Analysis of Peer Group Behavior Among University Students

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Abstract
Satisfactory peer group interactions within a university, through the formation of close associations, define a student's personality and help in deterring the rise of depression caused by academic, financial or emotional troubles. In this work, we conduct a pre-study survey of 177 students in a University setting to assess the requirement for a smartphone-based study to detect and monitor group formation, evolution and engagement. The preliminary results from this investigation reveal that students' social interactions are not limited to one but several groups, and the satisfaction levels associated with each type of group are indicative of the average time spent engaging with said group(s). Intra-group bond strength took precedence as a satisfaction determinant over the location or activity engaged in. Further, we present design recommendations for a minimally invasive smartphone-based study.

Author Keywords
Social Computing; Smartphone Sensing; Group Behavior; Contextual Inquiry; Empirical Study; Mental Health

ACM Classification Keywords
H.5.m [Information interfaces and presentation (e.g., HCI)]: Miscellaneous; H.1.2 [Models and Principles]: User/Machine Systems; J.4 [Social and Behavioral Sciences]: Psychology; K.4.m [Computers and Society]: Miscellaneous

Introduction

Understanding students' interactions and their emotional impact within peer groups is crucial to assess their overall mental state. Consider a residential university where academic performance is based on attendance, graded assignments and term examinations. Students study, eat and live within the confines of the campus and have interactions with a limited set of people. While previous work such as [10] have focused on the academic impact of the various social interactions in a student's life, we aim to discern the satisfaction levels students associate with different social activities they participate in with different peer groups.

In this work we conduct a formal contextual survey of the underlying group parameters (size, purpose, time spent on average etc.) on 177 students within a fully-residential university. The survey was primarily designed to investigate whether there exists a reasonable degree of variation in patterns of group formation, evolution and engagement across different groups. Further, we wished to characterize the behavior within these groups with satisfaction quotients, evaluate the preconditions of developing such a survey as an unobtrusive smartphone sensor-based assessment platform, and articulate the design challenges that one might face while deploying such a system. Through this work, we lay the groundwork and reasoning behind constructing a system in the future that obtains and analyzes peer engagement data to gauge indicators of mental distress and reports alarming data to expert stakeholders (such as counselors, psychiatrists and campus administration) that could provide intervention.

Through this work, we aim to make the following key contributions:

- We undertake a pre-study survey of 177 students within a fully residential university using accepted contextual inquiry methods to understand factors that influence group satisfaction.
- We present insights into qualitative aspects of group behavior that may aid university counselors in diagnosing mental well-being relating to peer-rejection and unsatisfactory social interactions in a residential campus.
- We make the case for a smartphone-based sensing study for peer interaction analysis and provide design recommendations for StuGru – a platform for group-detection and monitoring, augmented by utilizing event-triggered Ecological Momentary Assessments (EMAs).

In the following sections, we describe the related work, pre-study survey methodology and insights, and design recommendations for StuGru.

Related Work

Measuring Mental Health

The recent revival of interest in the importance of mental well-being, particularly among communities with larger percentages of millennials, has led to significant breakthroughs in research that aims to gauge individuals' mental health and provide timely interventions. Rabbi et al. [6] discuss the feasibility of simultaneous assessment of both mental and physical well-being through smartphone sensors. Works such as [2, 4] present unobtrusive methods for monitoring physiological and psychological data streams to observe the correlation between mental health markers and physical activity. While the aforementioned work is focused on the derivation of accurate individual mental health parameters and their correlation with physiological activity, there is a pronounced dearth of investigation of mental states resulting from human interactions, except perhaps for measuring speech engagement influences.

Survey Demographics:
34% Female, 66% Male
86% Undergraduates, 14% Graduates
Mean Age: 20, S.D: 3

Similarity Factor:
The MR_i is introduced to accommodate for the incidence of the scenario that some subsets of groups might be constituents of other groups as well. MR_i is defined as the average of group member similarity across all other preliminarily identified groups. The similarity factor between two preliminary groups is calculated by the total number of common members between the two groups employed over the summation of members within both the groups.

An alternative approach being adopted to identify markers of mood instability or mental illnesses is through the analysis of social media signatures of individuals. Choudhury et al. in [3] and Saha et al. in [7] work towards identifying markers of mental instability and suicidal ideation among social communities on Reddit and Twitter. While the aforementioned approaches work towards incorporating social interactions into this investigation, we hope to motivate the CHI community to look further beyond the individual while assessing and quantifying psychological states.

