

Quantitative Assessment of Smartphone Usage in College Students—A Digital Phenotyping Approach



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Abstract Community-related health monitoring and prediction have become the focal points of research and development in the last decade. Health care particularly garnered much interest from the research fraternity. With powerful sensing capabilities, smartphones have become the de-facto measurement platforms. Digital phenotype is a new paradigm that aims at exploring and quantifying individual-level human behavior characteristics through an in-situ method of data collection primarily from personal digital devices such as smartphones and wearable sensors. Various works have attempted digital phenotype on different scales for varied populations to study user behavior across three dimensions, namely physical (motor activities performed, device usage styles,); social (online and offline interaction); and mental (psychological behavioral aspects). In this work, we conduct a behavioral sensing experiment through digital phenotype on a cohort of 47 college students over one and half months at our institute. We quantify the total time spent on physical activity, social interaction, and sleep. We also quantify the smartphone usage duration per day and discuss the potential impact of phone use on student life behavior and health. Our findings indicated that most students seem to be on the idle side of the physical activity spectrum, are sleeping less and are using their smartphones for a wide range of purposes and for extended hours.

Keywords Mobile sensing · Smartphones · Activity · Sleep

1 Introduction

The major invention that the human race witnessed in the past decade has been the smartphone and the hardware and software technological developments associated with it. Coupled with these is the proliferation of digital platforms, solutions, and applications blurring the line between real and virtual life. Smartphones with built-in

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networking and communication technology have broken geographical boundaries, making lives more comfortable but at the same time impacting human behavior. Reduction in physical and sleep activities is manifested due to extensive use of social media, games, entertainment, and even mindless scrolling of applications on phones.

Researchers discovered that the built-in sensors in smartphones could be used for sensing purposes, and coined the term mobile sensing which essentially involves sensing various physical quantities such as motion, orientation, ambient sound, light, etc., and extracting useful information from that data to study behavioral patterns (Lane et al., 2010). Digital phenotyping an extension of mobile sensing quantifies behavior on the individual-level phenotype through in-situ sensing. Applications include health (Marsch, 2021), social science (Raento et al., 2009), mental health (Servia-Rodríguez et al., 2017), psychiatry (Melcher et al., 2020), (Liang et al., 2019; Insel and TR, 2020), and psychology (Chein et al., 2017). The phenotype-based study's motivation is the ease in data collection facilitated through the wide availability of smartphones with users ranging across all age groups. With Android and iOS mobile operating systems' evolution, young adults seem to be the significant users and contributors to mobile applications (Statistica, 2013) and (TCS, 2013).

Most studies on phone use by students in India followed a qualitative assessment method through questionnaires (Subba et al., 2013), (Davey, 2014), (Bisen et al., 2016) and interviews (Dixit et al., 2010). The studies compiled information on the brand of phone preferred, type of applications installed and used, and the psychological feeling of losing a phone. Responses for such methods may not be accurate since it is difficult to recall actions or events of the past. For instance, one may not remember accurately his/her phone usage duration in the past week. This could lead to incorrect responses or even personal bias (Vaizman et al., 2017), potentially producing skewed conclusions. In contrast, exhaustive work on mobile sensing methods has shown to be reliable and complement qualitative data (Lane et al., 2010).

Our study aimed to quantify smartphone usage behavior and its impact on health. Daily routine activities of people include work, regular physical exercise, sleep habits, and socializing. Sudden changes in such behaviors could show adverse effects on health. Research shows that some kind of physical activity on a regular basis is critical (Maher et al., 2013). Research also says that gradual reduction in physical activity has a profound impact on the muscle strength irrespective of the age (Lieberman et al., 2017) and (Laforest et al., 1990). Similarly, inadequate sleep over the long term affects the biological clock and health of a person (Rod et al., 2018). With the advent of social media, there seems to be more online presence of oneself than offline interaction. Having a healthy socializing routine has shown positive outcomes of removing loneliness in people (Cohen, 2004). Student life particularly poses challenges such as handling academic stress, language or cultural barriers for social interaction leading to loneliness, depression, and other mental health issues (Douglas et al., 1997). Mobile-health (mHealth) applications and interventions are already being applied (Gowin et al., 2015; Lathia et al., 2013).

