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Deriving College Students' Phone Call Patterns to Improve Student Life

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This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by Nethealth Mobile Health Study Dataset.

ABSTRACT When high school students leave their homes for a college education, the students often face enormous changes and challenges in life, such as meeting new people, more responsibilities in life, and being away from family and their comfort zones. These sudden changes often lead to an elevation of stress and anxiety, affecting a student's mental health and well-being and academic progress. With the outbreak of a pandemic, such as COVID-19, this transition moment can worsen with frequent, long-lasting lockdown and associated academic disruption. To help this young population, researchers are increasingly relying on smartphones and wearables, such as smartwatches, to continuously monitor students' daily lives to identify various factors that can affect students' phone call patterns associated with their health and well-being and academic success. In this work, we use different visualizations and statistical techniques to find various geographical places and temporal factors that affect students' phone call patterns (in terms of phone call duration and frequency) to foster the design and delivery of future smartphone-based health interventions using predictive models; thereby, potentially helping students adjust to college life with or without the presence of an emergency, such as pandemic that adversely impacts academic calendar and student life. From our detailed analysis of an 18-month dataset collected from a cohort of 464 freshmen, we obtain insights on communication pattern variations during different temporal contexts, e.g., epochs of a day, days of a week, the parts of a semester, social events, and in various geographical contexts (i.e., places of interest). Finally, we also obtain a negative correlation of -0.29 between physical activity and phone call duration, which can help provide guided feedback to improve future health behaviors.

INDEX TERMS Mobile health, phone call, temporal factors, geographical factors.

I. INTRODUCTION

A. MOTIVATION

When starting their on-campus college life, most students leave their families and school friends for the first time. During this transition period, students go through a stage where they may suffer from extreme stress, anxieties, and depression [1] as they experience many changes, such as adapting to a new lifestyle, meeting new people, peer pressure, and facing academic deadlines. These changes impact not only their mental and physical health but also their academic performance [2], [3]. Therefore, social engagements have been recommended to cope with these challenges and improve well-being [4], [5].

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However, during times of emergency, such as an outbreak of a pandemic, social engagements are often restricted due to stay-at-home orders or lockdown. Such long lasting abnormal conditions not only disrupt regular life and academic progress [6]–[9], but they also bring additional challenges that adversely affect students' health and well-being [10]–[19]. According to a National Academies report, a spike in the dropout rate of 43% – 86% for students with diagnosed mental health problems has been witnessed in 2020 [15]. From a study with 195 college students, researchers have found that 71% of students suffer from increased stress and anxiety due to the COVID-19 outbreak [10]. From the same study, researchers have also found that 89% of students report difficulty in concentrating, 86% of students report disruptions to their sleeping patterns, 86% of students report decreased social interactions due to physical distancing, and 82% of students report increased concerns about academic performance. Additionally, from a separate survey of over 5,400 people, researchers have found that 46% of young adults (aged 18 – 24 years) reported COVID-19–related trauma- and stressor-related disorder (TSRD) symptoms, and 25.5% of those young adults seriously considered suicide during the outbreak [16]. Additionally, 24.7% of those young adults had started or increased substance use to cope with pandemic-related stress or emotions. In other studies conducted on college students, researchers have found similar mental health and well-being-related issues, such as increased loneliness, depression, anxiety, sleep difficulty, suicidal ideation, and increased use of substances, among the students due to the COVID-19 outbreak [11]–[13], [18], [19].

A group of researchers has found that talking on the phone can be a way to promote mental health [20]. Similar to other populations, phone calls can also positively impact students' mental health and well-being, as well as their academic performance [21]. Therefore, researchers recommend phone calls as a medium to deliver mobile health interventions to cope with mental health and well-being-related difficulties and challenges during times of long-lasting pandemics, such as COVID-19 [22]–[25]. While phone calls can be a medium to deliver health interventions, knowing the impacts of various geographical and temporal contexts/factors, such as places of interests, epochs of a day, social events, and physical activities on phone call behaviors, such as call duration and frequency, can provide helpful insights to design and deliver adaptive health interventions [26]. Additionally, young adults frequently use smartphones in their daily lives. This phone use can further be intensified in times of emergencies, such as lockdown and stay-at-home orders due to various smartphone-based services, ranging from online classes to social engagements [27]. Therefore, a better understanding of various geo-temporal factors and their impacts on phone call patterns will be helpful to develop predictive models [26] and to design and deliver health interventions to cope with changes in lifestyles.

B. RELATED WORK

Researchers have been investigating various factors that contribute to positive and negative health choices, stress, and changes in academic performance for a college student. For example, a group of scientists investigated various health behaviors, such as spiritual habits, exercise, eating patterns, and sleep habits related to students' academic performance using one-time surveys on 200 students living on campus [28]. However, the subjective self-reported surveys often suffer from human errors and various biases, such as the recall bias [29]–[31]. Thereby, the development of accurate behavioral tracking is essential to continuously and remotely monitor multiple spatial-temporal patterns of college students' behaviors. With an unprecedented expansion of smartphone sensing technology, researchers have begun capturing various types of automated sensor data uninterruptedly and seamlessly using smartphones and fitness trackers. Such datasets have then been used to assess students' health and wellbeing [32] and academic performance [33] to offer awareness for better management of student life and improve their quality of life. A group of researchers studied mobile phone data to analyze the activities of users to predict future changes in their activities [34]. In that work, researchers developed a behavior-oriented time segmentation technique, compared to the traditional equal interval segmentation, to apply more individualized time-dependent behavioral rules. The study was conducted over nine months to collect data from 94 mobile phone holders who were faculties, staff, and students. While the main focus of this work was to develop a firewall for incoming calls and reminder apps based on routine phone calls behaviors, this work did not investigate how students' communication behaviors change over the years. Another group of scientists analyzed the correlation between activity, mood, mental wellbeing, and sleep with educational outcomes via a 10-week long study on 48 graduate and undergraduate students utilizing surveys and automated cell phone data [33]. Similarly, others investigated the relationship between students' perceived happiness and mobility and attempted to predict changes in satisfaction using physiological signals, changes in location, and phone usage data along with subjective survey responses collected from a 1-month study on 68 undergraduate students [35]. However, all these works are limited by a short study period since several factors contribute to students' health and wellbeing, which might be better understood if a student can be monitored for an extended period of time. For example, the communication behavior of a student can vary from year-to-year, since a first-year student may be expected to talk more with family and school friends compared to sophomore as they may have begun to develop a new circle of friends on campus.

