SAD: Social Anxiety and Depression Monitoring System for College Students

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ABSTRACT
Mental health problems are highly prevalent and increasing in frequency and severity among the college student population. The upsurge in mobile and wearable wireless technologies capable of intense, longitudinal tracking of individuals, provide enormously valuable opportunities in mental health research to examine temporal patterns and dynamic interactions of key variables. In this paper, we present an integrative framework for social anxiety and depression (SAD) monitoring, two of the most common disorders in the college student population. We have developed a smartphone application and the supporting infrastructure to collect both passive sensor data and active event-driven data. This supports intense, longitudinal, dynamic tracking of anxious and depressed college students to evaluate how their emotions and social behaviors change in the college campus environment. The data will provide critical information about how student mental health problems are maintained and, ultimately, how student patterns on campus shift following treatment.

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Social anxiety; depression; smartphone sensing; mobile health; ecological momentary assessment;

ACM Classification Keywords
H.1.2 User/Machine Systems; I.5 Pattern Recognition; J.3 Life and Medical Sciences

INTRODUCTION
According to the American College Health Association, 27 percent of college students felt too depressed to function properly and 40 percent reported feeling overwhelming anxiety at least once in the preceding year. Beyond their high prevalence rates, social anxiety and depression also share common symptoms and underlying factors. In particular, a Major Depressive Episode is characterized by many symptoms that overlap with social anxiety, such as high negative emotionality, social withdrawal, and avoidance. At the core of each of these disorders are issues related to high negative emotionality, difficulty in exerting control over emotions, deviations from normal judgment and perception, and interpersonal dysfunction. Thus, research examining one disorder is likely to inform our knowledge of how to predict and treat the other [1]. At the same time, there are also key differences between social anxiety and depression; for instance, depression is characterized by a slowing of movement, known as motor retardation, that is not typical of social anxiety. Thus, the proposed integrative framework supports comprehensive monitoring of both social anxiety and depression.

The SAD framework and presented studies are specifically designed to measure indices related to social anxiety and depression. These studies are aimed at examining both between-person differences and within-person variability in separate samples composed of: (a) high- and low-socially anxious individuals (Social Anxiety "Live" Monitoring Study; SALMON); and (b) high- and low-depressed individuals (Depression Monitoring Study; DEMONS). In both studies, repeated assessments of emotion, cognition, and behavior, as well as reactions to social interactions, are administered via personal smart phones four times per day to allow for examination of temporal relationships between these variables and passively collected data (e.g., phone call and text frequency and duration, and location information). DEMONS also allows for dynamical modeling of self-reported mood/behavior and continuously measured physiological data (e.g., heart rate, skin temperature), collected passively via wristband sensor. Finally, inclusion of baseline laboratory measures of personality traits, automatic associations of oneself as anxious or depressed that are difficult to consciously control, self-reported experience of emotions, and actual response to stressors allows for examination of convergent validity between lab-based measures and data gathered from real-world settings.

The proposed micro-level research represents a true collaborative effort between clinical psychology and engineering, and affords the rare opportunity to study mental health behavior and outcomes outside of laboratory and traditional clinical settings (e.g., hospitals, mental health centers). The ability to unobtrusively monitor and model real-time fluctuations in emotions, cognitions, and behaviors in peoples natural settings is crucial to efforts by researchers and clinicians who hope to optimize prediction, as well as provide *in situ* treatment, of social anxiety and depression in college settings.

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We make the following contributions in this study. First, to the best of our knowledge, we are the first team to propose an integrated framework for the monitoring of social anxiety and depression, by examining the temporal links between social interaction and mood. Second, we propose two innovative study designs based upon participatory and event-driven opportunistic sensing. Our event-driven data collection methods can gather information related to social anxiety and depression while minimizing the human efforts of self-reporting, thereby allowing us to ultimately increase treatment effectiveness.

RELATED WORK

Traditionally, psychological research on factors related to anxiety and depression has relied on laboratory-based methods, thereby limiting the ecological validity of findings. Recent work using ecological momentary assessment (EMA) has been used to investigate socially anxious individuals' reactions to positive experiences and their ability to differentiate emotions; finding important differences in the social-emotional daily lives of anxious individuals, and demonstrating the feasibility of this methodology to investigate social interaction and emotion regulation in the context of psychopathology [2, 3]. However, these studies relied on repeated sampling at discrete time intervals on a palmtop PC and did not leverage mobile sensing.

Thanks to unparalleled technological advances in recent decades, it is now possible to monitor how emotional, cognitive, and behavioral systems unfold and interact in peoples natural settings, using personal smartphones and wearable sensors [4, 5, 6, 7, 8]. Deploying these systems in the wild and collecting real-time data is challenging but has great promise [9].

