Physiological Changes over the Course of Cognitive Bias Modification for Social Anxiety

Mehdi Boukhechba[1], Jiaqi Gong[2], Kamran Kowsari[1], Mawulolo K. Ameko[1], Karl Fua[3], Philip I. Chow[3], Yu Huang[4], Bethany A. Teachman[3], Laura E. Barnes[2]

Abstract— **Social anxiety disorder affects approximately 7% of the adult population in the U.S., yet a vast majority of these individuals do not seek treatment. Thus, it is critical to examine models that deliver treatment to them. Computerized Cognitive Bias Modification (CBM) training programs can be effective in targeting interpretation bias, a key cognitive mechanism underlying social anxiety, and have potential for widespread dissemination, especially if they can be delivered via smart phones, which are becoming ubiquitous. However, the efficacy of CBM interpretation training paradigms that are adapted to and delivered via smart phones remains unknown. We present a pilot study to investigate if physiologic data can be used to track the changes over a smartphone-based CBM intervention for social anxiety. In a 3-week open trial, pilot study involving 20 high socially anxious participants, self-report affect ratings, heart rate and accelerometer data were collected using a smartphone and smartwatch before, after, and during the CBM intervention. The study focused on the relationship between accelerometer and heart rate to track change following the intervention. Results provide preliminary evidence for the viability of using physiological data to identify the change in mental state influenced by CBM interventions.**

I. INTRODUCTION

Social anxiety problems are among the most common emotional difficulties youth face. They are characterized by intense fear and avoidance of socially evaluative situations, and associated with both academic challenges and negative developmental trajectories [1]. Cognitive Bias Modification (CBM) interventions are gaining some support, especially for targeting anxiety problems [2]. However, current CBM interventions, especially interpretation training, are typically delivered in laboratory settings, which consumes resources and time, or only via computer in the rare instances they have been offered online. It is thus important to improve the reach of these interventions to help address the large treatment gap.

The ubiquity of mobile technology offers tremendous opportunities to address one of the most pressing global challenges in health care: making care more accessible, tailored, and cost-effective [3]. For example, utilizing mobile health (mhealth) technology enables researchers and clinicians to examine human behavior in natural settings, rather than only in clinical or lab-based settings [4], and allows people to avoid the stigma of seeking in-person treatment and to complete interventions at times and locations that better match their needs and resources. There is thus an ongoing interest in developing assistive health technology to deliver interventions, and CBM is an ideal candidate given it does not require therapist assistance or even human coaching [3].

However, there is still much unknown about the (potential for) real-world deployment of mHealth interventions, including the optimal ways to examine the effectiveness of interventions in real-world situations, especially given that deploying clinician interviews or questionnaires is not always feasible in these settings [3]. Also, these measures involve considerable user burden because of the time spent responding, and they depend heavily on user motivation and self-report, which can be prone to bias given recall biases and the desire to present in certain ways (e.g., to present as improved after completing a treatment). Using mobile health technology, which can capture fine-grained physiological measures related to human behavior, creates the possibility to passively monitor physiological markers that correlate with patients' mental health state, reducing the reliance on burdensome and potentially biased self-report measures.

The current work is motivated by the desire to explore a method to examine physiological changes over the course of CBM interpretation training as it manifests in daily life. Our method includes an inter-modal analysis between heart rate and accelerometer in both pre-intervention and post-intervention periods. Our method also compares the physiological changes with changes in self-reported affect and interpretation bias to study if the passively-sensed physiological data can be used to identify the changes in mental state that follow CBM.

II. RELATED WORKS

The emergence of wearable sensing research has enabled new opportunities to study how mental health problems manifest in natural settings. Physiological sensor data streams (e.g., accelerometers, microphones, heart rate, and GSR (Galvanic skin response) sensor) provide continuous, unobtrusive measurements that can be windows into mental health status. A number of recent studies have investigated the potential use of mobile technologies for the delivery of interventions for a variety of mental disorders and challenges, such as depression, stress, and eating disorders [5], [6], [4].

In recent years, there has been a push by clinicians and researchers to exploit the technology to disseminate treatments to high-risk populations with low-treatment seeking

[1]Department of Systems and Information Engineering, University of Virginia, Charlottesville, VA 22904, USA
[2]University of Maryland, Baltimore, MD 21250, USA
[3]Department of Psychology, University of Virginia, Charlottesville, VA 22904, USA
[4]University of Michigan, Ann Arbor, MI 48109, USA

behavior. An ideal way to reach out to high-risk individuals is through the use of cost-effective, internet-based Cognitive Bias Modification-Interpretation (CBM-I) interventions [2]. CBM-I interventions target anxious individuals tendency to selectively interpret ambiguous situations in negative ways, typically by training individuals to assign more benign interpretations of ambiguous situations. CBM-I has been shown to be efficacious in varied domains such as anxiety and depression [7]. Given that CBM-I is generally internet-based, it is readily portable to mobile platforms. With the host of additional sensors afforded by smart phones, deployment of CBM-I on mobile platforms would allow more in-depth examination of outcomes associated with CBM-I interventions beyond self-report interpretation questionnaires.