C. CONTRIBUTIONS

Adapted from our previous work [36], [37], in this paper, we perform fine-grained analysis of college students' geographical and temporal patterns of communication behaviors (in terms of phone call duration and frequency) utilizing various visualizations (i.e., bar graphs, heat maps) and statistical (i.e., *One-way ANOVA*, *Two-Sample T-test*) techniques. Compared to our previous high-level coarse-grained geo-temporal analysis, in this work, we present detailed analysis of phone call patterns during different temporal contexts such as epochs and hours of a day, days of a week, parts of a semester (e.g., regular class days, breaks, exam days) as well as across places such as dorms, class buildings, athletic centers, and food courts along with their statistical significance. In addition to geo-temporal pattern analysis, we also assess phone call patterns during social events such as football events as well as physical activities (in terms of step counts). The analysis is based on Fitbit and smartphone data that was collected from more than 400 on-campus freshmen over three consecutive semesters. Our detailed hour-by-hour analysis shows more precise phone call patterns and depicts the change in students' life style during regular and break

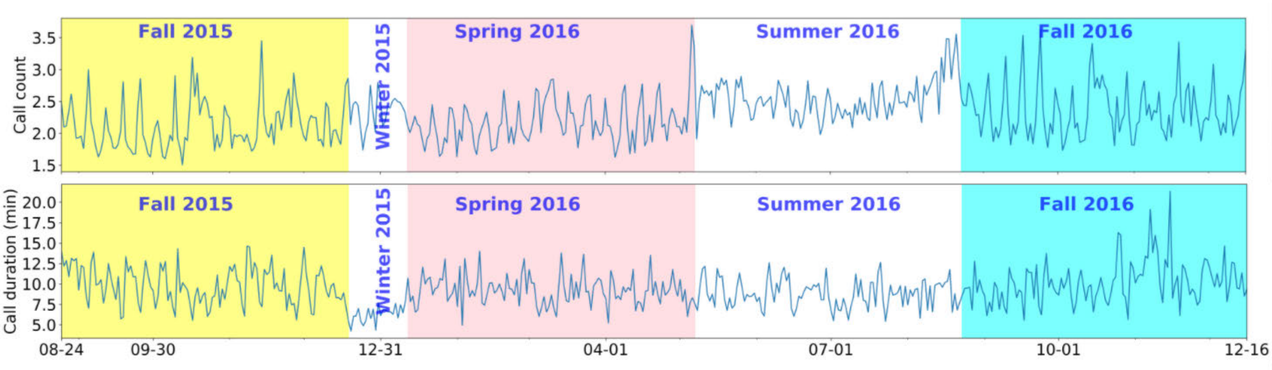


FIGURE 1. Time series of day-level average phone call count (top) and duration (bottom) during the study.

times of a semester. Knowing these precise patterns can help us develop predictive models to estimate future changes in phone call behaviors. Eventually, findings from this work will help develop automated digital tools or interventions that can be delivered during times of need to improve college students' physical and mental health as well as their academic success during early college life with or without the presence of an emergency, such as pandemic and its associated long-lasting lockdown that disrupts regular academic schedule and student life.

II. DATA COLLECTION AND METHODS

In this paper, we intend to demonstrate the links between phone call patterns and various temporal and geographical contexts of a cohort of on-campus freshmen. Before we describe the detailed analysis, we first introduce some phone call related terminology, and then we introduce the dataset and methods used in this work.

A. PRELIMINARIES AND DEFINITIONS

We primarily use two communication measures, namely "call count" and "call duration" to assess students' communication behaviors. They are defined as below:

- *Average call duration*, i.e., call duration per person in a unit time (e.g., in a day) is computed as:

$$D^j = \frac{\sum_{i=1}^{n^j} d_i^j}{n^j} \tag{1}$$

where d_i^j is the call duration of i^{th} person in the j^{th} day, n^j is the number of active person in the j^{th} day, and D^j is the call duration per person in the j^{th} day. Finally, the call duration per person per day is the average of per person call duration obtained from all days.

- *Average call count*, i.e., call count per person in a unit time (e.g., in a day) is computed as:

$$C^j = \frac{\sum_{i=1}^{n^j} c_i^j}{n^j} \tag{2}$$

where c_i^j is the call count of i^{th} person in the j^{th} day, n^j is the number of active person in the j^{th} day, and C^j is the call count per person in the j^{th} day. Finally, the call count per person per day is the average of per person call count obtained from all days.

Additionally, we use different terminologies defined as below:

- *Places of interest* (POIs) are the places where people either spend a significant amount of their day or visit frequently [33], [38], [39]. For example, for an on-campus freshmen cohort, POIs can be dormitories (DM), classrooms/buildings (CL), dining halls and other food courts (DI), athletic facilities (AL), as well as other indoor (OI) and outdoor places (OD) [40].
- To better understand temporal patterns of communication behaviors, we split entire days into four major *epochs*: *morning* (8 am – 12 pm or 8 – 12 in 24-hour clock), *afternoon* (12 pm – 6 pm or 12 – 18 in 24-hour clock), *evening* (6 pm – 12 am or 18 – 24 in 24-hour clock), and *night* (0 – 7 am or 0 – 7 in 24-hour clock) epochs [3], [29]–[31].
- Our dataset consists of three semesters, i.e., *Fall 2015* (F15), *Spring 2016* (S16), and *Fall 2016* (F16), as presented in Figure 1. Each semester is further segmented into different parts: *regular class* time (RgC), *mid-term* breaks (MdB), *short-term* breaks, such as Thanksgiving or Easter breaks (ScB), and *long-term* breaks, such as Winter and Summer breaks (LoB) [41].
- A phone call is considered to be *around* the University of Notre Dame if the student stays within 1500 meters from the center of the university (*latitude* = 41.700165 and *longitude* = −86.235113) during the call; otherwise, the call is considered to be *far away* from the campus [42]. If more than 50% of the phone calls of a user are marked as *around* the campus during a time period, then the user's stay for that period is considered as *around* the campus; otherwise, the stay is considered as *far away*.
- *Game Saturdays* are the Saturdays in Fall semesters (i.e., F15 and F16 in our case) when the University of Notre Dame has home games [43], [44]. Other Saturdays in Fall semesters are considered as *non-game Saturdays*.

B. NETHEALTH STUDY DATASET

The *NetHealth* mobile crowdsensing (MCS) study [33], [34], [38], [40], [45]–[57] began at the University of Notre Dame in 2015 with over 400 on-campus freshmen (average age of 17 years and 11 months with a standard deviation of 11 months) to investigate the impacts of "always-on connectivity" on the health habits, emotional wellness, and social ties of college students over multiple semesters. All procedures were fully approved by Notre Dame's Institutional Review Board (IRB) before distribution. Students were recruited using both e-mail and Facebook invites and were instructed to continuously wear a Fitbit Charge HR device that was provided to them. Further, they were given a data collection app for their iPhones. Both the Fitbit and smartphone app collected data for 24 hours a day.