Hence, understanding how much time students spend on physical activity, sleep, and sociability is imperative. Therefore, utilizing the smartphone as a platform, we

conducted an experiment-based study for 45 days to assess students' behavioral trends and health impact. For understanding the effect on health, we detect and quantify in hours per day the activity type (idle or moving or sleeping), the social interaction levels, and the mobility patterns on campus. Our study consisted of the following research questions:

- What is the total duration of smartphone usage?
- What is the total time students spend on physical activity such as walking?
- What are the sleep patterns of these students?
- How much time is being spent for face-to-face social interaction as opposed to online interaction?
- As a group, which location or areas on campus do students prefer to visit and how much time do they spend in those locations?

Our study resulted in the following findings:

1. Students were physically active for 4 ± 1.5 hours on average.
2. Smartphone usage was on average 6.7 ± 3.5 hours.
3. The sleep hours were on average 5.5 ± 2 hours.
4. Students had a healthy face-to-face interaction of 4 hours on average.
5. 40% of the students spent an average of 7 ± 1.5 hours in their dorm rooms.

This book chapter consists of ten sections. In Sect. 2, we present the methodology of our experiment wherein we discuss the study procedure, the data collection mechanism, and other logistics. Following this in Sect. 3, we introduce the readers to smartphone technology and its growth over the years. We further throw light on the embedded sensors, the working of the accelerometer and its application to activity recognition. The next three sections comprise of the results of our study. We start with activity recognition in Sect. 4, followed by sleep detection in Sect. 5, sociability analysis in Sect. 6, and analysis of mobility patterns in Sect. 7. Finally, we conclude with some discussions in Sect. 8 followed by Acknowledgments.

2 Experiment and Study Design

2.1 Study Procedure

The entire study consisted of student orientation, data collection, analysis, and presentation of results. The participants were primarily our own undergraduate students. Among the 48 students who completed the study, ten were from the final year, 20 were from the third year, ten from the second, and eight from the first year. We informed all participants what data we were going to collect and how the app works. The students signed a consent form agreeing to the data collection mechanism and the privacy policies. We showed how to install the mobile application. We also requested the students to fill in a survey form providing their demographic information, personality traits, and current smartphone usage preferences.

The students followed their regular routine of attending classes, hanging out during breaks, moving between multiple locations, etc. At the end of 24 hours, the app automatically transferred the data to a local server. Two research fellows interacted with each student twice a week to gather responses related to their daily routine which included mobility on campus, places frequently visited, physical exercising preferences, sleep routines, and socializing.

2.2 Incentives and Privacy Considerations

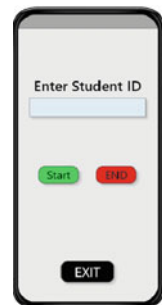
As an incentive, we paid each student INR 3000. We received around 990 hours of data for the entire study duration. To protect participants' personal information, anonymity of student's identity was maintained. We clarified that we collected and inferred only the type of applications used and not the content.

2.3 Data Collection

The data collection phase lasted for 45 days during the Autumn semester. We developed a mobile app that activates each of the sensors through Sensor managers provided by Android. The sensors respond to change in the physical quantity. After analog to digital conversions (ADC), a digital value is stored in array format and later written to a csv file. Figure 1 shows the interface of the mobile app.

The app was programmed to automatically collect accelerometer, proximity, microphone, light sensor data, location (Wi-Fi), and application usage. Using the data, we inferred (a) activity (stationary, non-stationary, i.e., walking or running or cycling), (b) sleep duration, (c) social interactions, (d) mobility patterns, and (e) overall smartphone usage hours. In the next section, we introduce the reader to smartphone technology and discuss aspects related to the operating system, the built-in sensors, and their use.

Fig. 1 The interface shows a textbox to enter student ID and a start and stop button for data collection. Once the student enters the ID and touches the Start button, the data collection starts and the app runs in the background. The Stop button is provided to stop the application if required



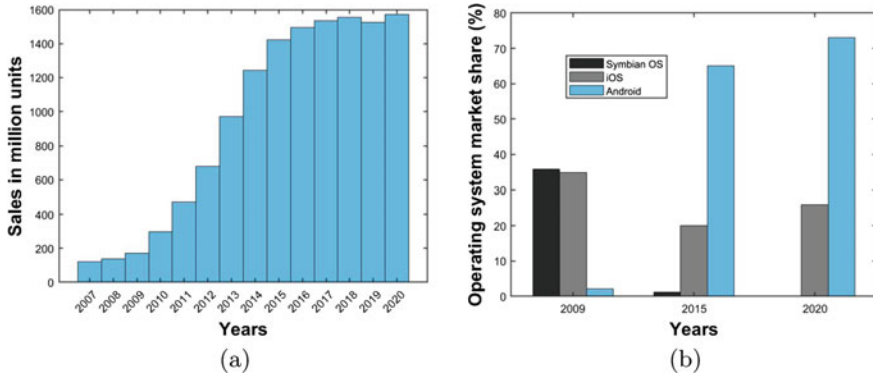


Fig. 2 a Mobile phone shipment sales increased by 196% between 2007 and 2020 b The rise in Android- based phones from 2009 to 2020 is around 188%, while Symbian OS-based phones and iOS-based phones show 196% and 26% decrease in sales