Behavior Analyses of Students in Educational Institutions
Factors such as peer pressure, academic overload and prevalence of loneliness among students have motivated research on students' day-to-day routines, stress levels, academic performance and responses to stressful situations [9, 10]. Bagroy et al. in [1] develop a campus specific Mental Well-being Index (MWI) based on 100 campus-based Reddit communities. The findings correlated various characteristics of universities with the students' MWI, including temporal changes of mental health discussions in sync with academic timelines and lower expressions of mental instability linked with students from institutions of higher prestige among others. Through our work, we intend to bring attention to more aspects of student life within universities by analyzing emotive factors within student groups.

Survey
In this section, we detail pre-study survey design along with the methodology used for peer group determination.The survey was circulated to the entire student population of Shiv Nadar University, resulting in 193 participants with a completion rate of 92%. For the analysis of the data, we took into account the responses of the 177 students who completed the survey (see margin note).

For the purpose of the survey, the data collected was anonymized and each participant was assigned a $studentID$ when they enrolled for the study. The participants were asked to provide their age, gender, program of study and number of years spent in the university. For each student, we collect the following information: (a) number of groups a student is a part of, (b) type of each group, (c) group members, (d) activities that one engages in with each group, (e) satisfaction level with each group, (f) amount of time one spends engaging in one or many activities with the group(s), (g) issues of discussion among groups and (h) major contributing factors to overall group satisfaction.

Group Determination
In order to accurately identify the number of distinct groups that exist within the community of observed participant students, we introduce the member recurrence factor MR_i for every group i (see margin note). We classify a preliminary group as a *Settled Group* if $MR_i < 0.3$, i.e, we classify an interaction group as significantly different from another if less than 30% of the group's constituents are same.

Preliminary Results
In this section, we detail the findings from our survey involving 177 participants and 113 groups. These preliminary findings act as the foundation upon which we base our recommendations for an in-depth study, which are subsequently presented in the next section. In addition to quantifiable properties of peer groups that can be detected through minimal participant intervention, we also try to learn the motivating factors behind group interactions.

How many groups is one part of?
The average number of groups that a student reported being involved in was 3, with 68% of the participant population claiming to be part of 2-4 groups. Most of these groups

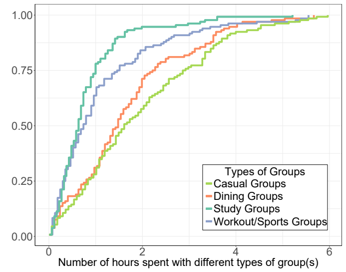

Figure 1: Cumulative Distribution Function of the number of hours spent amongst different types of groups

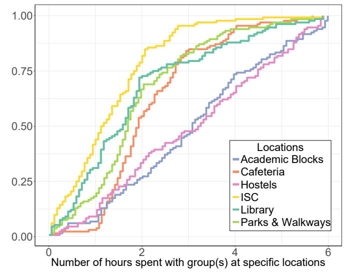

Figure 2: Cumulative Distribution Function of number of hours spent amongst groups at various locations

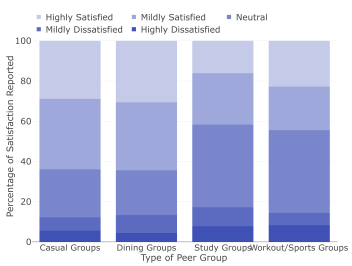

Figure 3: Reported satisfaction for interactions among various types of peer groups.

can be classified into one of the four categories – *Study Group(s)*, *Dining Group(s)*, *Workout/Sports Group(s)*, and *Casual Group(s)* – based on the group descriptions provided by respondents.

How do groups vary in size?
Based on our identification of groups (which has been described in the previous section), we observe the group sizes for each group type. Table 1 represents the variation in group size among the four different types of groups that participants reported to be a part of. 76% of the identified *Study Group(s)* consisted of 2-4 members, while only 1.48% of the identified *Study Group(s)* consisted of ≥ 10 members. Whereas in the case of *Dining Group(s)*, 42.11% of groups consist of 4-6 members and 31.58% consist of 2-4 members.