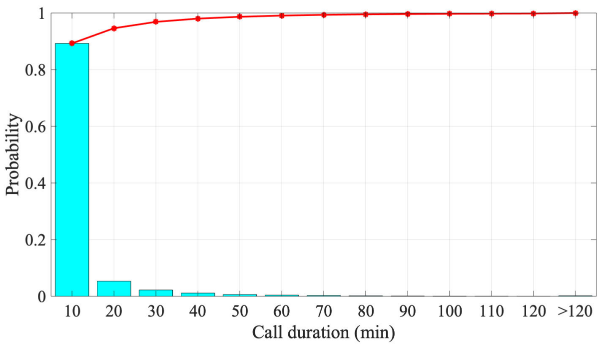


FIGURE 2. PDF and CDF of average call duration (in minutes).

The data collected by the smartphone app includes identifiers of the device's network connections (Wi-Fi, cellular), device state (e.g., battery charge level), screen state, geographic location, and user communications (e.g., phone calls). While some sensor data, such as Wi-Fi and cellular are recorded at a fixed sampling frequency, some data, such as the phone call, battery charge level, and screen state, are recorded using a callback mechanism. Location data are recorded with a period of 165s and are represented as series of location points. Each location point is defined as a tuple $\{\lambda, \vartheta, T\}$ [58], where λ and ϑ are the *latitude* and *longitude* of the lp, and T is the timestamp when the location was recorded. While most sensor data are transmitted to a remote server during a nightly upload, some data, such as communication data (phone calls, texts, etc.) and statistics, are transmitted via a desktop client. In this work, we use location data and phone call data that come with the time of call start, duration (measured in seconds), flags to check whether the call is answered and originated/received, and phone number on the other end. Figure 2 presents the probability density function (PDF) and cumulative distribution function (CDF) of phone call duration. In the figure, we observe that more than 99% of phone calls are shorter than an hour. Thereby, we exclude phone calls longer than an hour to drop the outliers since they might be incorrectly logged or they may represent extraneous incidents that do not resemble regular patterns that we are interested in investigating in this work. The data collected by the Fitbit device includes physical activity level, step count, heart rate, and calorie burn recorded at one sample in a minute granularity.

C. METHODS

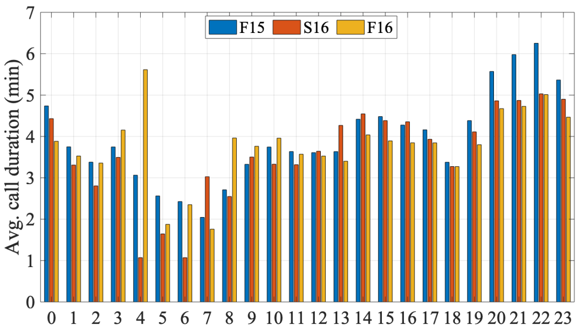
To assess students' communication behaviors (in terms of phone call duration and frequency, i.e., count in unit time), we first investigate various temporal and geographical patterns through different visualization techniques. Next, we determine statistical significance using the *One-way ANOVA* test and the *Two-Sample T-test*. Finally, we investigate communication patterns during social events, such as football matches and the association between phone call behaviors and physical activities measured in terms of step counts.

III. ANALYSIS

In this section, we first investigate students' communication patterns during various temporal contexts, such as parts of a semester, days of a week, and time of a day. We also investigate communication behaviors across different places, such dormitories, classrooms, dining halls and other food courts, athletic centers (sports ground, stadium, and gymnasiums), and other indoor/outdoor places. Next, we analyze the communication patterns across different combinations of temporal and geographical contexts. Additionally, we investigate college students' communication behaviors during social events, such as football games, as well as their association with physical activities. While investigating various geo-temporal patterns of communication behaviors, we first use different visualization techniques, followed by statistical significance tests. While performing the *One-way ANOVA* and *Two-Sample T-test* in the following sections, we present actual $p-values$ as well as a significance level representation using three levels of α, i.e., $p < .001$ (marked as "***"), $p < .01$ (marked as "**"), $p < .05$ (marked as "*"), and $p > .05$ (marked as ".") as per the APA guidelines [59].

A. HOURS AND EPOCHS OF A DAY

In this section, we first investigate students' communication patterns (both in terms of call duration and call frequency, i.e., number of calls in unit time) during the hours of the day. In Figure 3a, we observe that average call duration (calculated using Equation 1) drops to the lowest point at 6 am and gradually increases until 6 pm (i.e., 18 in the 24-hour clock as presented in the figure), which represents an active part of students' daily schedule full of classes and other activities. This gradual drop in average call duration at 18 can be representing dinner time. After 6 pm, call duration starts increasing until 10 pm (i.e., 22 in the 24-hour clock system) before it begins gradually dropping to the lowest point at 6 am. This can be explained by late evening communication, followed by sleep time. In Figure 3b, we observe that call count goes up as the day progresses, starting from 4 am to 6 pm (i.e., 18 in the 24-hour clock system in the figure), and after that, it starts



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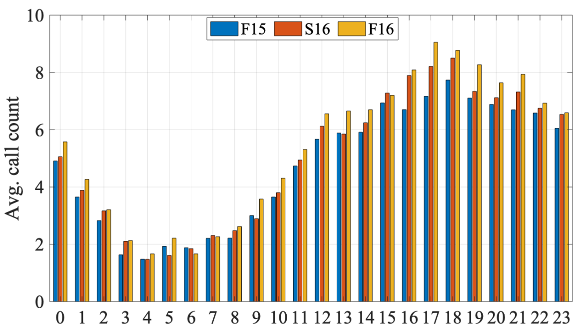
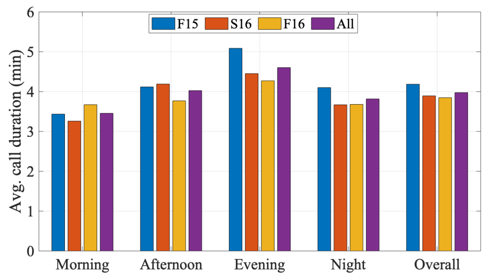


(b)

FIGURE 3. Bar graphs of average (a) call duration (min) and (b) call count during 24 hours of a day.



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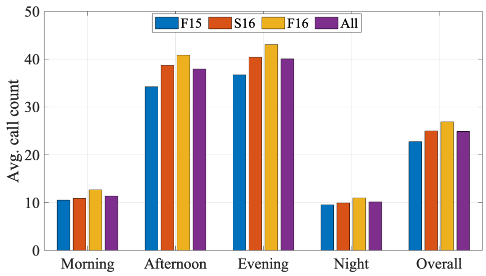


(b)

FIGURE 4. Bar graphs of average (a) call duration (min) and (b) call count during different epochs of a day.

to drop until 4 am, which can be indicating sleep time. Most interestingly, we observe that at 6 pm (18 in the 24-hour clock system in the figures), students make shorter (Figure 3a) but more frequent (Figure 3b) calls. While we observe an increasing trend in average phone call duration from 6 pm to 10 pm (Figure 3a), we observe an opposite direction in call frequency (i.e., call count). This increased call duration and decreased call frequencies could be representing the fact that the freshmen cohort might be communicating with their families and maybe school friends during this period before they go to bed, or they may be exploring new friendships. Such a social engagement is crucial and can play a positive role in the mental health and academic success of a student population who leave their school friends and families to start a new phase of on-campus college life.

