. There are 5 participants with compliance rate less than 20%. The compliance rate also changed across the duration of the study as shown in Figure 2. The initial participation rate was quite high, however, it dropped significantly at

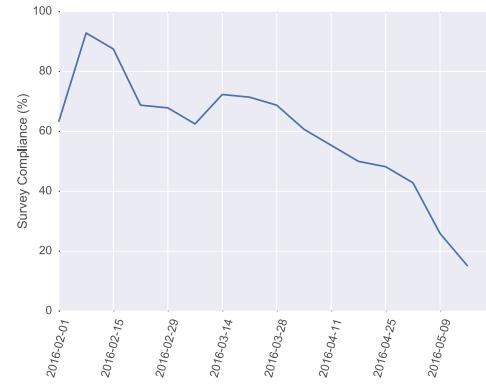


Figure 2: Compliance rate across the study duration.

the end of the study.

Findings

In this paper, we focused on identifying changes in survey and passive sensor data during the academic term. In particular, we looked into the trajectory of changes between periods with different academic pressure (i.e., break and exam periods). During the term, there were 2 official breaks — February break (Feb 13 – Feb 16) and Spring break (March 26 – April 3). After the last day of the class (May 11), it was study and exam period which ended on May 24th.

We were particularly interested to see how sleep duration changed across this period given the importance of sleep in the context of mental health. Figure 3 shows the overall sleep distribution with standard error of mean (SEM). As expected, the sleep duration during the weekends is significantly higher. Compared to the rest of the weekdays, the participants sleep more on Wednesdays.

Survey Data	Description
Pittsburgh Sleep Quality Index (PSQI) [7]	PSQI is used for assessing overall sleep quality
Epworth Sleepiness Scale (ESS) [19]	Assessing general level of daytime sleepiness
Munich Chronotype Questionnaire (MCTQ) [25]	Survey about chronotype and social jet lag
Patient Reported Outcomes Measurement Information System (PROMIS-10) [9]	Assessment of well-being and ability to function
Behavioral Health Measure (BHM-20) [6]	Assessment of psychological symptoms, life functioning, well-being and positive psychology
Connor-Davidson Resilience Scale (CD-10) [11]	Assessing resilience
Flourishing Scale [13]	Assessment of social-psychological prosperity
Perceived Stress Scale [10]	Assessment of perceived stress of a given participant
Big Five Inventory (BFI) [18]	Survey about different personality facets
Personal Health Questionnaire Depression Scale (PHQ-8) [21]	Diagnostic and severity measure for depression
UCLA Loneliness Scale [26]	Measurement of subject feeling of loneliness and social isolation

Table 2: Surveys conducted at the beginning of the term, mid-term and at the end of the term.

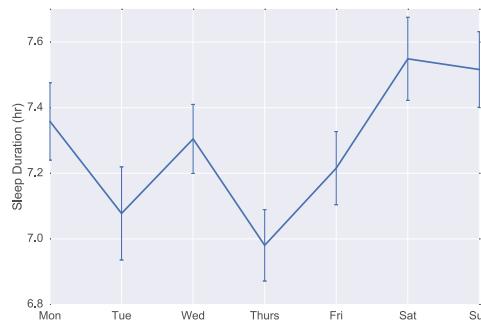


Figure 3: Sleep duration with standard error of mean (SEM) over weekdays and weekends.

We also compared the sleep duration during academic breaks and exam preparation period as shown in Figure 4. The sleep duration increased during the academic breaks. But, there was a significant drop during the study and exam

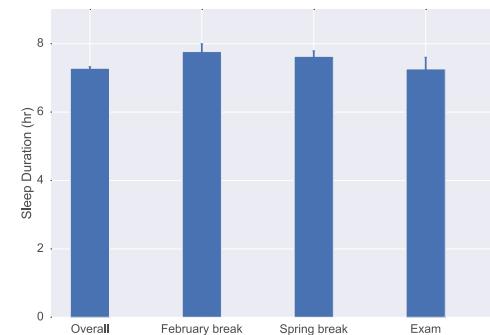


Figure 4: Comparison of sleep duration with standard error of mean during academic breaks and after the last day of the class (study and exam period).

period. In other words, the participants slept considerably less after the last day of the class compared to the rest of

the academic term.

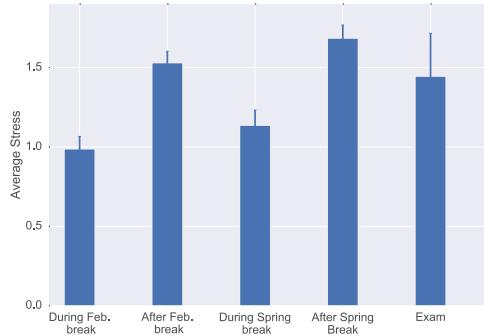


Figure 5: Average stress reported during the academic breaks, the immediate next week after the breaks and the exam period. The error bar indicates standard error of mean.