How is time divided between groups?
The time spent by students with each of their peer groups also tends to vary, as shown in Figure 1. However, it is to be noted that the distribution of time could depend on multiple factors such as time of the semester (just after the holidays v/s before examinations) or events taking place on campus.

Where do group interactions take place?
Figure 2 represents the amount of time spent by groups at various locations. A significantly high number of participants report that they spend the maximum amount of time with their peer groups in Hostels (29.82% of their time, on average). We posit that this engagement within hostels could be attributed to the unobtrusive environment and friendship with long term neighbors, which motivate student clusters to aggregate on a daily basis. We also observed that a significant amount of time is spent with peers in the Cafeteria, which accounts for 21.34%, on average, of their total time with peers.

	Group Size			
Group Type	*2-4*	*4-6*	*6-10*	*>10*
Study	76.3%	18.52%	3.7%	1.48%
Dining	31.58%	42.11%	23.31%	3.01%
Workout/Sports	68.25%	15.87%	11.11%	4.76%
Casual	27.13%	33.33%	33.33%	6.2%

Table 1: Average group sizes among different group types within the student community

How satisfactory are various types of group interactions?
We found significant differences in individuals' satisfaction with their interactions among different types of groups. As evident in Figure 3, while a large percentage of respondents are 'Highly' or 'Mildly Satisfied' with their *Casual* and *Dining Group(s)* (approximately 63% and 64% respectively), students reported a highly 'Neutral' response to *Study* and *Workout/Sports Group(s)* (41% in each category). We posit that this is due to the former two types of groups being formed largely by an individual's choice, while the latter are more circumstantial.

What influences group membership?
We began our qualitative inspection by inquiring about the factors that influence group membership within *Dining* or *Casual Group(s)*, as the formation of these groups is perspective-dependent, rather than being dependent on self-interest. When asked to rank the factors that motivate group membership from among *four* option – Activity of Interest (Dining, Strolling, Chatting, etc.), Location of Preference (Library, Hostels, Parks, etc.), Time of Availability (Evenings, weekends, etc.), and Constituent People (friends, partners) – a staggering 78% reported being most influenced by the constituent people.

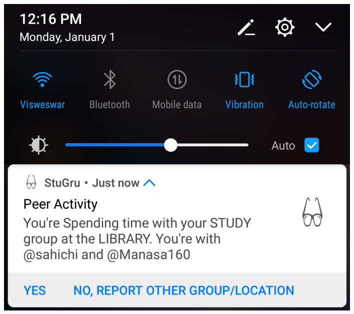

Figure 4: EMA to validate Peer Group members in proximity and Location

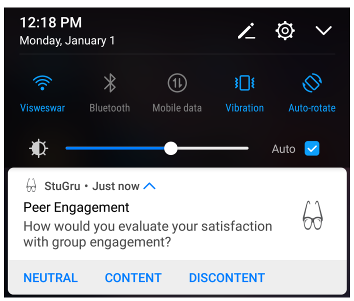

Figure 5: EMA notification with satisfaction survey

What issues do students discuss with peers?
Participant members were asked choose frequent topics of conversation within their groups from amongst Academic, Emotional and Financial matters. An unusually high fraction (54%) responded that they chose to discuss emotional issues while only 15% discussed both academic and emotional advice. Only a small section (5%) reported taking financial advice from their peers.

Study Recommendations

Based on the insights obtained from our survey, we now present the design recommendations for a long-term study on student peer-group interactions. The study will utilize an Android application, StuGru, to detect peer groups, monitor interactions and seek direct responses about students' satisfaction levels through EMAs.

Demographic Information
To examine the correlation of quantity and quality of interactions with the demographics of the group members, we plan to collect basic biographic information about each participant through an entry questionnaire. The data collected therein would include gender, age, program (undergraduate/graduate, the major a student is enrolled in etc.), number of years spent in the university, place of residence (since we plan to conduct the study in a fully residential university, this would entail recording the hostel block that a student lives in) and relationship status (single/in a relationship). These parameters would later help us evaluate the diversity of groups formed and examine if it is correlated to either the time spent with a group or the satisfaction perceived from engaging with its members.