Next, we investigate students' communication patterns across the four epochs, namely *morning*, *afternoon*, *evening*, and *night* epochs, of a day as defined in Section II-A. In Figure 4, overall bars are representing an average of four epochs of a day. In the figure, we observe that both the average call duration and call count is higher during the evening epoch compared to other epochs. To determine the statistical significance of our findings, we perform the *One-way ANOVA* tests with the null hypothesis: "the average call duration during different epochs of a day in a semester is the same." We reject the null hypothesis with $F = 160.28$ & p-value $= 1.08e-103$, while comparing call duration of the four epochs of a day considering all three semesters together. Therefore, the average call duration during different epochs of a day is significantly different while considering all three semesters together. Additionally, we perform the *One-way ANOVA* test for each semester, we find that $F = 93.69$ & p-value $= 2.03e-60$ (Fall 2015), $F = 46.61$ & p-value $= 4.61e-30$ (Spring 2016), and $F = 33.42$ & p-value $= 1.46e-21$ (Fall 2016). Therefore, the average call duration during different epochs are significantly different while considering each semester separately. Next, to compare the average call duration during different epochs, we perform a *Two-Sample T-test* with $H_0 : \mu_i = \mu_j$, where μ_i and μ_j represents the average call duration two separate epochs. We find that in Fall 2015 average call duration during all pairs of epochs, except *afternoon* and *night*, are significantly different. In Spring 2016, average call duration between all pairs of epochs are significantly different. However, in Fall 2016, average call duration during the *evening* epoch is significantly different from other epochs. While comparing average call frequency (i.e., call count per person per day), we observe that *afternoon* and *evening* epochs have very high call frequencies compared to the other two epochs, which can be explained by the fact that freshmen have most of their classes in the morning at the University of Notre Dame. So, *afternoon* and *evening* are the two active epochs for social activities for this cohort of subjects.

B. DAYS OF A WEEK

In this section, we investigate students' communication patterns during the seven days of a week. In Figure 5, bars are denoting average call duration (min) and count (calculated using Equations 1 and 2). Overall, bars are representing an average of seven days of a semester. In Figure 5a,

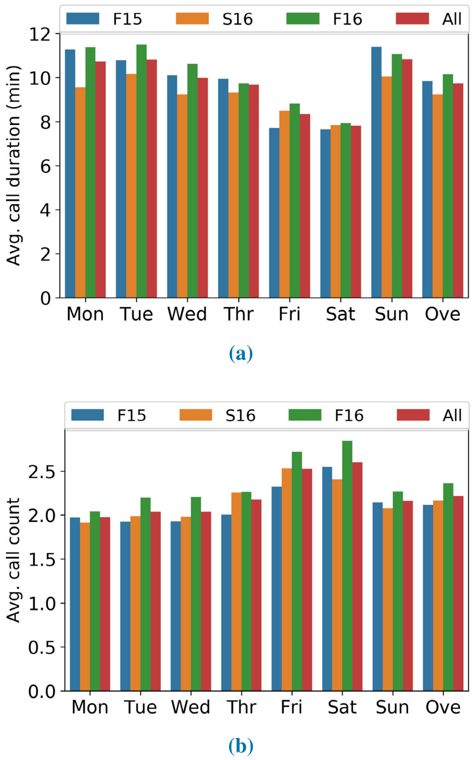


FIGURE 5. Bar graphs of average (a) call duration (min) and (b) call count during seven days of a week ("Ove" stands for overall).

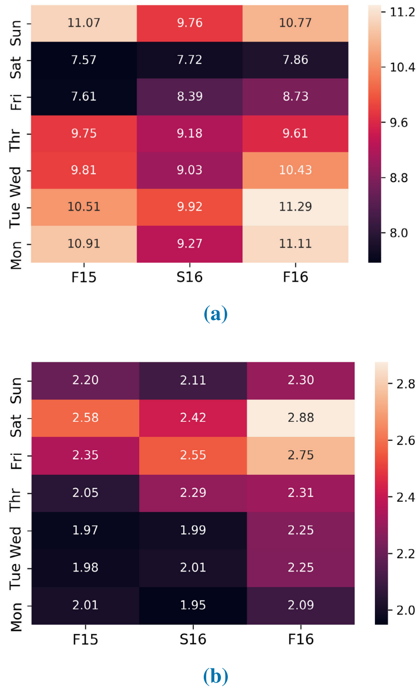


FIGURE 6. Heat maps of average (a) call duration (min) and (b) call count during seven days of a week.

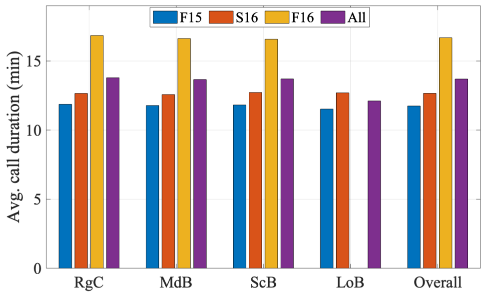
we observe that phone call duration (min) decreases from Monday/Tuesday to Saturday. The call duration again goes up on Sunday. However, in Figure 5b, we observe different patterns while checking call count during the seven days. The phone call count indicates an increasing trend from Monday to Saturday until it drops on Sunday. Therefore, based on our dataset, students are taking longer and less frequent calls on Sundays and Mondays, compared to shorter and more frequent calls from Tuesday-Saturday.

We further investigate communication patterns across seven days of a week using the heat maps. In Figure 6a, we observe that Sunday-Tuesday has the highest intensity shades. This shows that students make longer calls on Sunday compared to other days in a week, in general. But, in Figure 6b, we observe that Friday and Saturday have the highest intensity shades, which indicates that students make frequent calls on those days. It is possible that many students call their families and friends on Sunday-Tuesdays, which leads to more prolonged but less frequent calls. However, on Fridays and Saturdays, many students from our freshmen cohort could be communicating with their new friends. Due to the nature of communication, they may make shorter and more frequent calls, e.g., to coordinate school-related activities or for socialization (e.g., arranging meetings with their peers).