3 Smartphone Technology

The first smartphone was the LG G1 with a single core Qualcomm MSM7201A (528MHz CPU clock) processor, 192 MB RAM, and 256MB storage running on Android 1.1 operating system. The phone was embedded with a three axis accelerometer, magnetometer, and a microphone along with Bluetooth 2.0 and Wi-Fi radios. Fast forward to 2020, the latest phones contain six to eight cores Qualcomm Snapdragon 855 (2GHz clock) processor, 8GB RAM, and 128GB storage space running on Android 10. Embedded sensors include optical fingerprint, accelerometer, gyroscope, proximity, compass, and barometer. The built-in sensors when compared with sensors in a wireless sensor network are different in the fact that they are independent of each other and do not require any protocols to enable interaction or dependency. Below in Fig. 2, we visually illustrate the various statistics¹ pertaining to smartphone growth over the years in terms of smartphone shipments and operating system popularity.

We now discuss the working of an accelerometer.

3.1 Working of an Accelerometer

The accelerometer, in the context of a smartphone, measures the amount of force applied on the three axes x , y , and z . The sensor has a mass with comb-like protrusions and a capacitance associated with each pair of protrusions. Depending on the force, the capacitance changes which changes the voltage. The change in voltage is mapped to force values. The units are g force (1g, 2g, etc) or m/s^2 , where 1g is equivalent to

¹ All stats obtained from <https://gs.statcounter.com/>.



Fig. 3 The figure shows the x axis corresponds to the direction of travel, the y axis represents the horizontal axis movement and the z axis represents the vertical movement, i.e., measuring gravitational force. Any movement on the device applies force on the sensor which causes variations in the magnitudes on three axes. A static position captures only the gravitational forces across the z axis

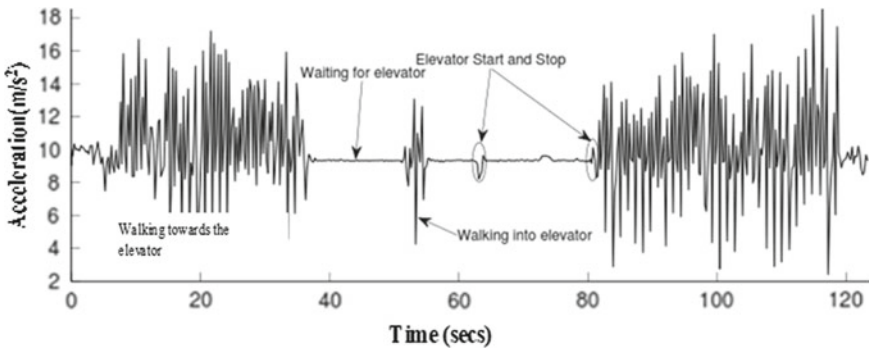


Fig. 4 The rhythmic movement of the legs causes the phone to move exerting forces on the x and y axes. When the user is idle, only gravitational force is exerted. Hence, the amplitude of idle activity varies around $9.8m/s^2$ when compared with highs and lows of walking. The intra-sample variance computed was also higher for walking than that of idle activity. This is a differentiating feature of both these activities. The small changes in the z axis were triggered by the elevator start and stop action

$9.8m/s^2$. Figure 3 shows the three axes along the phone and how the positive and negative directions of the axes are interpreted.

Figure 4 explains the variations in force exerted by human activity (walking or idle) along the three axes.

Apart from just detecting the type of activity, the three axes sensor data can also be used to interpret walking activity with more granularity. For instance, as listed in Table 1 (Kalyan Pathapati Subbu, 2011), changes in x axis mean taking turns while walking, whereas changes in y axis mean walking straight and so on.