Several studies have explored the relationship between mental health status and the physiological measures in natural and lab-based settings. In particular, Sano et al. [5] used features from multimodal sensor data captured by a wrist-worn sensor and mobile phone app, with the goal of recognizing the stress level of 18 subjects in the study. Sun et al. [8] conducted lab-based experiments to develop a stress-detection scheme using various features extracted from accelerometer, heart rate, and GSR sensors. Wu et al. [6] developed classification models with HRV data and accelerometer data captured by a chest patch to understand people's stress patterns. They also explicitly described a conjecture, strongly supported by results, that high heart rate together with low activity level would be a useful indicator of high-stress levels.

In spite of this widespread interest to understand the effectiveness of interventions using mobile sensing, no study to our knowledge has measured the effectiveness of interventions only from passively sensed data from wearable sensors. This paper further examined the relationship (e.g., joint probability distribution) between heart rate and accelerometer data to represent the physiological changes that may be influenced by CBM (note, we use the term "may' carefully here to acknowledge the limits of inferring a causal impact from CBM in an open trial that lacks a comparison control group).

III. Study Design

After receiving approval from the university Institutional Review Board, high socially anxious participants ($N = 20$ college students) were selected based on their response on the Social Interaction Anxiety Scale (SIAS) [7]. SIAS is a well-validated measure of trait social anxiety that assesses individuals' level of distress and anxiety in a variety of socially evaluative situations (e.g., when meeting a stranger).

Each participant attended 2 lab sessions (3 weeks apart). In both sessions, participants completed measures of social anxiety and interpretation bias (among other measures that were part of the larger study; full list of measures is available from the first author). Specifically, interpretation bias was measured using the Bodily Sensations Interpretations Questionnaire (BSIQ) and Recognition Ratings questionnaire [9] that both measure tendency to attribute positive or negative interpretations to ambiguous physical or social situations. Participants completed the CBM intervention, which comprises 6 online training sessions (10 min each; approximately 1 session per day), on their mobile phones in the second week of the study.

The participants were asked to install a custom app [4] on their smartphones. In each day of the three-week experiment period, the app prompted participants to fill out a short questionnaire up to 6 (random) times and one at the end of the day. The questionnaire included items about participants' current state, such as affect (e.g., "How negative are you feeling now?") and social context (e.g., "Who are you interacting with?"). Passive data (e.g., GPS, accelerometer, heart rate, skin conductance, etc.) were also collected continuously using the custom app and a wrist-worn sensor (*Microsoft Band 2*), issued to participants to monitor their physiological state (optical heart rate sensor, accelerometer, and GSR sensor) (see Figure 1).

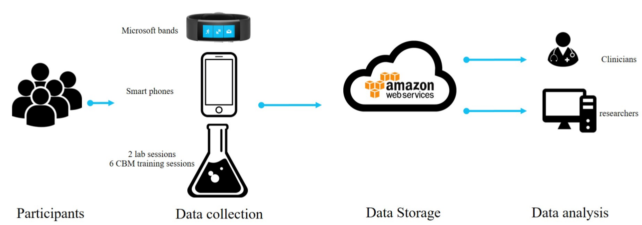

Fig. 1. The overall CBM study design. The data collected contain both passive data (e.g., data from different smartphone and wrist-worn sensors) and active data (e.g., self reported affect, social anxiety symptoms on the SIAS, and interpretation bias)

IV. Method

The aim of this work is to examine changes in physiological data before and after the CBM intervention. We focus specifically on the relationship between accelerometer and heart rate for this study because the relationship between activity level and heart rate has been used previously to detect stressful situations, based on the idea that if heart rate is elevated (indicating arousal, which typically accompanies stress) but activity level is low (suggesting the arousal is not due to being active and moving a lot), then the high heart rate is plausibly capturing a stressed state [6] (see Figure 2).

Our methodology is based on the comparison of the distribution of accelerometer and heart rate data between the pre-intervention and post-intervention periods. If participants' anxiety or interpretation bias decreased from the pre-to post-intervention period, as anticipated following CBM, we would expect less density in the top left cluster of Figure 2.