To determine the significance of our findings, we first perform the *One-way ANOVA* tests with the null hypothesis: "the average call duration during different days of a week in a semester is the same." We reject the null hypothesis with $F = 18.48$ & p-value $= 1.33e - 18$, while comparing call duration from all three semesters. Therefore, the average call duration during different days in a week is significantly different. Next, we perform the *One-way ANOVA* test for each semester. We find that $F = 11.89$ & p-value $= 3.12e - 10$ (Fall 2015), $F = 3.91$ & p-value $= 0.001$ (Spring 2016), and $F = 5.61$ & p-value $= 4.16e - 05$ (Fall 2016). Therefore, in all cases, we reject the null hypothesis. So, the average call duration during seven days are significantly different. Next, to compare the average call duration between pairs of days in all semesters, we perform the *Two-Sample T-test*s with $H_0 : \mu_i = \mu_j$, where μ_i and μ_j represent the average call duration of two separate days. From the *T-test*, we find that average call duration during Fridays and Saturdays are significantly shorter than (a) any other days (Fall 15), (b) Mondays, Tuesdays, and Sundays (Spring 16), and (c) other days of the week except Thursdays (Fall 16). Additionally, (a) in Fall 15, Thursday average call duration is significantly shorter than Mondays and Sundays, (b) in Spring 16, average call duration Thursdays is significantly longer than Saturdays, and (c) in Fall 2016, Thursdays are significantly shorter than Mondays and Sundays.

C. PARTS OF A SEMESTER

In this section, we investigate students' communication patterns during different parts of a semester. In Figures 7a and Figure 7b, we present average call duration (min) and count, respectively (discussed in Section II-A) across the four major parts of a semester, where all bars represent the average of each part of the semesters. Overall bars are describing the



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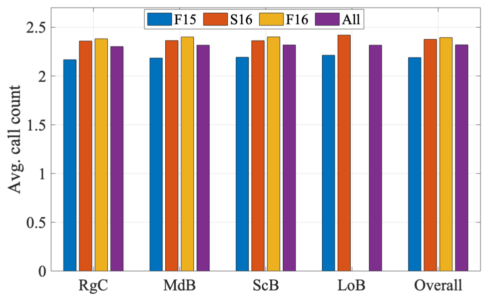
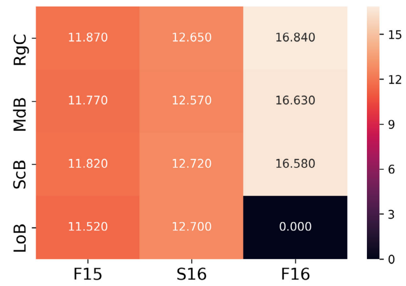
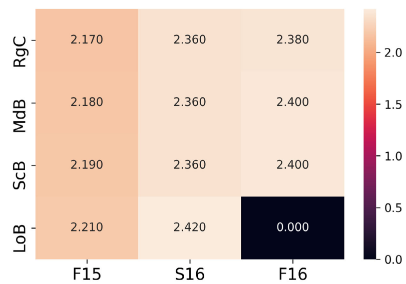


(b)

FIGURE 7. **Bar graphs of average (a) call duration (min) and (b) call count during different parts of a semester.**



(a)



(b)

FIGURE 8. **Heat maps of average (a) call duration (min) and (b) call count during different parts of a semester.**

average of all parts of each semester. In Figure 7, we observe an increasing trend in communication (both in terms of average call duration and call frequency) from Fall 2015 to Fall 2016. As the students get used to college life and make more friends on campus, their call duration might have raised. This increased social support can play a positive role in on-campus students' well-being and academic progress.

We further investigate the communication patterns using heat maps (Figure 8). In Figure 8a, we observe that average phone call duration across different parts of Fall 2016 longer than the other semesters. However, in Figure 8b, we do not find a noticeable difference between the three semesters. In Figure 8, the long break (LoB) is 0 since our study ends after Fall 2016, and it does not include Winter 2016.

Next, to compare the average call duration of different parts of a semester, we perform the *Two-Sample T-tests* with H_0 : $\mu_i = \mu_j$, where μ_i and μ_j represents the average call duration in two separate parts of a semester. We do not find any case to reject the null hypothesis. Therefore, the average call duration between two separate parts of a semester is not significantly different.

In Figure 9, we investigate how the students' behavioral attitude changes while sharing different types of data, such as location and phone call log data, during their presence in different temporal and geographical contexts. We find that 101 out of 464 students shared their communication data, but never shared their location data. This might happen due to their privacy concerns. However, some students share their location data in a restricted manner, e.g., they share during semester time, but not during breaks. The tendency to not share data during the breaks might happen if they do not

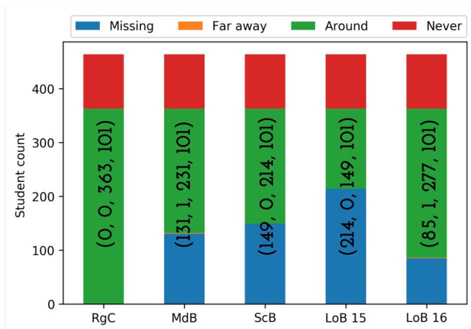


FIGURE 9. **Subject distribution during different parts of semesters. Numbers in the tuples representing counts across different categories.**

want to reveal where they go during breaks. If a student does not contribute location data during a specific time frame, we consider the student as a missing entry in terms of location. As defined in Section II-A, we also identify whether a student falls in one of the two categories, i.e., *around* or *far away* during a time frame. Thereby, we draw the stacked bars in Figure 9. In the figure, we do not observe any missing subject during regular class time (RgC); thereby, we find our on-campus students are willing/comfortable to share their location data while on-campus. However, situation changes over the breaks, i.e., mid-term breaks (MdB), short-term break (ScB) and long-term breaks (LoB – Winter break in 2015 and Summer break in 2016). As the number of missing count goes higher, this reflects students' sensitivity to share their location data during breaks, i.e., when they are *far away*; thereby, there is a high chance that the missing entries

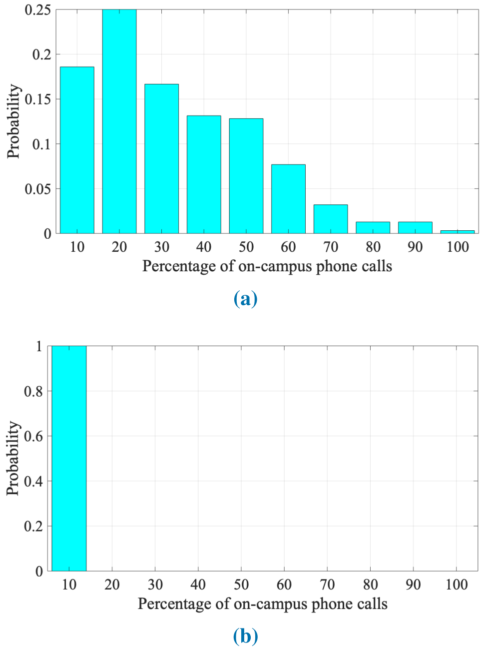


FIGURE 10. PDF of percentage of on-campus phone calls during (a) Spring 2016 and (b) Summer 2016.