We further looked into the daily stress reported by the participants during these periods as shown in Figure 5. In general, the exam period resulted in students being more stressed. The participants reported being less stressed during the breaks as expected. However, interestingly, there were significant spikes right after the breaks, in which the participants reported to be quite stressed. We speculate that this is due to the structure of the academic term. Having no class during the break allowed students to have a flexible sleep schedule and being less stressed. However, since prelims are scheduled within a few weeks after the breaks, the students might feel pressured to catch up right after coming back from the breaks resulting in increased stress. This is an interesting finding which needs further investigations.

Sensor data analysis

We were also interested in looking at whether students' behavioral change can be captured through sensor data, in

particular their daily routine. Usually, during instruction periods, students have relatively regular routines. However, during holidays, or as exams approach, their routines might become less regular. The regularity of daily routine is correlated with mental health [23]. Therefore, if we are able to detect anomaly in their daily routine, it could be used as an early warning sign indicative of mental health status of a participant.

In order to find out an individual's routine, we applied Robust PCA (RPCA) [22]. First, we aggregated the sensor data of each modality by hour and arranged the data across days as a matrix $D \in \mathbb{R}^{h \times d}$ with columns representing different days and rows representing the hour during the day, where h is 24, the number of hours per day, and d is the number of days. This data matrix can be decomposed into lower ranks if an individual has regular routines. We used RPCA to decompose D into two separate matrices, $A \in \mathbb{R}^{h \times d}$, a low-rank matrix comprised of the underlying pattern of individual's routine, and $E \in \mathbb{R}^{h \times d}$, a sparse matrix comprised of variations of routine.

By visualizing the the low-rank matrices of the sensor streams, we can see how an individual's daily routine changes throughout the academic semester. Some of the examples are shown below:

Weekdays versus Weekends

As shown in Figure 6, user 15's activity data indicates that the student had less time being active during 9:30 AM – 11:30 AM and 3:30 PM – 4:30 PM throughout the term. This suggests that the student might have classes during those two periods. There is also a weekly pattern in data showing that there is a drop in activity level reflecting the weekends.

Sensor data during academic breaks

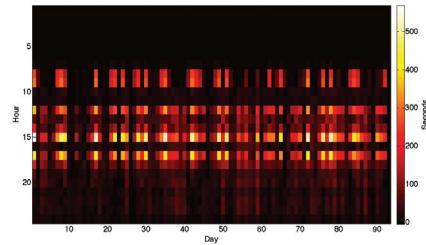


Figure 6: Daily routine and weekly routine. The active data from the low-rank matrix A after decomposition shows that the student was less active during 9:30 AM – 11:30 AM and 3:30 PM – 4:30 PM throughout the term indicating the class schedule during the weekdays. The activity level also drops during the weekends.

User 29's activity, step count, and phone usage data also differ during the academic breaks as shown in Figure 7. During the spring break, the amount of time the student being active was less, had fewer steps and used phone less often compared to the instruction period. These patterns are consistent with the trend in students' sleep survey data where on average they reported that they slept more during the break.

Conclusion

In this paper, we deployed a smartphone based tool among 22 students over the duration of an academic semester. The preliminary analyses of their survey data show that i) students slept less during exam periods and slept more during breaks, and ii) they felt more stressed during the breaks and exam period. And through the analysis of their daily routines, we found that some of sensor data are able to capture different routines during weekdays, weekends, and breaks. The consistency of passive sensor data with self-assessment shows promise for predictive models. For

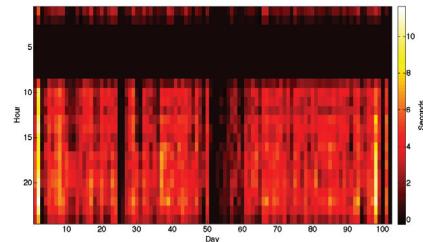
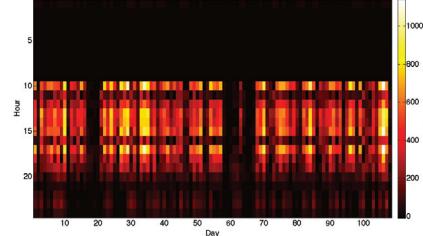
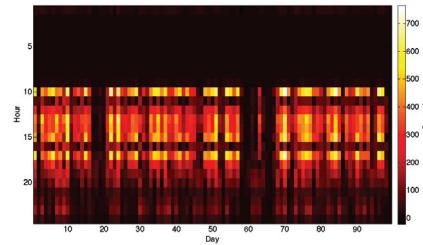


Figure 7: Different routines during instruction period and spring break. The top one is the student's activity data, the middle one is her step-count data, and the bottom one is her phone usage data after decomposition. This student became less active, walked less, and used her phone less during day 55 – day 65, which was during the period of spring break.

future work, we are going to integrate the multimodal sensor data for predicting stress level and overall mental health trajectory during the academic term. We are also interested

in identifying relationship between mental health and academic performance. Furthermore, we are focusing on providing early interventions to prevent onset of mental health issues based on the outcome of our predictive models.

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