Table 1 Interpretation of data from three axes

Axis	Direction	Walking mode
<i>x</i>	Left/Right	Taking turns
<i>y</i>	Front/Rear	Walking straight
<i>z</i>	Up/Down	Upstairs or Downstairs

In the next section, we discuss how we applied this concept in detecting activity type among students, what inferences were made pertaining to idle, non-idle, and sleep activity, and present the other major findings of the study.

4 Activity Detection

For recognizing the activity (walking, running, standing or sitting), a characteristic feature has to be selected. We chose the variance as explained in Sect. 3. This feature was then given as input to three classification algorithms, namely Support Vector Machine(SVM), Random Forest(RF), and Logistic Regression(LR) algorithms. SVM creates an optimally separating line (hyperplane) to distinguish samples into multiple classes. Random forests are multilevel decision trees and logistic regression tries to fit data to a certain curve (linear,quadratic) and create a model.

We labeled our initial data consisting of 10,000 data points using the variance feature. We then trained the classifiers on the data , tested the unlabeled data and computed the classification accuracy using F-score given by $F_{score} = \frac{2 \cdot precision \cdot recall}{precision + recall}$. However, not satisfied with the classification accuracies, we applied co-training principle which is a semi-supervised approach. Here, a small set of labeled data is used to train and test with a larger set of unlabeled data. The prediction rates were improved by combining two independent and different classifiers (Radu et al., 2014). Figure 5 shows the improvement in accuracy after applying co-training.

From the non-idle class samples, we computed the time in hours for each student. This was repeated for the idle class. Figure 6 illustrates a sample trend of student activity hours for the entire 45 days.

To summarize the numbers, students were idle for 13 hrs/day(excluding sleep hours) on average and active for 4 ± 1.5 hrs/day on average. The average error between ground truth (where we asked the students to estimate the number of hours of physical activity) and phone-based estimation across all students was 10.5 ± 2 hours for idle and 3 ± 2 hours for non-idle. We use a box plot, Fig. 7, to illustrate statistically the variations between the two activity states.

Curious to find out more from students about their low levels of physical activity, we inquired about their interest and preference in exercising. Out of 45 days, only 10% of the days, students claimed to exercise. Only three students exercised every

Fig. 5 The legend shows how for each pair of technique (SVM, LR or SVM, RF or LR, RF), co-training improved the accuracy when compared over that obtained when independently the techniques were applied

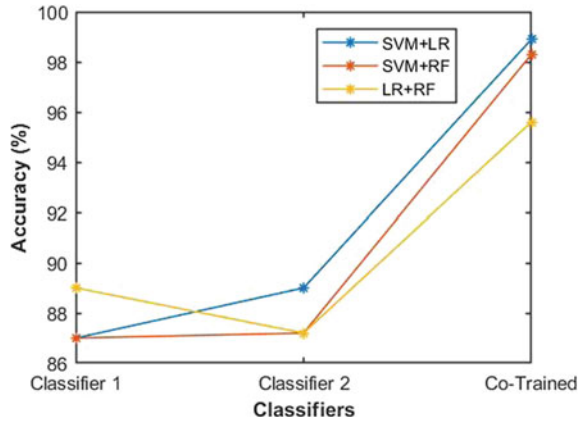


Fig. 6 The graph shows the average idle and non-idle activity hours trend. The idle hours are overwhelmingly higher than the non-idle hours

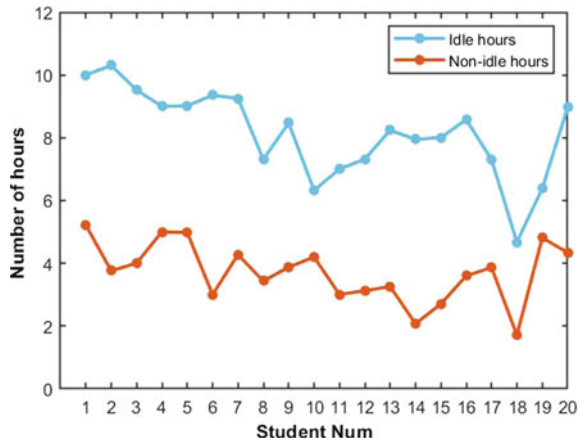
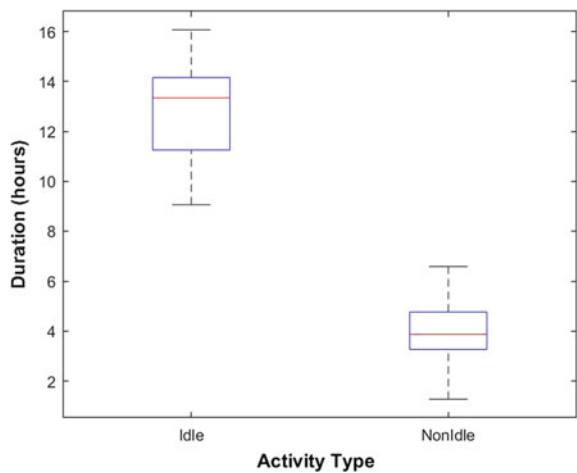