To provide a more concrete representation of the relationship between accelerometer and heart rate, we compare in Figure 3 the kernel density estimation [10] of activity and cardiac levels around self-reported positive and negative affective states (to provide some initial ground truth that a person is feeling relatively distressed). Self reported negative

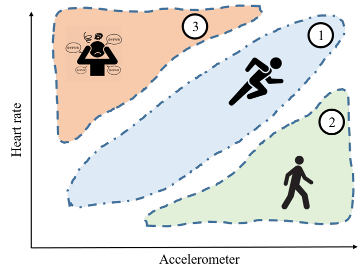

Fig. 2. The relation between accelerometer and heart rate. (1) During physical activity, heart rate increases linearly. (2) In less arousing activities (e.g., writing and washing dishes) heart rate may not increase significantly. (3) Highly stressful states may be represented by low accelerometer levels but high heart rate.

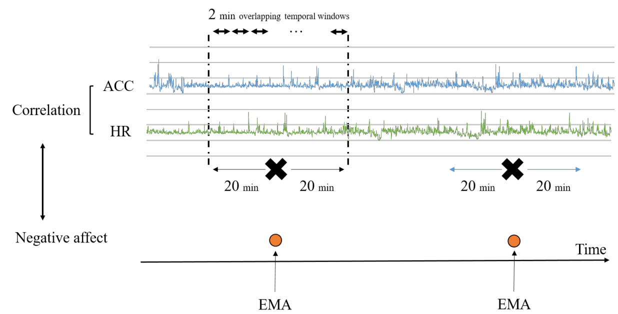

Fig. 4. This diagram describes the workflow of our physiological analytic method. (1) We preprocess both accelerometer and heart rate data, then (2) we study the correlation between the two types of data, and finally we compare the change in correlations with the change in negative affect happening after CBM.

affect We notice that during high negative affective states, there are more outliers having low activity level and high heart rate. This is in line with the hypothesis that high heart rate together with low activity level can indicate times of relatively high-stress.

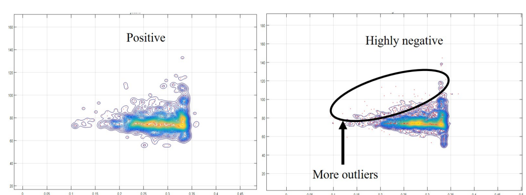

Fig. 3. A comparison of kernel density estimation of activity and cardiac levels around positive and negative affective states. Negative and positive affects have been reported on a scale of 0 to 100. We used an affect rating of 50 as a cutoff for low and high negative or positive affect classification given it represents the midpoint on the scale.

Based on these results, we hypothesize that the correlation between accelerometer and heart rate can be a predictor of changes in reported negative affect (as a proxy for anxiety or stress); the more accelerometer and heart rate data are positively correlated, the more we assume the state reflects activity-linked arousal (such as exercise; i.e., not anxiety), but when the correlation is lower, as occurs when heart rate is high but activity is low, the more likely we may be capturing an anxious or stressed state. As such, we developed a method to assess correlations between heart rate sensor and accelerometer data during both pre-intervention and post-intervention periods. Thereafter, we compared the change in correlations with the change in self-reported negative affect to investigate if the physiological measures detect the change in participants' anxiety states. To do this, we studied the correlations between heart rate and accelerometer around repeated ecological momentary assessment (EMA) prompts (around 6 times a day) during which participants reported their positive and negative affect.

The challenges of this analysis derived from the different sampling rate and heterogeneity (e.g., accelerometer has three-axis data) of two sensing modals. Because of lack of space, we briefly describe the method in three steps as follows: In step 1, we developed automated pre-processing techniques for both sensor data, in particular, removing noise (e.g., due to motion artifacts) and transforming data to the same spatial, temporal, and contextual scales using two-minute overlapping temporal windows. In step 2, we calculated the correlation between heart rate and accelerometer for each temporal window around the EMA prompts (20 min before and 20min after), providing approximately 40 2-minute level correlations for each reported affect state. In step 3, we studied the change in correlations between accelerometer and heart rate over the CBM intervention, and we compared this physiological change with the change in self-reported negative affect and the self-reported interpretation bias (the key mechanism targeted in our CBM) estimated using the well-established BSIQ score (higher scores imply more negative interpretation) [9]. Note, one limitation of the current approach is we are not including the change in SIAS scores in these analyses, in part due to concerns that the social anxiety symptom measure had limited sensitivity in detecting the changes in the brief one-week intervention period so was not a good indicator of the CBM effects, and in part because we wanted to emphasize the mobile-based measurement approach (i.e., the affect ratings based on EMA that reflect ecologically valid indicators of becoming distressed in the real-world, and are less prone to recall bias as occurs on the SIAS).