Group Detection
To detect peer groups, we propose employing an adaptation of the state-of-the-art group detection algorithm presented in GruMon[8], and later validated by empirical evaluation in [5]. We propose the adoption of a hierarchical approach to the problem, and the use of BLE-based ranging as a reliable proxy for inter-person distance in less-denser spaces. Further, we recommend capturing the features for group detection through two state-dependent kernels, chosen by a binary motion classifier. The Stagnant State Kernel, employed when the subject is identified as stationary, captures location traces and determines BLE based proximity. The Locomotive State Kernel, used when the subject is mobile, utilizes the Level Change Detector and the Micro-activity Detector.

Contextual Inquiry
Taking inspiration from Wang et al. in StudentLife [10], we suggest adopting a contextual inquiry methodology for recording student perception in each particular group-related context (location, group type, aberrant event etc.) using EMAs. We categorize these EMAs into two types. The first are *Event-triggered assessments* (tEMAs), which are pushed to the student when a group event occurs. These group events could either be short-term (e.g. an extended group gathering) or long-term (e.g. switching primary groups, abhorring all groups). tEMAs can also be utilized to validate group detection and to enable closed-loop feedback for the underlying group classifier. The second type are *Polled assessments (pEMAs)*, which are designed to obtain a better understanding of notions that are not necessarily associated with a detected event. For example, queries of this kind include individuals' satisfaction with different types of groups, free-text responses to inquiry regarding issues discussed with peers etc.

It is intuitive that while contextual inquiry is made possible using EMAs, it can also be a source of incorrect context cognition. As a measure against such inaccuracy, we propose an EMA validity checker that automatically expires the EMA (auto-removed from upstream notification on the student's device), given that the group-context of the student has changed or 15 minutes have passed, whichever is earlier.

REFERENCES

1. Shrey Bagroy, Ponnurangam Kumaraguru, and Munmun De Choudhury. 2017. A Social Media Based Index of Mental Well-Being in College Campuses. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*. ACM, 1634–1646.
2. Dror Ben-Zeev, Emily A Scherer, Rui Wang, Haiyi Xie, and Andrew T Campbell. 2015. Next-generation psychiatric assessment: Using smartphone sensors to monitor behavior and mental health. *Psychiatric rehabilitation journal* 38, 3 (2015), 218.
3. Munmun De Choudhury, Emre Kiciman, Mark Dredze, Glen Coppersmith, and Mrinal Kumar. 2016. Discovering shifts to suicidal ideation from mental health content in social media. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*. ACM, 2098–2110.
4. Andrea Gaggioli, Giovanni Pioggia, Gennaro Tartarisco, Giovanni Baldus, Daniele Corda, Pietro Cipresso, and Giuseppe Riva. 2013. A mobile data collection platform for mental health research. *Personal and Ubiquitous Computing* 17, 2 (2013), 241–251.
5. Kasthuri Jayarajah, Youngki Lee, Archan Misra, and Rajesh Krishna Balan. 2015. Need Accurate User Behaviour?: Pay Attention to Groups!. In *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp '15)*. ACM, 855–866.
6. Mashfiqui Rabbi, Shahid Ali, Tanzeem Choudhury, and Ethan Berke. 2011. Passive and in-situ assessment of mental and physical well-being using mobile sensors. In *Proceedings of the 13th international conference on Ubiquitous computing*. ACM, 385–394.
7. Koustuv Saha, Larry Chan, Kaya De Barbaro, Gregory D Abowd, and Munmun De Choudhury. 2017. Inferring Mood Instability on Social Media by Leveraging Ecological Momentary Assessments. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 1, 3 (2017), 95.
8. Rijurekha Sen, Youngki Lee, Kasthuri Jayarajah, Archan Misra, and Rajesh Krishna Balan. 2014. GruMon: Fast and Accurate Group Monitoring for Heterogeneous Urban Spaces. In *Proceedings of the 12th ACM Conference on Embedded Network Sensor Systems (SenSys '14)*. ACM, 46–60.
9. Vincent WS Tseng, Michael Merrill, Franziska Wittleder, Saeed Abdullah, Min Hane Aung, and Tanzeem Choudhury. 2016. Assessing mental health issues on college campuses: preliminary findings from a pilot study. In *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct*. ACM, 1200–1208.
10. Rui Wang, Fanglin Chen, Zhenyu Chen, Tianxing Li, Gabriella Harari, Stefanie Tignor, Xia Zhou, Dror Ben-Zeev, and Andrew T Campbell. 2014. StudentLife: assessing mental health, academic performance and behavioral trends of college students using smartphones. In *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing*. ACM, 3–14.