Fig. 7 The plot shows the median values and inter-quartile ranges for both idle and non-idle activities. The idle hours are overwhelmingly larger than the non-idle



day, whereas 18 exercised once in three days. The remaining 26 students did not prefer exercising. All of these results tied together strengthen the general belief or hypothesis that the sedentary levels of the younger generation are on the rise.

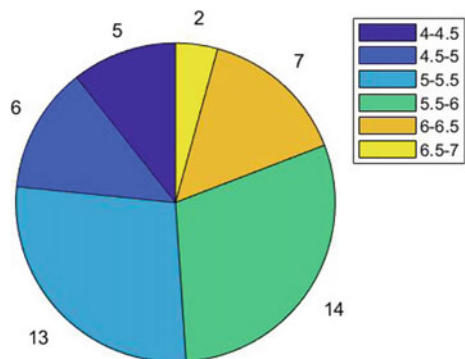
5 Sleep Detection

Sleep is a vital aspect of human health and sleep routines vary between individuals. However, disruption of sleep occasionally or continuously for prolonged periods does have detrimental effects on future health (Rod et al., 2011; Cappuccio et al., 2010). Human sleep continuously goes through a cycle of stages starting from rapid eye movement (REM) to non-REM and finally to the deepest stage called slow-wave sleep. The duration of sleep cycle usually lasts anywhere between 90–110 minutes (Lockley, 2018).

Existing research has started to focus on assessing technology, or to be precise, smartphone impact on sleep duration and sleep quality (Rod et al., 2018). However, most works look at the impact through qualitative methods. We, on the other hand, use mobile sensors inside the phone. We detected the sleep activity by considering the following features. The user activity state, ambient light and noise levels(low), and phone screen status (locked or unlocked). A decision tree predicts the activity state as sleep if the student, i.e., the phone is idle, the screen is locked, and the light and noise levels are low continuously for a minimum of 30 minutes. We borrow this idea from (Chen et al., 2013). Figure 8 depicts the frequency of sleeping hours of students.

From Fig. 8, we can conclude that higher number of students (35.9% of students) averaged five to six hours of sleep. Only one student had more than seven hours of sleep time (2.6% of students). An average error of 55 ± 10 minutes was obtained between the ground truth (student recorded sleep and wake times) and sensor estimated.

Fig. 8 Sleep hours distribution: The pie chart shows the distribution of students according to their sleep hours. Majority of the students (27) slept for less than six hours and this routine was observed from their data for close to 18 days



In Sect. 8, we compare this finding with the sleep quality responded by students. In the next section, we move on to discussing the location preferences on campus and the mobility patterns of students

6 Sociability

Sociability means preference for being and interacting with some company (a group of friends, close aides, etc.,). Most existing studies on sociability of students use self-reporting methods to questions such as who they like to be with, how many people do they like being with, and so on. The gap in such works was the accuracy in estimating the actual duration of interaction.

For understanding sociability, we consider the duration of interaction students have on campus with peers. This involves quantifying their conversation levels. For this process, we utilized the microphone which records audio from various backgrounds including classrooms, lecture halls, cafeterias, libraries, and so on. The sensor samples every two minutes the amplitude value of the sound signal. In our earlier work (Subbu et al., 2009), we proposed a context-aware system by extracting some features from audio data to distinguish classes of background like silence, speech, and other environments. These features can be considered as elements of a multidimensional vector, and when trained on these features, classifiers can detect the environment present and provide contextual information. Borrowing the method in this work, we first classify the background between noisy and silent. Then we further extract speech from the noisy environment detected.

After data collection, preprocessing of data included sampling, segmenting the recordings into 256 samples, each of 30 ms duration audio files. We further labeled each sample according to the environment where they were captured. A Hamming windowing was applied on each frame to reduce discontinuities at the beginning and end of the signal pertaining to that frame. After this, a frequency domain analysis was conducted to obtain appropriate features for classification. However, before classification, feature extraction had to be performed. The power spectrum of the audio signal presents itself with features that were extracted in the form of amplitudes.

