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Understanding behavioral dynamics of social anxiety among college students through smartphone sensors

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ABSTRACT

The way people use smartphones provides a window into the relationship between behaviors and mental health. This relationship is of particular significance to individuals with elevated social anxiety, as it helps to reveal when and where their stress increases in relation to social interactions, ultimately leading to more precise treatment delivery and interventions. In this collaboration between engineers and psychologists, we present the first study to use smartphone sensors to examine socially anxious individuals' fine-grained behaviors around periods in which they engage in some form of social interaction, and how these behaviors differ as a function of location (e.g., at home, at work, or at an unfamiliar location). In a two-week study of 52 college students, we show that there is a significant difference in behaviors for individuals based on social anxiety levels and locations, in that individuals higher (vs. lower) in social anxiety symptoms exhibit more movement (as tracked by the accelerometer) around the time of phone calls, especially in an unfamiliar location (i.e., not home or at work). Finally, we discuss the implications of these findings for developing better interventions for socially anxious individuals.

1. Introduction

Social anxiety is characterized by an intense fear and avoidance of socially evaluative situations [1] which has been identified as a risk factor for future health issues (e.g., alcohol use disorder) among college students. Socially anxious individuals tend to exhibit behaviors that are consistent with their subjective states, such as trembling, sweating, and fidgeting during social interactions perceived as threatening [2,3]. Importantly, these behaviors are part of a feedback loop whereby socially anxious individuals experience or imagine rejection from others due to their (perceived or real) impaired social functioning, which in turn reinforces their fears and negative beliefs about the threatening nature of social interactions [3,4]. It is therefore critical to detect objective behavioral markers indicating heightened anxiety which may inform potential opportunities for prevention and intervention.

Traditionally, psychological research on factors linked to social anxiety has relied on laboratory-based methods, thereby limiting the ecological validity of findings. Advances in recent decades have made it possible to monitor how behavioral systems unfold in people's natural settings, such as by leveraging sensors embedded in personal smartphones [5–10]. Psychology research and theory suggest that variations in micro-level behavior (indicating a heightened state of arousal) around times of social interaction are more pronounced in unfamiliar settings (e.g., public areas) in which the threat of social evaluation is high relative to a familiar setting like one's home [11,12]. The identification of key features of micro-level behaviors associated with social anxiety is an important first step to the development of personalized interventions delivered via mobile phones. Several studies have explored the relationships between mental health, psychological interventions, communication patterns and preferences, and smartphone usage [13–23], and indicated the importance of when, where, and how an intervention should be delivered [24–26]. It is also important to note that naturally arising variations among mobile phone user behaviors are not yet well understood, though steps have been taken in that direction [27].

There is ongoing interest in understanding how patterns of human behavior in real-world settings relate to mental health (particularly social anxiety) for three primary reasons. Recall that the majority of existing work examining calling and text messaging behavior in socially anxious individuals relies predominantly on lab-based studies and self-reported data [14]. In addition, there is a limited understanding of the link between physical and psychological dimensions of human behavior that makes designing and optimizing micro-interventions difficult. To help address these challenges, we seek to further elucidate human be-

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havior in real-world contexts by leveraging mobile sensing technology and feature exploration.

In this paper, we passively sense (1) micro-level motion via accelerometer sensors, and (2) physical locations (e.g., home, restaurant) via GPS sensors before, during, and after phone calls and text messages. We hypothesize that subtle user motions covary with social anxiety level and social context (e.g., hands may shake more when in a public setting where the chance of negative evaluation by others is high). We refer to these motions as the user's *behavioral dynamics*. We aim to examine whether information fusion from these sensors reveal systematic differences in movement patterns associated with social anxiety symptoms. In particular, we explore the relationship between the behavioral dynamics of smartphone use and an individual's social anxiety level with the future goal of optimizing the delivery of personalized interventions when and where they are most needed. Additionally, we propose a new fusion method for capturing the behavioral dynamics of smartphone use. We model the accelerometer data as a linear dynamical system (LDS), extract features from the LDS, and then use these features to understand behavioral differences across social anxiety levels, communication media (text messages and phone calls), and semantic locations.

The contribution of this research is threefold.

1. We demonstrate a statistically significant relationship between information fusion from smartphone sensors and social anxiety level of college students that varies as a function of physical location (i.e., in familiar vs. unfamiliar settings).
2. To address the problem of capturing behavioral dynamics of smartphone use, we propose a new sensor fusion framework to fuse smartphone sensor data including accelerometer, GPS, and call and text logs. Our technique first develops a linear dynamical model of the phone with the accelerometer data as the output around the time participants engage in phone calls and text messaging. The features are then used to explore behavioral differences across communication media and locations and their relationship with social anxiety levels.
3. We present the implications of these findings for future work in the design of personalized interventions. Specifically, we discuss implications for optimizing delivery of social anxiety interventions by smartphone, and how this work may extend to other applications. Our findings have implications for how, what, and when an intervention is delivered to an individual to maximize efficacy.

Section 2introduces relevant prior research in mobile sensing and social anxiety. In Section 3, we describe the study design, data collection procedures, and mobile sensing system used in the study. Section 4 describes the specific techniques used to model and represent behavioral dynamics. Section 5 presents the relationships between behavioral dynamics and subjects' social anxiety levels, and Section 6 summarizes and discusses our study's results, limitations, and implications for future work. Finally, Section 7 presents concluding remarks.

2. Related work

This research is motivated by previous studies in psychology demonstrating distinct differences in smartphone communication and usage pattern with regards to psychopathology, as well as more recent work establishing a connection between smartphone data and mental health. Our work aims to extend knowledge in both of these areas by developing new methods to continuously measure behavior in real-world settings using smartphones. We consider previous work from three areas: (1) human behavior monitoring and modeling with smartphones, (2) smartphone data and mental health, and (3) mobile phone communication and social anxiety.

2.1. Human behavior monitoring and modeling with smartphones

Despite the ubiquity of smartphones and mobile health applications, there still remain many research questions surrounding these technologies. Smartphones produce a vast amount of multi-modal contextual sensor data that enable the inference of complex human behaviors [28,29], but there remain systemic challenges when translating lab-based research into real-world settings. Informative smartphone sensor data streams (e.g., from inertial measurement units or GPS sensors) can vary in their reliability, quality, and completeness. This variability has critical implications for measuring micro-level behaviors [30]. Thus, researchers have developed information fusion techniques [29,31–33] to recognize behavioral patterns from these multi-modal signals.

Chen et al. [33] developed a information fusion architecture, called smart personal health advisor (SPHA), to monitor both physiological and psychological states of users. Alshurafa et al. [34] developed a supervised learning framework leveraging a sparse representation of high-dimensional features to achieve robust activity recognition. Furthermore, to reduce the requirement for extra labor and domain expertise when labeling training sets, Bao and Intille [35] developed a data collection protocol that enables acquisition of training sets from subjects themselves without the direct supervision of a researcher. Meanwhile, Hoque et al. [36] and Mondol et al. [37] developed a mobile application to help users record labels for events in their daily lives. These labels can be fed to a supervised machine learning algorithm to extract meaningful patterns from the sensor data. Beyond these signal-based features, scholars have developed other body-model based feature extraction techniques [38–40] that produce models from prior knowledge of the underlying patterns and then apply these models to the feature extraction process. Typical models include Hidden Markov Model (HMM) [38,40] and Linear Dynamical Model [39].

Regarding human behavioral modeling, Spruijt-Metz et al. [41] have presented the necessity of developing multilevel feature extraction including event-based, model-based, and signal-based features. Harari et al. [42] demonstrated the use of multilevel feature analysis integrating sensor features, questionnaires measures, and sociability features to identify patterns of behavioral change among college students. Min et al. [43] integrated event-based features such as call features and message features to classify life facets. Our work leverages these previous efforts to develop a framework for exploring features and identifying individuals with similar social anxiety levels.