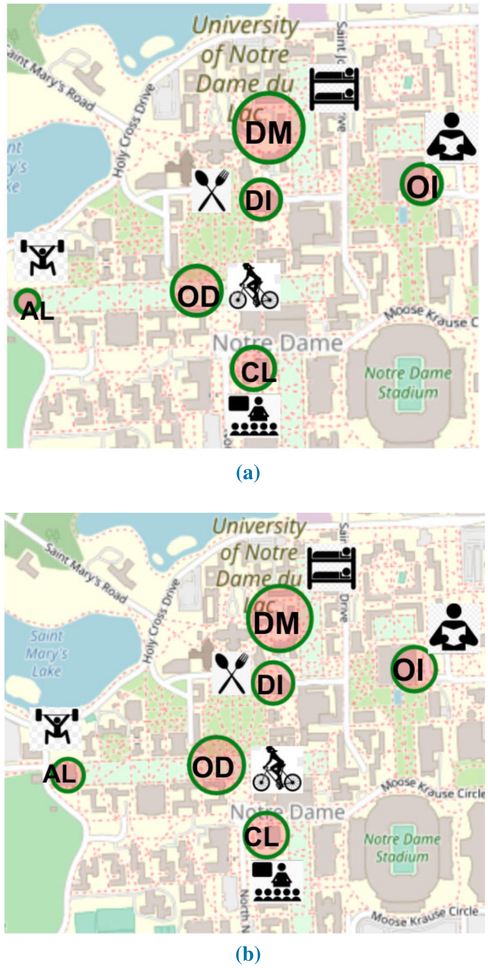


FIGURE 11. Bubble map of average (a) call duration and (b) call count across different on-campus *places of interest* (POIs).

could actually be *far away*, but we neither have location data nor any other modality to verify.

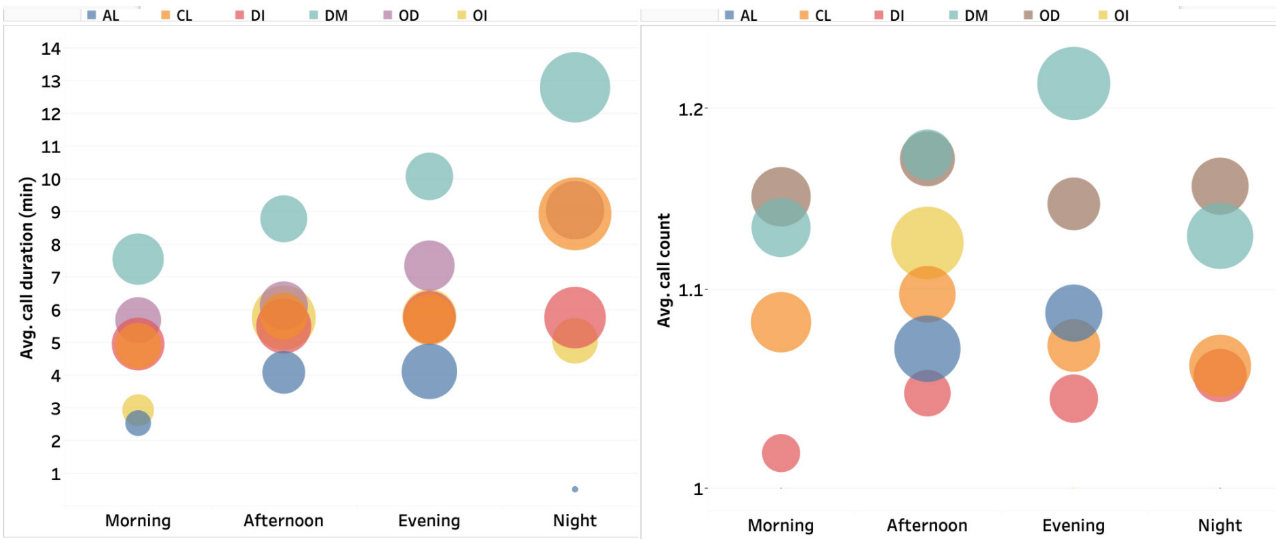
In Figure 9, Summer 2016 (LoB 16) looks a bit different than other breaks since it has fewer missing entries. One possible reason could be students stay on-campus after Spring 2016 ends or before Fall 2017 starts and share their location data during those days. Since in our *around* vs. *far away* identification, we check whether more than 50% phone call are around the university campus; thereby, if someone stays on-campus a few days out of the three months of Summer break and share his/her location data during that period, he/she can be marked/counted as *around*. To verify our assumption, we compute the percentage of on-campus phone calls that a student makes in a specific time frame, e.g., in Summer 2016 and Spring 2016. To calculate the ratio, we divide the number of on-campus phone calls by the number of days in Spring 2016 and Summer 2016, which are 102 and 106 days, respectively. Then we present our findings using the probability density function (PDF) in Figure 10. In the figure, we observe that in Summer 2016, all students fall in the 0 – 10% interval, compared to Spring 2016, where we follow a normal distribution. This finding strengthens our previous claim that students stay on-campus for a brief period and shares location data only for those short periods, i.e., they do not share location data when they are away from the campus.

D. GEOGRAPHICAL PATTERNS

In this section, we explore communication patterns that vary across different *places of interest* (POI)s. In Figure 11, DM, CL, DI, AL, OI, and OD stand for dormitories, classrooms, dining halls and other food courts, athletic centers (sports ground, stadium, and gymnasiums), other indoors, outdoors, respectively, the list on-campus POIs as described in Section II-A. The size of each bubble is representing the average call duration and count. In the figure, we observe that students call longer and frequently in the dormitories than any other places followed by outdoor locations since students make a fair amount of phone calls when they are commuting or doing something outside. While comparing the sizes of OD bubbles with other POIs both in those two figures, we observe that students make shorter but more frequent calls while in ODs. Athletics and dining areas are indicating the smallest bubbles compared to the other places. Students are less likely to communicate over phones when they are in one of these two on-campus POIs. In our analysis, libraries are also considered as classrooms. Students sometimes make phone calls when they are in libraries, and that leads to a noticeable phone call duration and count.