The human auditory system does not recognize audio with frequencies over 1KHz. Such audio signals are mapped to human audible frequencies on a scale called the mel scale. For frequencies below 1000 Hz, a linearly spaced filter is applied, whereas for those above 1000Hz, a logarithmic spacing is used. For details on filter banks and the Mel Frequency Cepstral Coefficients (MFCC) process, we urged the readers to refer to (MartInez, 2012). After this step, for the classification of the audio samples into vocal and non-vocal, we used the VQ method (Makhoul et al., 1985) due to its ease of implementation and accuracy. Figure 9 shows the interaction pattern of a sample of 20 students. We can see the variations for each student.

Figure 10 presents the distribution of students' conversation levels across different time slots.

Fig. 9 Total hours of social interaction are excluding interaction during class. The presence of the student or rather his phone at the classroom location was obtained from Wi-Fi data and those hours were deducted from the total conversation hours of the day

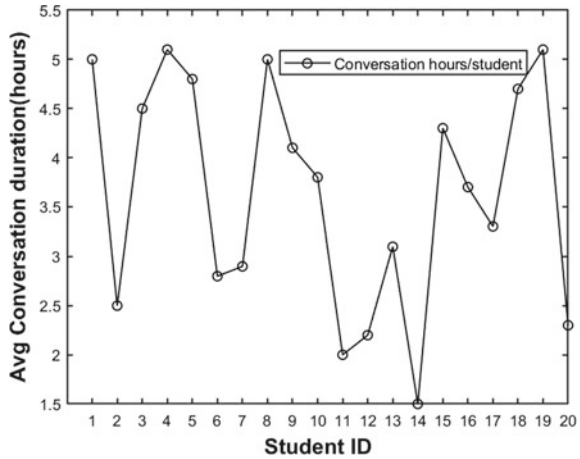
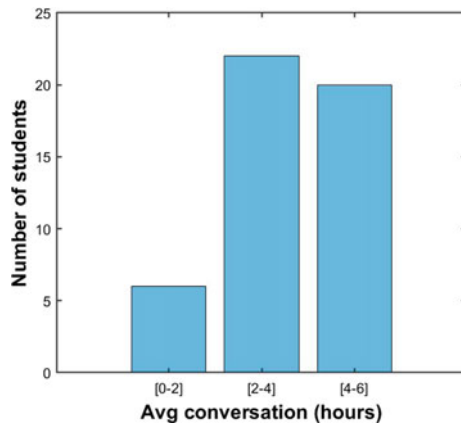


Fig. 10 The duration is split into two hour slots showing that a majority of the students had 4–5 hours/day of interactions with their friends which is a healthy sign



7 Location and Mobility Patterns

Mobility mainly includes extracting the various places/locations one visits, the frequency and duration of the visits. Existing research has shown that decreased mobility levels (i.e., moving around multiple locations) when combined with reduced sleep hours (Thomé et al., 2011) and excessive smartphone usage are associated with symptoms of depression. In other words, depressive people tend to confine themselves to one or two places only (say home or office) for a long term (months), are addicted to their phones (Aggarwal et al., 2012), and prefer not to interact with anyone. In some cases, if qualitative responses are biased or skewed towards lower scales, conclusions lead to false positives such as detecting depression in a person when he is otherwise not (Demasi et al., 2016).

Fig. 11 The box plot shows that most students preferred spending time in their hostel rooms, followed by cafeteria

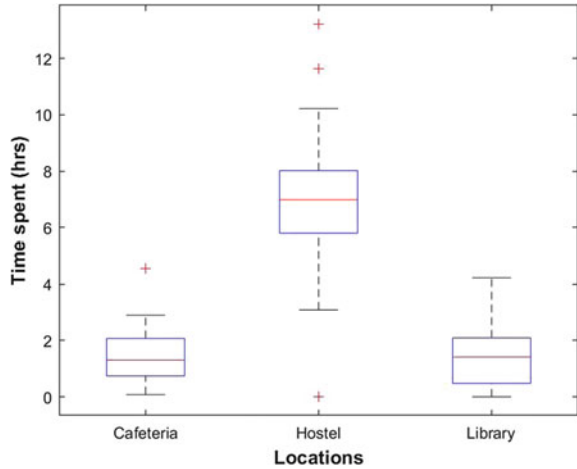


Fig. 12 a During this time slot (lunchtime), the density of student movement was high indicated by the red color near the cafeteria, whereas in **b**, there was no major movement, the reason being laboratory hours requiring presence of students