2.2. Smartphone data and mental health

The emergence of smartphone sensing research has created new opportunities to understand how mental health disorders such as anxiety and depression manifest in real-world settings. Smartphone usage data and sensor data streams (e.g., accelerometers, microphones, and GPS) provide continuous, unobtrusive measurements of variables critical to mental health status (e.g., social interactions, location semantics, and physical activity) [8,27,44–49]. Furthermore, patient-centered [50] and context-aware mobile sensing systems have the potential to deliver personalized healthcare services [51,52] at the right time, in the right place, and in the right manner [53].

Wang et al. [44] monitored a group of 48 college students over 10 weeks and identified several significant correlations between smartphone sensor data (e.g., sleep and conversation frequency) and mental health and educational outcomes. Shin and Dey [54] developed an automated approach to detect problematic usage patterns of users with mental health problems. They extracted features from multiple available smartphone data logs, such as text messaging log, call log, battery information, network information, and screen status. They then built a machine learning classifier to detect usage that results in negative personal and social aspects of one's life. Their classifier is able to identify problematic usage with 89.6% accuracy. Madan et al. [45,46] developed an application for smartphones to collect heterogeneous data, including proximity, communication logs, location, and battery impact to measure characteristic behavior changes in symptomatic individuals, and concluded that that it is possible to predict the health status of an individual without having to collect actual health measurements.

Although the above research has implications for mental health, relatively little work has focused on a more fine-grained analysis of sensor data to understand the behavioral dynamics associated with mental health with the goal of identifying when and where to intervene. We have found no such prior work for social anxiety.

2.3. Mobile phone communication and social anxiety

Psychologists have investigated mobile phone usage patterns and the relationship to mental health [9,17,55]. Several works have explored the relationship between social anxiety and patterns of mobile phone usage and communication [8,9,13–16,19–23]. In particular, Reid et al. [13,14] investigated the preferences for phone calls and text messages among anxious and lonely people. Their results indicate that, whereas lonely participants preferred making phone calls, anxious participants preferred to text. Further, Leep et al. [15] analyzed the relationship between smartphone use, academic performance, anxiety, and satisfaction with life in college students.

This work has identified patterns in mobile phone usage and mental health status. However, none of these studies has examined the micro-level behavioral dynamics associated with social anxiety. There is a large body of research developing interventions for mental health disorders such as social anxiety [17,18,20,56,57]. Of particular interest in the research community is how to optimize the how, when, and where of intervention delivery. The research presented herein has implications for both the recognition of micro-level behaviors as well as for delivery of interventions.

3. Study design

In this section, we introduce the design of our study, data collection procedures, and participant recruitment. We then present data pre-processing and modeling.

3.1. Study organization and data collection

Participants were undergraduate students with varying levels of social anxiety recruited from undergraduate psychology classes. These students received course credit as participation incentives. A subset of participants received monetary compensation. We recruited students for two reasons: (1) young adults exhibit high rates of social anxiety, and (2) recruiting young adults in a university setting provides a relatively homogeneous sample in terms of life phase, psychological stressors, and life experiences, thereby eliminating many confounds.

With approval from the Institutional Review Board (IRB) of the University of Virginia, 52 participants were recruited from the psychology department's participant pool. Researchers from other two institutions were included in the IRB protocol and only granted access to the de-identified data to conduct data analysis. The demographical characteristics of these participants are all undergraduate students with mean age (20.5 ± 3.8) and % female 68. Before the study began, each participant was assessed on the Social Interaction Anxiety Scale (SIAS [58]). The SIAS measurement contains 20 items rated from 0 to 4; total scores range from 0 to 80. Generally, a higher SIAS score indicates higher anxiety and fears associated with general social interactions. Fig. 1 shows the histogram distribution of SIAS scores among the 52 participants in our study. Our participants' SIAS scores have a mean of 35.02 and a standard deviation of 12.10. In our two-week study of 52 participants, we collected 1642 phone calls and 28,381 text messages in total.

We explained the study to each participant and conducted a pre-assessment before receiving consent. We then installed a mobile app, Sensus [59,60], on each participant's personal smartphone. Participants

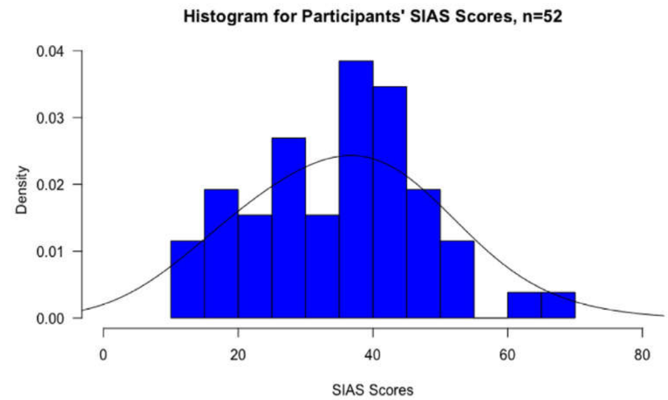

Fig. 1. The distribution of SIAS scores for recruited participants. The demographical characteristics of these participants are all undergraduate students with mean age (20.5 ± 3.8) and % female 68.

were informed that the application passively collects GPS location information every 150 s, accelerometer data every second (1 Hz), time and duration of all calls, and time of all text messages. For this study all participants were Android users and in the whole experiment all participants used their own Android phones. All data were initially stored on the collection device and then uploaded to a central Amazon Web Services S3 account once per hour as compressed JSON. All identifying information was anonymized on the device before upload to S3.

3.2. Understanding behavioral dynamics of social anxiety

We investigated three primary research questions:

1. Do behavioral patterns occurring around social interactions vary across social anxiety level?
2. Do these behavioral patterns vary across communication media?
3. Do these behavioral patterns vary across semantic locations?

4. Approach for modeling behavioral dynamics

In this section, we discuss the approach for the proposed study. Fig. 2 illustrates the data structure and framework of our methodology for learning behavioral dynamics. We first collect GPS data, accelerometer data, and communication events (i.e., phone calls and text messages). Next, we pre-process the data by aligning observations temporally. The accelerometer data consist of three dimensions (X, Y, and Z axes), and the communication event data include the time and duration of a phone call or text message. The raw GPS data are transformed into semantic locations that integrate social context. After structuring the data, we used a sliding window to isolate periods of time before, during, and after each phone call or text message. Next, by modeling the smartphone as a linear dynamic system, the three-dimensional accelerometer data in the sliding windows belonging to a single call or text message were reduced to a one-dimensional system stimulus. Finally, we construct a distance matrix using the histogram distribution of the system stimulus and combined this with the GPS semantic labels for further analysis. These distance matrices allowed us to characterize the behavioral dynamics of a participant before, during, and after a phone call or text message.