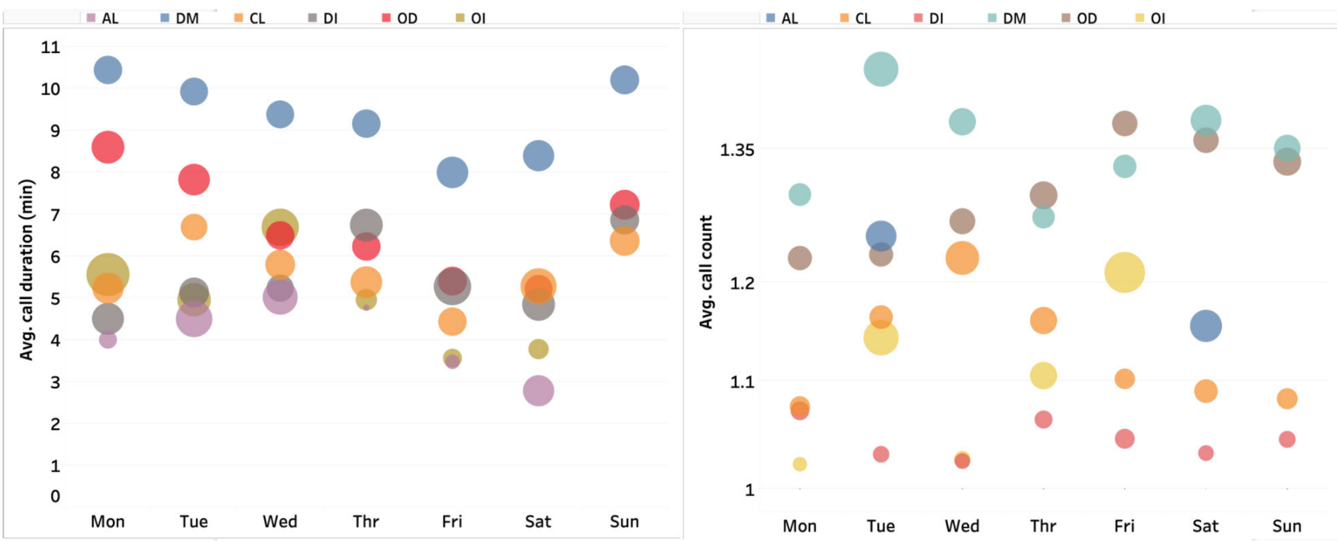
E. GEOGRAPHICAL AND TEMPORAL PATTERNS

In this section, we explore college students' commutation patterns that vary across different POIs during different temporal contexts (Section II-A). Call duration and count are



(a) (b)

FIGURE 12. Bubble charts of average (a) call duration (min) and (b) call count across different on-campus POIs during different epochs of a day.



(a) (b)

FIGURE 13. Bubble charts of average (a) call duration (min) and (b) call count across different on-campus POIs during different days of a week.

computed using Equations 1 and 2. In Figures 12, 13, and 14, we use bubble charts to present geo-temporal context-varying phone call patterns. In the figures, the y-coordinate of bubble-centers are average call duration or count, and radii of bubbles are the standard deviation of call duration or call count. We present our geo-temporal analysis in three steps based on the types of temporal context/factors. First, we analyze phone-call patterns that vary across different POIs and epochs of a day, such as a morning, afternoon, evening, and night. Second, we analyze the call patterns across different POIs and the days of the week. Lastly, we analyze phone-call patterns across different POIs and parts of a semester.

In Figure 12a, we observe that most students make longer and frequent phone calls in dormitories independent of the four epochs in a day. The result is very intuitive since students spend a significant part of their day in dormitories. In the evening, the second-longest call duration is from outdoor POIs (ODs). We observe that during the night, the average call duration becomes the longest. The outdoor POIs (ODs) are always the second dominant group in terms of both average call duration and count, and we observe a steady pattern across all epochs of a day. In Figure 12b, we observe that the highest average call count is in evenings and at dormitories (DMs). Furthermore, students make shorter and more frequent calls in the evenings while making longer

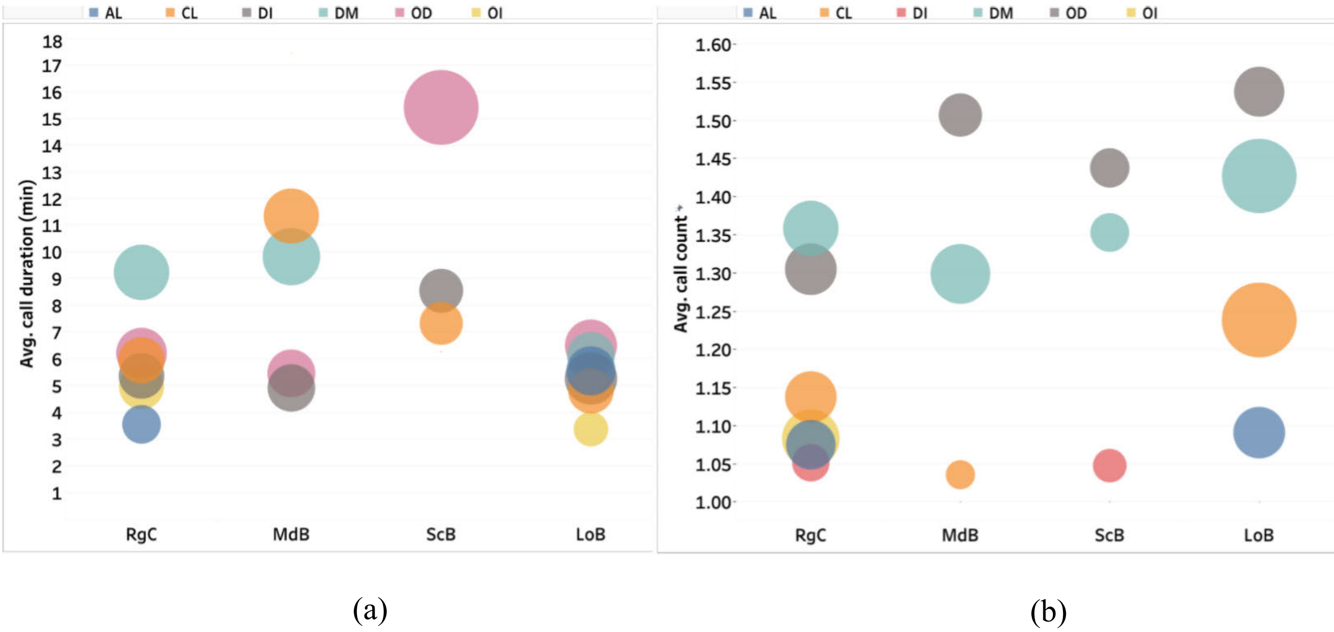


FIGURE 14. Bubble charts of average (a) call duration (min) and (b) call count across different on-campus POIs during different parts of a semester.

and less regular calls at night, particularly in dormitories. Additionally, the standard deviation is higher at night, which shows that call duration varies significantly across individuals during this epoch.