We have not delved into mental health specifically, but have looked at how physically active the students were and their mobility behavior inside the campus. The Wi-Fi access point ID was continuously logged by the mobile app every two minutes. Later, we mapped the access point data to human understandable location tag (library, classrooms, lab, hostel, cafeteria, etc.). For each student, we obtained a set of most visited locations on campus, by setting a threshold of at least 10 mins as stay time at a particular location. Figure 11 illustrates the distribution of the top three locations preferred by students.

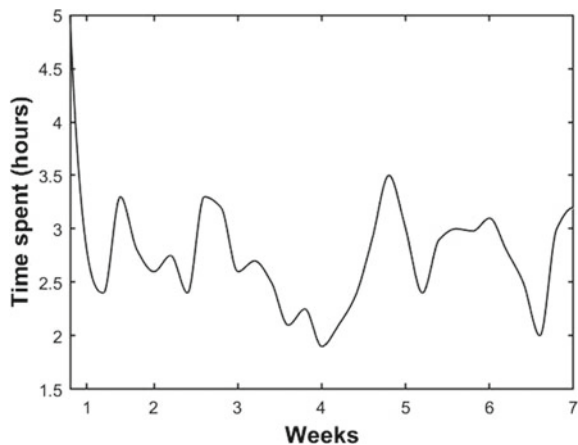
A web-based interface showing the heat map of student movement Fig. 12 during different times of the day was also created as a byproduct of this analysis. Such information could help the administration in understanding the student movement for better campus crowd management.

7.1 Mobility Patterns

Now that the most common locations visited and the time spent at each location have been discussed, we now discuss students' mobility trends for the 45 day period. To understand the trend, we correlate it with the academic calendar on a week by week basis for roughly 7 weeks. The activity data in hours was averaged across all students per day and plotted to infer the movement activity on the campus. The academic calendar lists events such as examinations, cultural festivals, sports day, and other extracurricular activities that happen on the campus. Figure 13 illustrates the findings.

- Week 1: The mobility levels were average but gradually toward the third day of the week, the graph saw a rise as the weekend was approaching.
- Week 2: During the start of the week, a technical fest was organized. This created more movement around the campus as can be seen by the rise from the mid of the second week. Again, once the fest ended over the weekend, students stayed in their rooms as indicated by low mobility.
- Week 3: At the start of the week, their mobility levels were high but gradually reduced. As the semester progressed, the students were settling down, focusing on classes, visiting libraries, so they had low mobility.
- Week 4: Mobility levels were low at the start of the week after which we observed a gradual increase, the reason being the start of the sports fest at the campus.
- Week 5: This week did not see major ups and downs in the mobility.
- Week 6: This week was the mid-semester exam week. So, as natural behavior, the mobility started to decline.
- Week 7: Once the exams completed, the mobility started to increase.

Fig. 13 Mobility pattern trend of students for a period of 7 weeks



8 Discussions

In this section, we first present the overall mobile phone usage including the categories of apps used often. Following this, we discuss students' perception of sleep quality.

8.1 Smartphone Addiction: Mobile Usage Hours

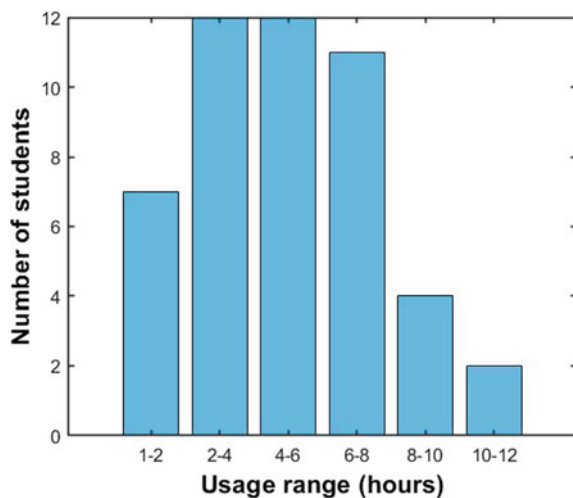
As mentioned in the Sect. 2, our mobile app monitors the usage which includes the screen time, the type of app currently being used, and its duration. Figure 14 illustrates the overall usage distribution of smartphones across all students.