4.1. Pre-processing

There are several steps taken to pre-process our data to build the linear dynamical system and perform feature extraction:

1. Cluster raw GPS data to identify social semantics (e.g., "food and leisure" for a GPS location of a restaurant).

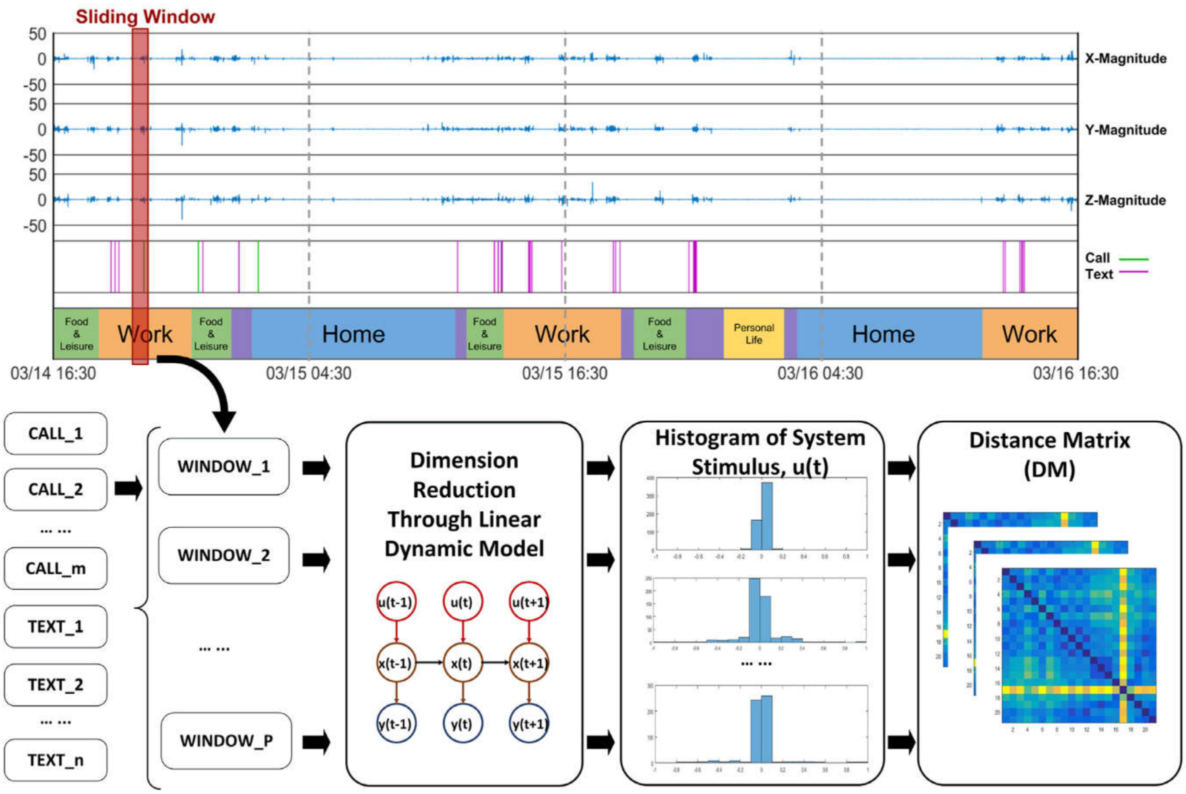

Fig. 2. Study framework: The top portion of this image shows an example of the data and the sliding window used to segment it. The three-dimensional accelerometer data (*X, Y, Z*) are temporally aligned with communication data (phone calls and text messages) and semantic GPS locations. For the GPS locations, green represents food and leisure places, brown represents work places, blue represents home, yellow represents personal life locations, and purple represents a transition between places. The bottom portion shows the feature extraction method: After segmenting the data into sliding windows and reducing dimensionality through the linear dynamic model, the three-dimensional accelerometer data, $y(t)$, is reduced to a one-dimensional system stimulus, $u(t)$. Each phone call and text message is represented by features extracted from distance matrices that contain Euclidean distances between pairs of histogram distributions of the one-dimensional system stimulus. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

2. Segment the time period around a phone call or text message into sliding windows.
3. Retrieve the accelerometer data in each window to capture motion information for specific phone calls or text messages.

4.1.1. GPS data

To acquire the location semantics for GPS trajectory data for each individual, we first clustered the GPS trajectories by spatial and temporal locality [8,61]. We then used Foursquare to obtain Point-of-Interest (POI) information (e.g., residence area, academic building, and restaurants) for each location cluster. We grouped the clusters into five location labels:

- *Work:* For the college students in this study, work locations are mostly within the campus.
- *Food & leisure:* This location set includes restaurants, bars, clubs and shopping centers.
- *Home:* Some participants have multiple home locations—we do not distinguish between them.
- *Transition:* This includes the time the participants spent on transit (e.g., walking and driving).
- *Personal life:* Locations that do not belong to other categories, such as post office and grocery store.

The labels extracted from GPS data confer semantic location information to provide deeper contextual meaning about the interaction between behaviors, locations, and social anxiety levels. Additionally, the labels help identify potential locations where interventions might be needed.

4.1.2. Communication events

In our study, communication events refer to phone calls and text messages. To capture the behaviors around these communication events for a better understanding of the relationship between social anxiety and behavioral dynamics, we first defined the observation period for a communication event: α_1 minutes before and after a communication event (and its duration if it is a phone call). Our choice of the observation period was based on the anticipated impact of social anxiety on behavioral dynamics. For instance, a subject might hesitate for a period before calling an important person or struggle when no one answers the call.

4.1.3. Accelerometer data

After defining the observation period as described in Section 4.1.2, we used the accelerometer data within that time period to analyze behavioral dynamics. Fig. 3 gives an example of a 29 min accelerometer data session that captures the motions of the smartphone when the subject makes a 9 min phone call and $\alpha_1 = 10$ min. We applied a sliding window process to segment the observation period and the accelerometer data in it into smaller, fixed-size chunks before conducting further analysis. Section 4.3 describes the analysis in more detail.

4.2. Mathematical formulation

In this section, we present the mathematical formulation of the proposed framework shown in Fig. 2. For individual *i*, the observed behavioral data $X(i)$ can be represented as:

$$X(i) = \{[AC(i)(1), LC(i)(1), LG(i)(1)], \dots, [AC(i)(j), LC(i)(j), LG(i)(j)], \dots, [AC(i)(m), LC(i)(m), LG(i)(m)]\} \quad (1)$$

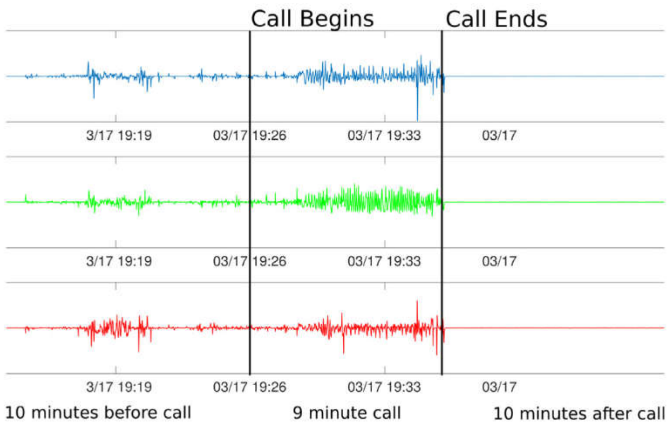

Fig. 3. Accelerometer data for a 9 min phone call, with 10 min of data before and after the call.

AC(*i*)(*j*) represents the accelerometer data in the observation period *j*, which also corresponds to the specific communication event *LC*(*i*)(*j*) ∈ {'Call', 'Text'}. As described in Section 4.1.2, the period length is: $2 * \alpha_1 + \text{DurationOfCommunicationEvent}$. *m* is the number of communication events for individual *i*, including phone calls and text messages.

$LG(i)(j) \in \{\}Home', \}Work', \}Food\&Leisure', \}Transition', \}PersonalLife'\}$represents the GPS label in the observation period *j*.

Since this study aims to increase understanding of the relationship between behavioral dynamics of smartphone use and social anxiety, the goal of the proposed learning framework is to extract metrics and features from the observed behavioral data and analyze the correlations between these features and the SIAS score, *SIAS*(*i*). Using *FAC*(*i*)(*j*) to represent a feature extracted from the accelerometer data of the observation period *j*, AC(i)(j), a metric example that represents behavioral dynamics of a phone call event for individual *i* is represented as:

$$MC(i) = \overline{FAC(i)(j)} \qquad \{j : LC(i)(j) == \}Call'\} \tag{2}$$

Eq. (2)is the average value of the features extracted from the accelerometer data that belong to the observation period *j* of individual *i*. Similarly, an example that represents behavioral dynamics of individual *i* of a text event is formalized as:

$$MT(i) = \overline{FAC(i)(j)} \qquad \{j : LC(i)(j) == \}Text'\} \tag{3}$$

Eq. (3)is the average value of the features extracted from the accelerometer data that belong to the observation period *j* of individual *i* during a text event.