There are basically two sensing paradigms in such systems [10]: participatory sensing and opportunistic sensing. In participatory sensing, participants are required to contribute sensory information periodically (e.g., input their mood every two hours). In opportunistic sensing, participants contribute sensory information when a certain event occurs as determined by the sensing system (e.g., input their mood after a communication is sensed). These two sensing paradigms can help to determine the trade-off between the quality of collected sensory information (e.g., accuracy, completeness, and timeliness of data), and the cost of sensory information collection (e.g., human effort/interactions, energy consumption). Participatory sensing with higher frequency (e.g., GPS location per 30 seconds vs. per 5 minutes) provides higher quality sensory information but consumes more energy in battery or human efforts and can lack context. While opportunistic sensing via some specific events (e.g., connections to low-power communication) can help to reduce energy consumption or lower the human efforts, it may limit data quality. Real-world studies are forced to make trade-offs between these design paradigms [4, 5, 6, 7, 8].

The StudentLife continuous sensing app [5] monitored students in a smartphone programming class over the course of the semester and identified strong correlations between sensing data and PHQ-9 measures. Another study uses an app called Purple Robot to detect location, movement, phone usage and other activities to assess a user's likelihood of depression [4]. Movement trajectories sensed from smartphones also have a demonstrated correlation with the PHQ-8 depression test [6].

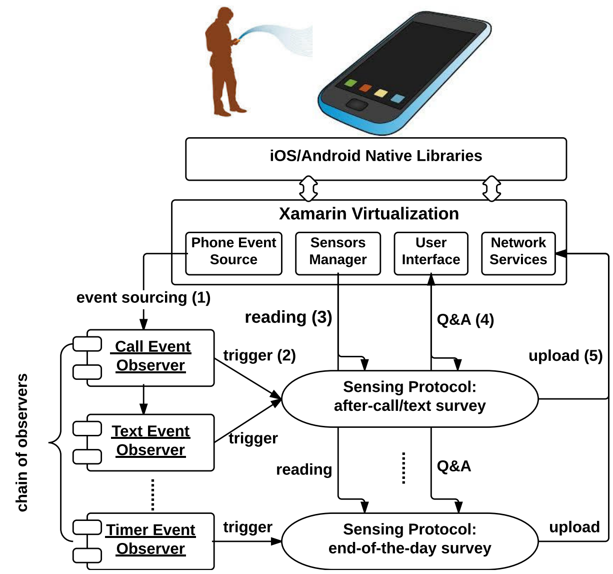

Figure 1. SAD Framework Design

Each of these studies [4, 5, 6, 7, 8] identified feature sets that correlate with individual mental health status from the unstructured/semi-structured [11] mobile data (e.g., trajectories of GPS locations). These studies first (pre-)assessed the mental health status of participants using psychological tests, such as PHQ-9, then collected data using smartphones. Further, these studies correlated the mobile data with the assessed mental health status (e.g., PHQ-9 scores) through extracting heuristic features (e.g., entropy of trajectories) and the features with the highest correlations were considered as the metrics to assess the mental health status. While some of these studies leveraged opportunistic sensing [4, 5], the primary reason was energy consumption and not for the collection of context-driven information.

Compared to the existing work in mental health monitoring [4, 5, 6, 7, 8], SAD is distinct in two ways. First, our work is the first to propose an integrated framework for monitoring of social anxiety and depression exploiting the temporal link between social interactions and mood. Second, our framework is centered upon both event-driven opportunistic sensing as well as limited participatory sensing data to capture information that can characterize social anxiety and depression as a function of social interactions. The event-driven opportunistic sensing protocols are driven by capturing data as social interactions occur.

SAD MONITORING FRAMEWORK

In this section, we introduce the SAD monitoring framework and describe each of the key components. Then, we describe the SALMON and DEMONS studies.

As shown in Figure , the design of the SAD framework follows the *Observer Pattern* [12] on top of the iOS and Android event systems. Specifically there are three key modules used in SAD:

- **Xamarian Virtualization Layer**: In order to leverage both Android and iOS mobile participants, SAD leveraged Xamarian to virtualize the native implementation of each mobile phone. Among all virtualized services, SAD adopted the four major services: (1) Phone Event Source, (2) Sensors Manger, (3) User Interface, and (4) Network Services. Specifically, the Sensor Manager provides real-time sensor readings such as GPS location, accelerometer data and phone usage status to SAD; User interface service can prompt users and inquire self-report information. Network services allow SAD to communicate with the cloud for data uploading/gathering. For SAD, one of the key components is Phone Event Source (PES). PES detects if a certain event happens (e.g., phone call or reading the end of day) and pushes the event to the Observer chain for further execution. Note that PES is capable of generating events based on internal phone activities (e.g., screen off/on), telecommunication activities (e.g., calls and texts), mobile APP activities (e.g., start/stop/resume certain apps), timer as well as the pseudo-random timer (e.g., a random time in a certain duration).