We also categorized the usage among entertainment apps, social media, gaming, education, and so on. Our other findings include the following:

- 70% (33 of 48) of students spent 4 hours/day on social media.
- 53% (25 of 48) of students spent 3.5 ± 1.5 hours on gaming apps.
- 20% (10 of 48) of students played PUBG for close to two hours/day.
- 60% students preferred using their phones for not just communication and entertainment, but also for education.

Although the results resonate with most existing work in terms of excessive usage of phones, reduction in sleep and increasing levels of inactivity, we found some positive impacts too. For instance, as mentioned, many students used their smartphones for sharing educational materials, watching video lectures/tutorials, and using productivity apps. Even though this may have seemed unacceptable, the last few months have seen even greater usage of smartphones. The pandemic has forced education

Fig. 14 The average mobile usage among the students was 6.87 hours per day on average. The skewness toward the right shows that a majority of the students' phone use was higher than average



to go online making humans even more dependent on phones, laptops, and other gadgets. To conclude, using technology for longer time periods now has become inevitable.

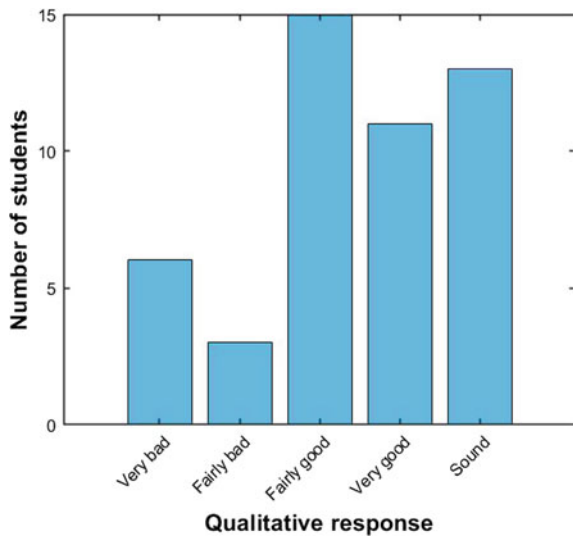
8.2 Sleep Quality Impact

Looking at the sleep duration results, we felt that students lacked the appropriate amount of sleep. To gauge the students' feelings about whether the reduced sleep routine impacted them, we asked them to rate the quality of their sleep on a scale of 1 to 5. with 1 being Very bad, 2—Fairly bad, 3—Fairly good, 4—Very good, and 5—Sound sleep. Figure 15 illustrates the distribution of sleep quality responses from students.

The students reported that, for almost 37 days of the study, they had good sleep. Only for seven to eight days (16%), some reported difficulty in sleeping. Our future work aims to analyze the subset of those who reported sleeping difficulties. To conclude, we can say that students managed to remain fresh without feeling fatigued with a sound sleep of five hours.

Overall, our study has highlighted how smartphone has impacted student behavior. This is a first of its kind study attempted on Indian students and some comparisons that can be drawn from the existing work is that students irrespective of the geographical location, spend major chunk of their time on smartphones. The activity and sleep duration also seem to be on the same lines. Other factors such as sociability and mobility were different. This could be due to the social background, personality

Fig. 15 A majority of them reported to have fairly good and very good sleep even though their average sleep hours were 5.5 h



types, and so on. On the bright side, education technology backed by companies like Google, Microsoft, Zoom, and others is banking on smartphones by developing apps such as Google meet, Teams, and Zoom.

9 Conclusions

Due to the digital era's tremendous growth, we witness how technology is becoming a dominant factor in our daily lives. Smartphone-based passive sensing has become an emerging technique to understand human life and behavior. This study presented a novel method, namely digital phenotype, to monitor and assess college students' health-related behaviors. The method attempted on a student cohort for the first time in India proved the viability of using smartphones and their embedded sensors as platforms for collecting, analyzing, and inferring behavior. This study provided trends on the physical activity, sleep, sociability, and mobility patterns of students while carrying out daily routines on campus during an academic term.

The activity levels indicate that students may be preferring a sedentary lifestyle; possible factors contributing to this behavior could be prolonged usage of smartphones, social media, gaming, and reduced sleep hours. Social interaction on the campus was healthy with no sign of deterioration even with increased use of mobile phones. Our future work, among many, plans to take up the mental health issue that is plaguing the student community and understand how smartphone technology can be used as an intervention platform.

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