In Figure 13, we obverse that dormitories are the dominating POIs considering both call duration and count across the seven days of a week. In Figure 13a, we observe that the average call duration at dormitories is significantly higher than the average call duration in any other POIs. Outdoor POIs (ODs) are the next dominating POI in terms of average call duration. Call duration in athletic POIs (ALs) is very low across all days of a week with very high standard deviations. Other indoor POIs (OIs) reach the highest on Sundays because OIs include the university churches, where the main mass is held on Sundays.

In Figure 14, we analyze communication patterns across different on-campus POIs during various parts of a semester. In Figure 14a, we observe the highest average and standard deviation of call duration during *short-term* breaks (Thanksgiving and Easter) in outdoor POIs (ODs). A possible scenario can be a group of freshmen staying on-campus during the *short-term* break may talk to their families and/or friends with widely varying call duration. In Figure 14b, call counts in outdoor POIs (ODs) reaches the highest average value during the breaks, including *long-term* breaks (LoB) (Winter 2015 and Summer 2016), *short-term* breaks (ScB) (Thanksgiving 2015 and 2016 as well as Easter 2016), and *mid-term* breaks (MdB). These findings reflect the general trend for outdoor phone calls among students.

F. SOCIAL EVENTS

Historically, football is a major social event at the University of Notre Dame. During football season (i.e., Fall semesters), the university takes a festive look as alumni come to campus to celebrate home-game Saturdays. In this section, we analyze students' phone call patterns during the *home-game* (referred as *game*) Saturdays versus non-home game (referred as *non-game*) Saturdays. Our study covers two football seasons, i.e., Fall 2015 and Fall 2016 [43]. In Figures 15a and 15b, we notice a similar pattern in Fall 2015 and Fall 2016, where the call duration is shorter, but call counts are higher during the *game* Saturdays, compared to the *non-game* Saturdays. If a game is on campus, the students, especially freshmen, spontaneously attend the game.

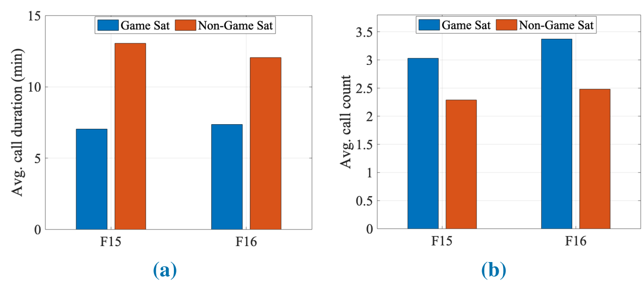


FIGURE 15. Bar graphs of average (a) call duration (min) and (b) call count during *game saturdays* and *non-game saturdays*.

We compare the average call duration during *game* and *non-game* Saturdays in Fall 2015 and Fall 2016 using the *Two-Sample T-tests* with $H_0 : \mu_i = \mu_j$, where μ_i and μ_j represent the average call duration *game* and *non-game* Saturdays in one Fall semester. In Table 1, we present our findings from the *T-tests*. In the table, we find that Fall 2015 *game* Saturdays are significantly different compared to Fall 2016. While investigating further, we find that the Fall 2015 season was promising for the University of Notre Dame, compared

TABLE 1. The *Two-Sample T-test* summary of phone call duration (in minutes) during game and non-game saturdays.

Seme- -ster	Avg. call duration		$t-$ $stat.$	df	signi- ficance
	game Sat	non-game Sat			
Fall 15	7.04	13.06	-3.13	10	*
Fall 16	7.37	12.06	-2.08	10	.

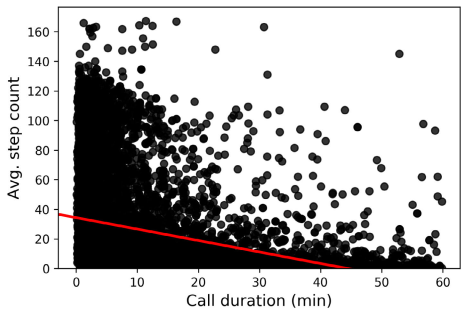


FIGURE 16. Scatter plot of call duration (min) vs. average step count.

to Fall 2016. In Fall 2015, the university football team won around 84% of their matches, but in Fall 2016, they won only approximately 33% matches [60], [61]. This could have led to a lot of excitements among the freshmen cohort we analyzed in this work, and that may lead to our findings from the *T-tests*.

G. PHONE CALL DURATION VS. STEP COUNT

In this section, we perform correlation analysis to determine whether there exists an association between phone call duration (min) and minute-level average step counts. In Figure 16, we observe that with the increase of call duration, step count drops, i.e., students move less when they talk for a more extended period. From the statistical test, we obtain a linear correlation (also known as the Pearson correlation coefficient) of -0.29, with $p < 0.001$, which is statistically significant. Therefore, phone call duration and step counts are negatively correlated. That is when students are on longer calls, they are not walking as much as they are in shorter calls. This analysis can lead to design and delivery of health interventions, e.g., when a student talks longer, they may be advised to walk.

IV. DISCUSSION AND FUTURE WORK

To the best of our knowledge, this is the first work that investigates the change of phone call patterns (in terms of call duration and frequency/count) specifically targeting first-year college students through analysis of objective data from smartphones and Fitbits collected over 18 months, which include three consecutive semesters. In our analysis, we find that on Sundays and Mondays, students make longer and less frequent calls compared to the other days when the students make shorter and more frequent calls. Similarly, we find that students make longer and less frequent calls during evening epochs compared to the afternoon epochs when the students make shorter and more frequent calls. In general, students make frequent calls in dormitories and outdoor places; however, calls in dormitories are longer, and outdoor calls are shorter. We also find that students make shorter, but frequent calls during *game* Saturdays compared to *non-game* Saturdays, i.e., communication patterns vary across social events. Finally, we find a statistically significant negative correlation of -0.29 between step counts and phone call duration, i.e., long calls are more or less sedentary.

This work has some limitations, which we plan to address in the future. First, our analysis do not consider the individual difference. However, this may not be feasibly applicable to every student and also not representative of the total student population. In the future, we hope to find a more useful and practical model to help students to adopt a new life on campus. Second, some students' primary method of communication might not be by regular phone. They could use applications such as text app or video calls app to communicate with others, which we do not take into consideration for this study.

In the future, we will extend our study to analyze more on location data with the help of Google API to investigate off-campus geographic patterns in addition to on-campus patterns, as well as weather varying patterns. Associating activity and geographic information with temporal information will further provide a better insight into students' phone call patterns to design and deliver different mobile health interventions using predictive machine learning modeling techniques to improve students' physical and mental health as well as to succeed academically during early college life with or without the presence of an emergency, such as the outbreak of a pandemic and associated long-lasting lockdown.

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