- **Observers and the Chain**: A chain of observers is attached tightly behind the PES, where each observer corresponds to a specific type of event and also links to a set of sensing protocols (for data collection). When a specific event is pushed to the observer chain, the corresponding observer is activated and dynamically starts the linked sensing protocols for data collection. For example, when the user finishes a call, the call event would be detected by PES and pushed to the chain of Observers; then among all observers in the chain, the call Event Observer would be activated by the event and trigger the corresponding sensing protocols for "after-call prompt".

- **Sensing Protocols**: Sensing protocols are highly customizable components for the user data collection. Each sensing protocol consists of the business logic of data collection for a specific experiment. Generally, when a protocol starts, SAD first reads the sensor readings that the protocol is interested in and then, if applicable, prompts user for self-report information inquiries. Finally, SAD uploads the collected data to the cloud through Network Services.

Note that SALMON and DEMONS are all based on the same SAD framework but with different sets of sensing protocols. To facilitate the development, SAD provides a Luna-based scripting language for sensing protocol development and extensions.

Study Design

Participants are high or low social anxious or depressed undergraduate students recruited from University of Virginia psychology classes who receive course credit as compensation. A subset of participants was recruited via flyers and received monetary compensation. The decision to recruit university students was based on two main reasons: (a) there are high rates of anxiety and depression among young adults; and (b) recruiting young adults in a university setting provides a relatively homogenous sample in terms of life phase, psychosocial stressors, and life experiences, thereby eliminating a wide variety of potential nuisance factors.

The target sample size for both SALMON and DEMONS is 100 participants. Selection of participants is based on those scoring unusually low or high on the Social Interaction Anxiety Scale (SIAS; [13], or the 7-item Depression subscale of the Depression, Anxiety and Stress Scale (DASS-21; [14]) during the pre-screening assessment conducted by the psychology department at the beginning of each semester. For DEMONS, those who endorse experiencing a past Major Depressive Episode (endorsement of 5 or more items) are not allowed in the low depression group only, due to potential difficulty in isolating the impact of current/past depression between groups.

After completing baseline laboratory measures (described in the Introduction), participants in both studies receive a one-on-one tutorial of how to install and use the SALMON and DEMONS smartphone application on their personal device. They are told that the application will passively track communication (e.g., number of phone calls), activity, and location information, and will prompt them with questions immediately after a phone conversation, at four random times per day, and at the end of each day (at 10pm). After phone call, prompts assess information such as purpose of the call, who the call was with, desire to engage in future social interactions, and current emotional experience. Random day prompts are timed to occur once within every 3.5-hour window, from 8am to 10pm, and assess state information such as current emotions, desire and efforts to change current emotional experience, predictions for emotional experience at the next prompt, and current activities and social interactions. End of day prompts assess information that occurred over the course of each day, such as stressful events, emotional experiences, efforts to change emotional experiences, and amount of time engaged in in-person versus virtual interactions (e.g., Facebook, Twitter). Participants in DEMONS wear a commercially available wristband sensor that continuously collects heart rate, movement, skin temperature and galvanic skin response.

Data collection for SALMON and DEMONS lasts for 10 and 14 days, respectively. If there are any issues during the study, study administrators are notified. Data collection is closely monitored and emails are sent to participants who are not logging information to improve adherence. Participants are then brought back to the laboratory for a debriefing session. Those in DEMONS are asked to invite up to 3 peers to complete an online evaluation of the participant. Informants are asked to report on the frequency of interactions with the participant, as well as the participants apparent emotions and social behaviors over the past two weeks.

Because we want to achieve the highest quality of data and study adherence, participants in SALMON and DEMONS studies utilize their own mobile phones. Data varies slightly between Android and iPhone users because of security and privacy limitations imposed by iOS platforms. Recent surveys demonstrate statistically significant differences between iPhone and Android users, including technical skills, education level, and socio-economic status [15], so we will examine the data for differences on mental health variables as a function of platform.

CONCLUSION

Current methods for identifying and diagnosing mental disorders are often based on unreliable, retrospective self-report that is dependent on high levels of client motivation and insight. Further, common modes of clinic- or lab-based mental health assessment and treatment delivery are severely limited in scope and only serve a fraction of those in need. Thus, the mental health field must do a better job of identifying those in need of mental health services and delivering those services to a wider audience. By using a combination of actively and passively collected *in situ* data, each of the designed studies will allow researchers and clinicians to understand the temporal links between emotions, stressors, and social interaction, in order to optimize prediction and interventions. To our knowledge, this is the first integrated framework for the monitoring of the temporal links between social interaction and mood in social anxiety and depression.

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