Based on previous work on self-reported behavioral preferences of socially anxious subjects [14] and the greater social demands of typical phone calls relative to text messages [13], we hypothesize that the impact of social anxiety on behavioral dynamics of phone call events should be higher than the impact on text events. In other words, we anticipate that the correlation between *MC*(*i*) and *SIAS*(*i*) should be higher than the correlation between *MT*(*i*) and *SIAS*(*i*). The goal of our study is to validate this in-lab conclusion in a natural environment with micro-level motion analysis.

4.3. Feature extraction from accelerometer data

In this section, we introduce the details of the feature extraction from accelerometer data through the linear dynamic model. Specifically, we discuss the process to calculate *FAC*(*i*)(*j*), which represents the feature extracted from the accelerometer data of the observation period *j*, *AC*(*i*)(*j*).

4.3.1. Sliding windows of accelerometer data

As introduced in Section 4.2, *AC*(*i*)(*j*) represents accelerometer data in the observation period *j* for individual *i*, which corresponds to a specific communication event *LC*(*i*)(*j*) ∈ {'*Call*', '*Text*'}. To begin extracting the features of behavioral dynamics from *AC*(*i*)(*j*), we first segment it with sliding windows. Recall that each observation period spans several minutes (depending on the value of α_1). We consider multiple fixed-size windows over the length of the observation period.

We use α_2 to represent the length of a single sliding window and α_3 to represent the stride or offset of each window into the observation period. For example, the accelerometer data of the observation period in Fig. 3 for the 9 min call is segmented as 20 sliding windows, each of which has 10 min of accelerometer data when $\alpha_2 = 10$ min and $\alpha_3 = 1$ min. Therefore, *AC*(*i*)(*j*) is segmented into data pieces, each of which has a fixed-size length. Each window is represented as:

$$AC(i)(j) = \{AC(i)(j)(1), \dots, AC(i)(j)(k), \dots, AC(i)(j)(n)\}, \tag{4}$$

Where *AC*(*i*)(*j*)(*k*) represents the accelerometer data of the *k*th sliding window of the observation period *j* (and also the corresponding communication event) of individual *i*, and the sample length of the accelerometer data *AC*(*i*)(*j*)(*k*) is $\alpha_2 \times \text{SamplingRateOfAccelerometerSensor}$. The dimension of *AC*(*i*)(*j*)(*k*) is $3 \times \alpha_2 \times \text{SamplingRateOfAccelerometerSensor}$ due to the nature of accelerometer data. After segmenting the accelerometer data into sliding windows, we reduce the dimensionality of the accelerometer data *AC*(*i*)(*j*)(*k*) to generate features that characterize behavioral dynamics.

4.3.2. Dimensionality reduction through linear dynamical model

After data pre-processing and segmentation, the raw time-series accelerometer data for a single communication event *AC*(*i*)(*j*) have been segmented into data pieces (see Eq. (4)) by using sliding windows. Each data piece has identical dimensionality. Here, we adopt a model-driven technique [39] to reduce the dimensionality of the data piece *AC*(*i*)(*j*)(*k*) from $3 \times \alpha_2$ to a chosen value *x*.[1] With $\alpha_2 = 10$ min and our chosen value $x = 11$, we reduced dimensionality from 3×600 to 11.

We view smartphones as dynamical systems. Ekkekakis [62] discussed how mood affects one's appraisal of a situational event. In our study, social anxiety is a mood-related measure, and each communication event is a situational event. Accordingly, the behavioral dynamics of phone usage are appraisals of these communications events. Thus, a socially anxious individual will produce behavioral dynamics consistent with her anxiety, stimulating the accelerometer sensor to generate rich information.

Thus, we propose that a smartphone can be viewed as a dynamical system that the subject operates with stimuli caused by social anxiety. Using this analogy, the human can be viewed as a control system, while the smartphone is an observer system with certain states, and the accelerometer is the measurement system. The salient information is the motion stimuli that are highly related to the behavioral dynamics caused by the social anxiety of each subject. Therefore, we adjust a linear dynamical model to estimate the motion stimulus of the accelerometer data.

The proposed linear dynamic model is described as follows:

$$\begin{cases} \| u(\bullet) \|_{l0} \leq k \\ |u(t)| \leq 1 \qquad \forall t \\ \Sigma_t \| CA^t B \|_1 \leq \mu \\ x(t+1) = Ax(t) + Bu(t) \\ y(t) = Cx(t) + N \end{cases} \tag{5}$$

In this model, we use $y \in R^{3\times T}$ to represent the data piece, *AC*(*i*)(*j*)(*k*), while $T = \alpha_2$ times the accelerometer's sampling rate. We also used $y(t) \in R^{3\times 1}$ to represent the accelerometer data at time *t*. Thus, based on the insight of modeling the smartphone as a dynamical system, $y(t) \in R^3$ is the output of the linear dynamical system (the smartphone) driven by a one-dimensional sparse and bounded stimulus, $u(t) \in R$. The

[1] *x* refers to the number of bins used when quantizing the accelerometer data. For this paper, we chose $x = 11$.

dynamical system for estimating the motion stimulus includes two parts: the linear state space transition (the fourth line in Equation 05) and linear observation (the fifth line in Eq. (5)). The linear state space transition is defined by a system matrix $A \in R^{p\times p}$, a stimulus matrix $B \in R^{p\times 1}$ and a system state vector, $x(t) \in R^{p\times 1}$. The linear observation is defined by an observation matrix $C \in R^{3\times p}$ and the probability $N \in R^{3\times 1}$ of the random noise. In the above definition, p represents the system order of this linear dynamic model, which determines the complexity of the model. The dimensionality of the observation $y(t)$ is 3×1, because the accelerometer data are tri-axial. $\|u(\bullet)\|_{\ell 0}$ is the number of nonzero elements in the stimulus sequence.

An expectation-maximization (EM) algorithm is applied to estimate the A, B, C, X, and u with the assumption of system linearity and time invariance. Although the observation matrix C, which is related to the accelerometer sensor, depends on the physical characteristics of the sensor, and the probability function of random noise N depends on the noise characteristics of the accelerometer sensor, we make a simplifying assumption that both are linear and time-invariant.

After the EM algorithm, we estimate the system motion stimulus, u, of the accelerometer data piece y. Here u has a dimension of $1\times T$. To construct a feature to represent y, we extract the histogram of the stimulus vector u, $h(u)$. Each histogram is quantized into 11 bins, equally spaced in a range from −1 to 1. Until now, the previous high-dimension accelerometer data piece is reduced to 1×11 dimensions. This 11-dimensional feature can be represented as $HU(i)(j)(k)$, which is extracted from $AC(i)(j)(k)$.

4.3.3. Accelerometer metrics for communication events

After dimensionality reduction through the linear dynamic model, the raw high-dimensional accelerometer data of a communication event, $AC(i)(j)(k)$, can be represented as a series of low-dimensional features:

$$AC(i)(j) = \{HU(i)(j)(1), \dots, HU(i)(j)(k), \dots, HU(i)(j)(n)\} \tag{6}$$

Next, we develop features that capture the behavioral dynamics of a communication event $AC(i)(j)$. Prior research has explored metrics of feature arrays including statistical features [63], autoregressive modeling [64], and singular value decomposition [65]. Since our work is the first attempt to explore the behavioral dynamics and analyze the relationship with social anxiety levels, we simplify the process by adopting statistical features. Ideally, the extracted features would characterize motions around a communication event. For example, if a subject is very anxious when placing a phone call, the subject's hand may shake more than usual or the subject may pace with the phone. The features should be able to capture such anxiety-related motion. Thus, we generate features that can show the variations of the motions by first creating a distance matrix, DM, that calculates the similarity between pairs of $HU(i)(j)(k)$ of a communication event, $AC(i)(j)$. Each element of the distance matrix $DM(i)(j)$ is the Euclidean distance between the pairs of the 11-dimensional features, $HU(i)(j)(k)$:

$$DM(i)(j)(a)(b) = Distance[HU(i)(j)(a), HU(i)(j)(b)] \qquad a, b \in \{1 \dots n\} \tag{7}$$

Then, we use the mean value and standard deviation of the distance matrix $DM(i)(j)$ as the metrics of a communication event $AC(i)(j)$. In this way, the accelerometer data of $AC(i)(j)$ generate two metrics corresponding to the representation in Eqs. (2) and (3), $FAC_1(i)(j)$ and $FAC_2(i)(j)$ refer to the mean value and standard deviation of DM, respectively:

$$FAC_1(i)(j) = \overline{DM(i)(j)} \tag{8}$$

$$FAC_2(i)(j) = std(DM(i)(j)) \tag{9}$$

In summary, after pre-processing and applying a linear dynamic model, we are able to reduce the high-dimensional raw temporal motion data to a low-dimensional feature array. These arrays are considered pairwise to construct a distance matrix that uniquely characterizes each subject's behavioral dynamics during smartphone use around communication events.

5. Analysis and results

In this section, we present the analysis and results of our study. We first summarize the features, and then the relevant parameters for further exploration of the relationship between social anxiety status (measured by SIAS score) and behavioral dynamics.

5.1. Summary of features and parameters

As discussed in Section 4, we extract features from the motion information during phone calls and text messages along with GPS semantic information.

5.1.1. Features for analysis

We also developed features from the percentage of phone calls and text messages at different GPS locations. Table 1 presents the features we used in our analyses. These six features are extracted from the raw data we collected from the participants with linear dynamic model and the distance matrix described in Section 4. They are used to further explore the relationship between behavioral dynamics and social anxiety status together with the study parameters.

5.1.2. Parameters for relationship exploration between mental state and behavior

For further analysis, we defined two parameters for the study:

1. GPS locations: We conducted an analysis exploring the relationship with and without GPS semantic information to understand the effect of locations on social context.
2. Grouping of the participants: According to the SIAS measure of all participants, we grouped the participants in two different ways to analyze the effect size:
   - Two-group setting: We used one SIAS threshold to divide the participants into two groups, and then we computed the effect size between the two groups. This setting provides a general division of our participants.
   - Three-group setting: We used a low SIAS and a high SIAS threshold to split the participants into three groups: (1) low social anxiety risk, (2) medium social anxiety risk, and (3) high social anxiety risk. We analyzed the effect size between the low social anxiety risk group and the high social anxiety risk group. This setting provides a more detailed grouping of the participants.

5.1.3. Comparison with baseline approaches

We compare our work against six baseline approaches based on human activity recognition literature [66]: mean, median, standard deviation, variance, skewness, and zero crossing rate (zcr).[2] We consider several basic statistics and compute Cohen's d accordingly. We compare these d values with those produced using our linear dynamic modeling approach. We also discuss the implications of these approaches on future work.

5.2. Correlation analysis

In our study, with the features in Section 5.1, we calculate the Pearson correlation coefficient and significance analysis to explore the relationship between human behavior of smartphone use and social anxiety status.

[2] Skewness refers to the degree of asymmetry of the accelerometer signal distribution, and zcr refers to the total number of times the signal changes from positive to negative or vice versa.

Table 1
Terms used for features and the definitions.

Term	Definition
$Call\_Proportion$	The proportions of phone calls at different locations
$Text\_Proportion$	The proportions of text messages at different locations
$\overline{FAC_1}$	The average of the mean values of all distance matrices ($DM(i)$) belonging to a subject
$\overline{FAC_2}$	The average of the standard deviations of all distance matrices ($DM(i)$) belonging to a subject
MC	The metric for a phone call event
MT	The metric for a text message event

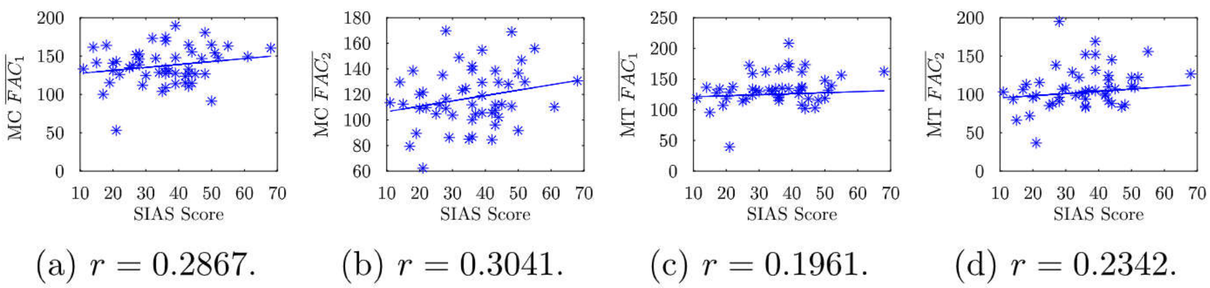

Fig. 4. Correlation plots of SIAS score vs. matrix features (cf. Table 2).

Table 2
Correlation and significance Analysis of motion data around phone calls and text messages vs. SIAS score: Pearson correlation (with p-values) between participants' SIAS scores and the features extracted from the smartphone accelerometer data around phone calls and texts. In this table, two features are explored: 1) the average of all distance matrices mean ($\overline{FAC_1}$), and 2) the average of all distance matrices standard deviation ($\overline{FAC_2}$).

	Call (MC)		Text (MT)	
Matrix feature	Pearson r	p-value	Pearson r	p-value
$\overline{FAC_1}$	**0.2867**	**0.0457**	0.1961	0.1634
$\overline{FAC_2}$	**0.3041**	**0.0336**	0.2342	0.0946

Table 3shows the Pearson correlation and significance analysis between the pre-assessed SIAS measures and the percentages of phone calls ($Call\_Proportion$) and text messages ($Text\_Proportion$) participants made in different locations. We found that the proportions of both phone calls and text messages made at home have a significant positive relation with the SIAS score (with a p-value of 0.0045 and 0.0028). In other words, the higher the social anxiety level is, the more phone calls and text messages are made at home. This may suggest that people with high social anxiety prefer to communicate in the comfort of their home, perhaps because they are less likely to be exposed to other people or an unfamiliar environment. In this table, the proportion of text messages in personal life locations also shows a significant negative correlation with social anxiety status.

Through the linear dynamic model, Tables 2 and 4 show the Pearson correlation and significance analysis between the pre-assessed SIAS measures and the behavioral dynamics features (the mean value of FAC_1 and FAC_2 cf. Table 1). Table 2 describes the correlation between participants' SIAS scores and the feature extracted from the smartphone from the linear dynamic model when making phone calls and text messages. The correlation plot is shown in Fig. 4. For both features, we can conclude that the motion dynamics of phone calls have a significant positive association with the SIAS scores (with a p-value of 0.0457 and 0.0336). Considering the definition of FAC_1 and FAC_2, we can infer that people with higher social anxiety levels have more motion variations when they are making phone calls, but there is no significant relationship between text messaging behavioral dynamics and SIAS scores.

Table 4shows the same the analysis but with the integration of GPS semantic information. Interestingly, these results indicate that higher (vs. lower) social anxiety is associated with more variation in participants' motions when making phone calls at a food or leisure location, where there are likely more opportunities for scrutiny by unfamiliar others.

5.3. Effect size analysis

We also use effect-size analysis to explore the characteristics of behavioral dynamics between low and high social anxiety groups (separately for the two-group and three-group settings) with their GPS location semantics. In this analysis, Cohen's d is used to calculate the effect size of social anxiety with locations on human behavioral dynamics. In the tables that present the effect-size analysis, results that have at least a medium effect size (≥ 0.5) are shown in bold typeface.

In Fig. 5, we present the effect size analysis between low and high social anxiety groups using the mean value of FAC_1 and FAC_2. Left figure of Fig. 5 uses the two-group setting we described in Section 5.1.2, while the right figure uses the three-group setting. Our choices for the *SIASlow* and *SIAShigh* in the right figure of Fig. 5 are based on making the number of participants of the low and high social anxiety groups equal. The three pairs of SIAS low and high scores, (27, 44), (28, 43), (30, 39), generate a group of 15, 17, and 20 participants, respectively, for both the low and high SIAS group. In both the two-group and three-group settings, different behavioral dynamics between the low and high social anxiety groups can generally be seen during the time surrounding phone calls. This difference is more pronounced with the three-group setting in which the distributions of SIAS scores of the low and high social anxiety groups are further apart.

Figs. 5–7 summarize the effect size differences that result from not only low and high social anxiety, but also location semantics in which calls and text messages were made. Both Figs. 6 and 7 show that for locations in "food and leisure" and "personal life", there is a significant social anxiety-linked difference in behavioral dynamics on phone calls. Such an effect was also observed while in transition to these locations. However, due to the uncertainty in transitions (transition periods include many kinds of environments), we do not draw strong conclusions here. In this analysis, the effects were more pronounced with the three-group setting, regardless of whether the subject was calling or text messaging. Notably, call behavior effects are more pronounced overall than text message effects.

Table 3
Correlation and significance analysis of proportions of phone calls made at different locations vs. SIAS score: Pearson correlation (with p-values) between participants' SIAS scores and the portions of phone calls that were made in specific types of locations. Additionally, the normalized mean ($\bar{x}$) and standard deviation (σ) of participants' portions of phone calls at each location are shown.

	Call_Proportion				Text_Proportion			
Location	Pearson r	p-value	$\bar{x}$	σ	Pearson r	p-value	$\bar{x}$	σ
Work	−0.1806	0.2142	0.0935	0.1074	−0.2511	0.0725	0.1441	0.1040
Home	**0.3983**	**0.0045**	0.3868	0.2484	**0.4059**	**0.0028**	0.3989	0.2128
Food & leisure	−0.2342	0.1053	0.1188	0.1551	−0.0882	0.5340	0.1412	0.1423
Personal life	0.1234	0.3982	0.0138	0.0346	**−0.2917**	**0.0359**	0.0166	0.0228
Transition	−0.0715	0.6141	0.3200	0.1812	−0.0707	0.6045	0.2381	0.1153

Table 4
Correlation and significance analysis of motion data around phone calls and text messages at different locations vs. SIAS score: Pearson correlation (with p-values) between participants' SIAS scores and the features extracted from the smartphone accelerometer data around phone calls and text messages at different locations. In this table, two features are explored: (1) the average of all distance matrices mean ($\overline{FAC_1}$), and (2) the average of all distance matrices standard deviation ($\overline{FAC_2}$).

	Call (MC)				Text (MT)			
	$\overline{FAC_1}$		$\overline{FAC_2}$		$\overline{FAC_1}$		$\overline{FAC_2}$	
Location	Pearson r	p-value	Pearson r	p-value	Pearson r	p-value	Pearson r	p-value
Work	−0.1204	0.5115	0.0477	0.7954	−0.2107	0.1461	−0.1192	0.4148
Home	0.1066	0.4858	0.2083	0.1697	0.1586	0.2712	0.2242	0.1174
Food & leisure	**0.3679**	**0.0323**	**0.446**	**0.0082**	0.1591	0.2800	0.2181	0.1365
Personal life	−0.331	0.3502	−0.3531	0.3169	−0.0532	0.7760	−0.0345	0.8539
Transition	0.2204	0.1364	0.2503	0.0896	0.1382	0.3333	0.1395	0.1183

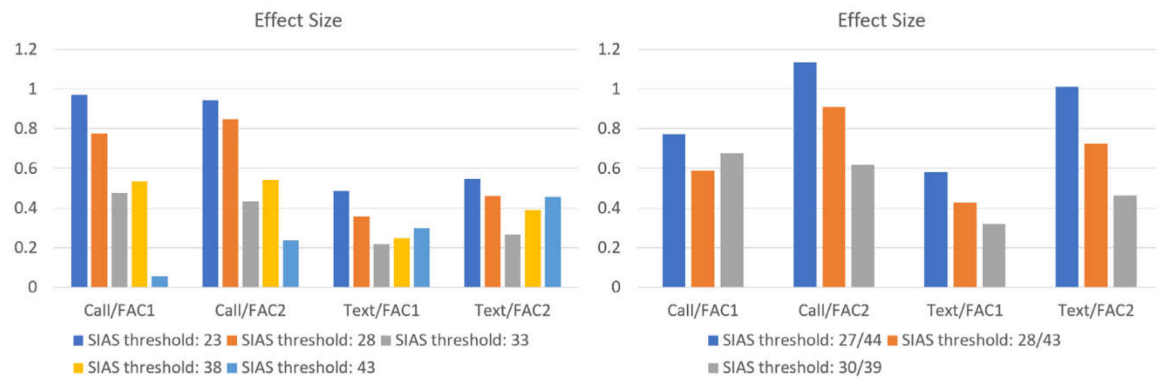

Fig. 5. Effect size analysis of the motion data around phone calls and text messages between groups with (relatively) low vs. high levels of social anxiety: In this table, two features are explored: (1) the average of all distance matrices mean ($\overline{FAC_1}$), and (2) the average of all distance matrices standard deviation ($\overline{FAC_2}$). The low and high social anxiety groups are selected in two different ways: (1) all participants are split as two groups using a SIAS threshold score, and (2) all participants are split into three groups using a low SIAS threshold and a high SIAS threshold.

In Fig. 8, we consider the effect size analysis results of six baseline approaches based on human activity recognition literature [66]: mean, median, standard deviation, variance, skewness, and zero crossing rate (*zcr*). Similar to $\overline{FAC_1}$, we use the average of the mean values of baseline features and calculate the Cohen's d between the low and high social anxiety groups with both the two-group and three-group settings. To summarize, we highlight only the baseline approach results by analyzing the accelerometer data without the location context with effect sizes that are greater than 0.5 in bold typeface.

Fig. 5compared to Fig. 8 demonstrates that the LDS approach generally exposes more substantial behavioral differences between high and low social anxiety groups as exhibited by the larger effect sizes. For phone calls, standard deviation reflects the significant difference between low and high social anxiety, but not to as great an extent as the LDS approach. In future work, we will investigate both the LDS approach and baseline features coupled with deeper contextual information to gain more intuition about the features that most distinguish high and low anxiety individuals.

6. Discussion

Our results indicate that behavioral metrics observed in temporal proximity to phone calls have stronger associations with social anxiety scores than metrics observed in temporal proximity to text message events. Moreover, the behavioral dynamics of phone calls that occurred in locations identified as "Food & Leisure" and "Personal Life" were significantly different for individuals with higher (vs. lower) social anxiety. In addition, the proportions of phone calls and text messages made at home have a significant positive correlation with social anxiety levels.

6.1. Implications for designing personalized interventions

To our knowledge, this was the first attempt at examining fine-grained accelerometer data in the context of variable social anxiety

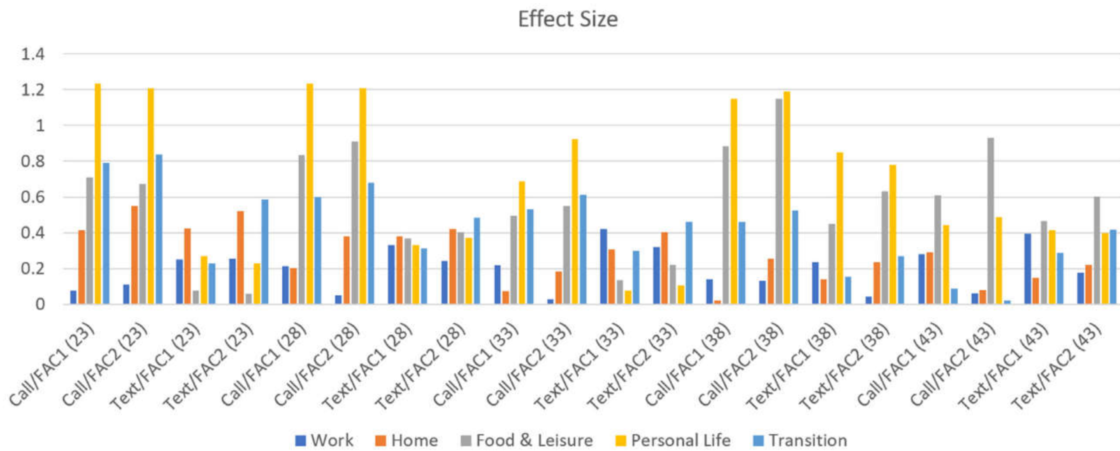

Fig. 6. Effect size analysis of motion data around phone calls and text messages at different locations between groups with low social anxiety and high social anxiety: In this figure, two features are explored: (1) the average of all distance matrices mean ($\overline{FAC_1}$), and (2) the average of all distance matrices standard deviation ($\overline{FAC_2}$). All participants are split as two groups using a SIAS threshold.

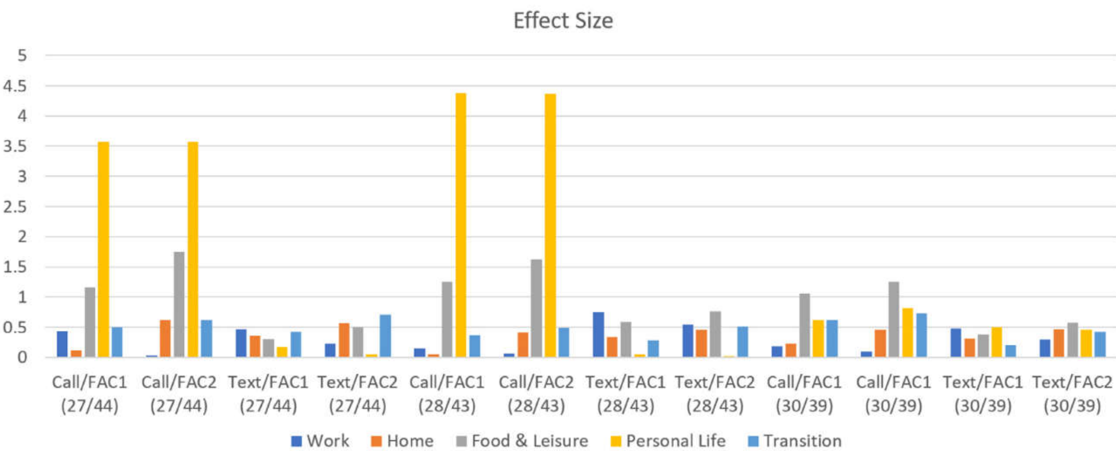

Fig. 7. Effect size analysis of motion data around phone calls and text messages at different locations between groups with low social anxiety and high social anxiety: In this figure, two features are explored: (1) the average of all distance matrices mean ($\overline{FAC_1}$), and (2) the average of all distance matrices standard deviation ($\overline{FAC_2}$). All participants are split into three groups by using a low SIAS threshold and a high SIAS threshold.

symptoms. Thus, a goal of the present research was to establish a framework for examining the association between self-reported social anxiety symptoms and passively sensed motion patterns from accelerometer data. The effect of a higher (vs. lower) level of social anxiety being associated with more variation in fine-grained motion is consistent with a wealth of psychological research demonstrating that a higher level of anxiety is linked to higher levels of nervousness, fidgeting, apprehension, and physiological arousal [3,67,68]. Importantly, our findings also indicated that in public locations, where we assume the chance of evaluation by strangers is generally high, individuals with higher social anxiety showed greater movements than did individuals with lower social anxiety. However, this was not the case for the home location, where the threat of social evaluation is presumably much lower. Taken together, findings from the present research suggest that it is possible to integrate fine-grained accelerometer data with GPS data to identify behavioral markers associated with social anxiety in various locations. Moreover, examination of movement patterns around the time that phone calls or text messages occurred provides a means to identify markers of anxiety temporally closer to known periods of social interaction using only passive sensors (i.e., accelerometer, GPS, calls, and text messages were all passively sensed), thereby greatly minimizing the users measurement burden.

An exciting future implication of the present work is the combined use of accelerometer, GPS and other passive sensors to deliver just-in-time adaptive interventions [69], which involve “personalized, localized, and on-demand interventions in ways previously unimaginable [and enabled through technology]” [7] for socially anxious people. For example, it may be possible to deliver a brief psychological intervention to a socially anxious individual via their smartphone when they are in a public location (as sensed through GPS) and when their movement patterns (as sensed through accelerometer) suggest they are experiencing increased fear and arousal. By enhancing the ability to both passively monitor symptoms and deliver empirically-supported interventions through mobile technology, when and where they are most needed, researchers and clinicians may be able to overcome many of the barriers inherent in face-to-face treatment [69,70], which typically follows a rigid schedule (e.g., once a week, largely based on the clinician’s schedule).

Our results have implications for how, when, and where interventions are needed [71].

1. *How?* The differences in behavioral dynamics between phone call and text messaging is largely consistent with the communication preferences of individuals found in prior studies. Our findings support the implementation of text-messaging interventions [56,57] rather than phone-call interventions [17]. We hypothesize that socially anxious people will be less behaviorally reactive to

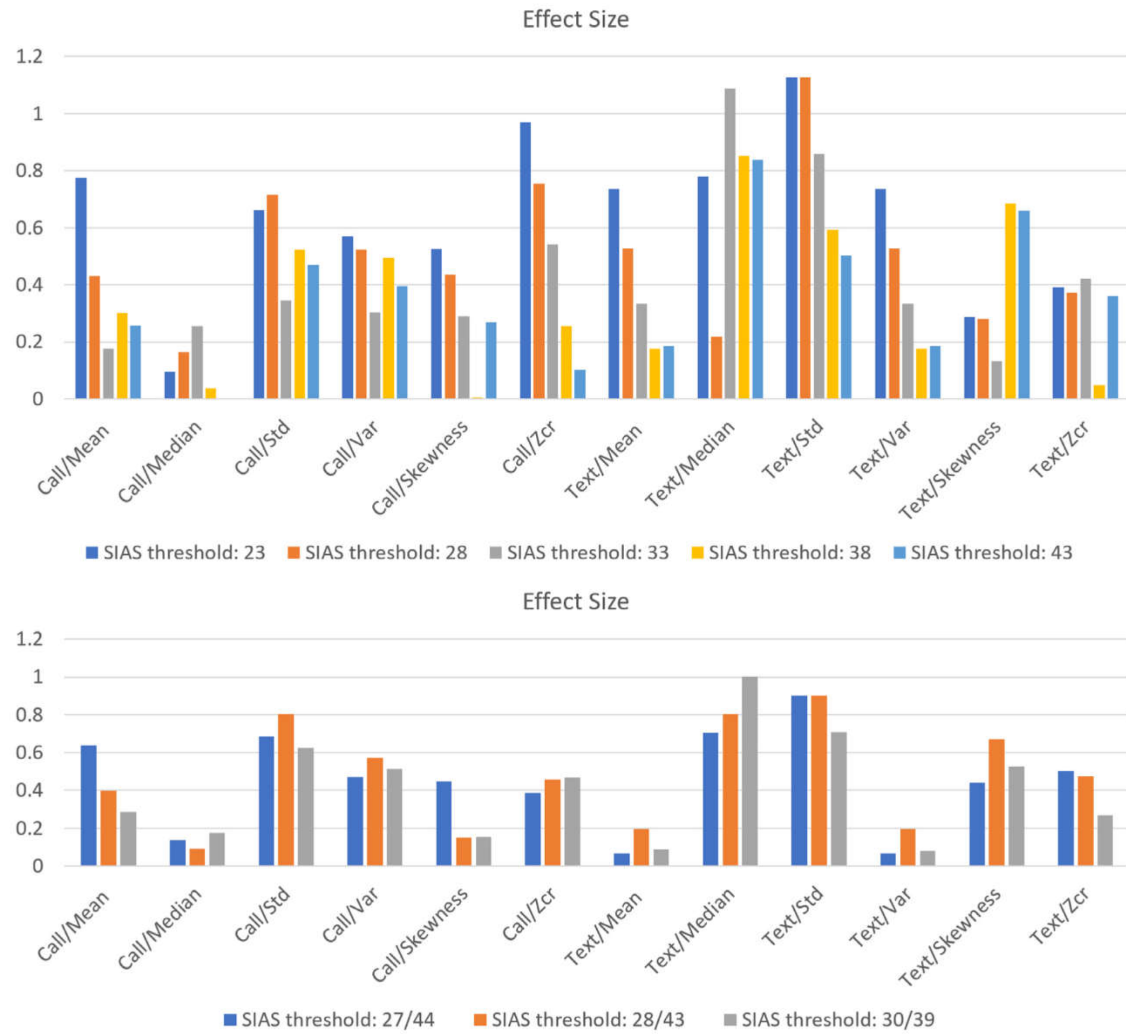

Fig. 8. Baseline approaches: Effect size analysis of the motion data around phone calls and text messages between groups with (relatively) low vs. high levels of social anxiety. In this figure, 6 baseline features are explored for both phone calls and text messages. The low and high social anxiety groups are selected in two different ways: (1) all participants are split into two groups using a SIAS threshold score, and (2) all participants are split into three groups using a low SIAS threshold and a high SIAS threshold.

texts than calls, and that phone call interventions could potentially exacerbate people's anxiety levels

2. *When?* The metrics representing behavioral dynamics provide information that can be used to identify moments when interventions might be needed; for example; when increasing anxiety is reflected in more variable motion dynamics. Developing adaptive thresholding techniques to detect or predict these moments would aid in determining when the interventions are needed.
3. *Where?* Location semantics provide information regarding where interventions should be delivered. Our findings suggest that delivery of interventions may be most needed when an individual is in a location outside the home, including “Food & Leisure” and “Personal Life” venues.

6.2. Generalizability of the proposed approach

The proposed framework is generalizable to multilevel feature exploration applied to human behavioral modeling. In this work, the proposed method integrates body-model based features and event-based features (communication events and location semantics) to explore markers that identify groups with different social anxiety levels. In another study, we adopted a similar framework to understand exactly when the feature differences emerge [72]. We have also applied this framework to data generated by wireless home monitoring systems [73] that are designed to monitor dementia patients, with the goal of identifying behavioral and environmental markers for early detection of agitation and caregiver notification. The dataset includes accelerometer sensor data from wristband wearables, events recorded by the caregiver, and other environmental parameters such as ambient light and noise. The framework explores the signal-based features and body model based features from accelerometer data, event-based features, and environmental features. Our preliminary results demonstrate promising markers [74]. Future integration of other physiological sensors into the framework and optimizing feature extraction and selection are major steps toward generalizing the proposed method.

6.3. Study limitations and future work

Our findings carry several limitations that should be addressed in future research. First, our analyses were based on 10 min windows surrounding call and text messaging events. We used these events as proxies for social interactions. We cannot claim that movement patterns for all forms of social communication (including remote and face-to-face interactions) are different among individuals with high and low social anxiety, nor can we claim that movement patterns differ during an interaction since the duration of calls and text messages were typically relatively short. To examine this issue more closely, future work may wish to examine accelerometer data only when calls and text messages are being made. Alternatively, researchers may want to integrate accelerometer data with other sensor streams that would allow inference of a face-to-face social interaction. To better understand the influence of calls and text messages on movement patterns, future work could compare movement patterns before, during, and after a call or text messaging event. For example, one might expect individuals with high (vs. low) social anxiety to have a notable increase in erratic movements immediately after a call or text as well as a longer recovery period to baseline. Because the current research was based on an undiagnosed sample of 52 college students, future work should replicate these results in a larger clinical sample.

Another potential limitation of the current study is that phone call and text messaging behaviors may be impacted by age and/or cohort effects, thereby limiting generalizability of our findings to an older population. Future work should examine whether age is a significant factor in movement patterns and how people use their phones to communicate. Further, the present research did not assess the specific nature or content of the calls and texts (e.g., job interview vs. casual conversation with a best friend), which could provide valuable information about mediators of the observed effects and how the social demands of the communication impact behavioral dynamics. Thus, in future work, we wish to acquire information to better contextualize the communication and associated accelerometer data. Unfortunately, even if we have analyzed the accelerometer data, we do not know what the actual physical interaction between the smartphone and the participant was actually occurring around the communication event (e.g., talking on the speaker while putting the phone on the table). However, we have checked the system stimuli data using the linear dynamic system model for all phone calls and texts. The results demonstrate that 3.65% of phone calls (60 out of 1642) have no obvious motions (i.e., the system stimuli are all zero), whereas 3.68% of text messages (1045 out of 28,381) have no obvious motions. This reduces the likelihood of effects from motions such as putting the phone on the table. But this is one of the challenges we would want to resolve in the future work. Finally, our analyses did not include differentiating between incoming and outgoing communications. But we have explored this as a preliminary data exploration work in another paper [72].

We plan to explore three future directions in this work. As mentioned in the beginning of the discussion section, the future work could have a deeper exploration of texting behaviors using other approaches, e.g., standard deviation of the motion data, to find other valuable behavioral markers. Thus far, we have focused on accelerometer, GPS, and communication data, and now plan to explore whether other sensor data, such as application usage, heart rate, and skin conductance can further elucidate behavioral differences in individuals with low and high social anxiety. Also, the optimization of feature extraction and selection within the proposed framework is an important next step. Second, the impact of smartphone communications, including call, text, and self-reported surveys, on other aspects of human behavior (besides movement) have not yet been comprehensively studied. Third, based on our understanding of behavioral dynamics, we plan to develop implementation and evaluation methods for mobile interventions for socially anxious students.

7. Conclusion

Current methods to monitor social anxiety are usually based on retrospective self-reporting with little data to contextualize people's experiences. These methods are also hampered by low scalability and a reliance on the individual to actively initiate and accurately complete assessment. This paper presents a new methodology for measuring the behavioral dynamics of smartphone use around phone calls and text messages. We developed an feature extraction framework and created metrics to represent behavioral dynamics using accelerometer, GPS, and communication history. We demonstrated that there is a significant difference in movement behaviors tied to social anxiety level and that these behaviors further vary across different semantic locations. This work opens up possibilities of passively monitoring behavioral markers of social anxiety through integration of accelerometer and GPS data, a method that is scalable to serving large populations. By passively sensing movement patterns and locations, researchers and clinicians may better understand behavioral markers in social anxiety that can optimize models of prediction and, ultimately, intervention.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.inffus.2018.09.002.

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