The results of these three steps are presented in Figure 5. In A, we present the percentage of positive and negative 2-minute-level correlations before and after CBM (the total number of correlations is around 12100) while excluding correlations around zero ($corr \in [-0.05, 0.05]$). In B we present the percentage of self-reported high and low negative affect states of 14 participants (6 participants were excluded due to low compliance rate). The total number of reported affective states is 347. Negative affect has been reported on a scale of 0 to 100. We used an affect rating of 50 as a cutoff for low and high negative affect classification given it represents the midpoint on the scale. In C we present the change in the BSIQ score to investigate if the physiological changes correlate with the changes in self-

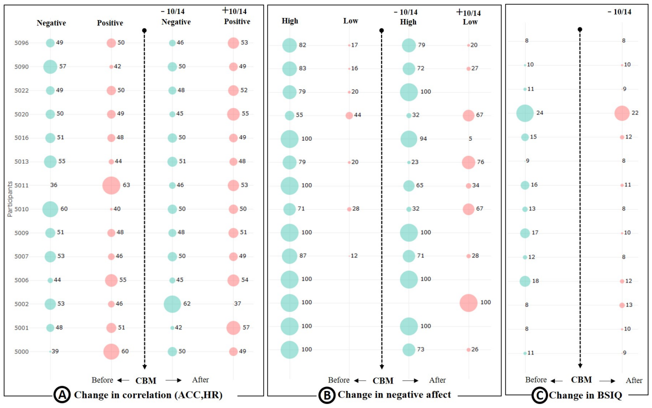

Fig. 5. Tracking the change over the course of CBM using active and passive data. In (A) we present the changes in the correlations distribution, in (B) we present the changes in the distribution of negative affect, and in (C) we present the change in the Bodily Sensations Interpretations Questionnaire (BSIQ) score.

reported interpretation bias.

We notice that the changes in correlations followed the same pattern as the changes in self-reported negative affect and interpretation bias. We recorded that for 10/14 of participants, the correlations have increased; i.e, the percentage of positive correlations has increased and the percentage of negative correlations has decreased (see A in Figure 5). Similarly, 10/14 participants reported less negative affect after the CBM intervention; i.e., the percentage of high negative affective states decreased and the percentage of low negative affective states increased (see B in Figure 5). We also recorded a decrease in the interpretation bias for 10/14 participants following the CBM intervention.

The intersection between the change in correlations and the change in negative affect is 8/10, and the intersection between the change in correlations and the change in interpretation bias is 7/10. Thus, the correlation between accelerometer and heart rate followed the same pattern as the changes in negative affect and interpretation bias during the post-intervention period. These results provide preliminary evidence of the viability of using physiological data to measure the changes following CBM interpretation training.

V. Conclusion

This paper examined physiological changes that occur following CBM interpretation training, based on an intra-model analysis of accelerometer and heart rate data. Thus, a contribution of the current study is to present a framework for how to use passively collected data to understand outcomes of brief computerized interventions, such as computerized CBM. Results suggest that changes in the correlation between accelerometer and heart rate data can be useful in tracking changes to participant mental state in response to CBM training, as evidenced by the frequency of their negative affective states and their tendency to assign threatening, negative interpretations in ambiguous situations.

An exciting aim of the current research is to use mobile sensing data to inform Just-in-Time interventions, by using ongoing user data to trigger an intervention at precise moments and contexts. For example, an enhanced understanding of how heart rate and accelerometer is linked to mental stress can be used to deliver a mobile CBM intervention before a downward spiral occurs (e.g., crucial moments before the onset of a panic attack). This line of work is promising given the rapid advancement of sensor technologies.

Future work will further explore the possibility of using passively-sensed data to estimate the effectiveness of interventions, which may eventually limit our dependency on self-report methods that require user motivation and are prone to response bias. Importantly, the ability to integrate different types of passively sensed data may allow researchers and clinicians to understand patient outcomes through triangulation. For example, whereas the combination of accelerometer and heart rate data provides insight into the balance between physical and mental load, adding GPS data may allow for a refined understanding of the types of contexts that are most stressful. This is consistent with a research program that tries to identify what types of interventions are most useful, for whom, and under what circumstances. Further, continuously sensed data allows for a greater potential to understand how people respond to brief interventions in both the short- and long-term (e.g., proximal versus distal outcomes).

Acknowledgment

This research was supported by the Hobby Postdoctoral and Predoctoral Fellowships in Computational Science, and NIMH R34MH106770 and NIMH R01MH113752 grants.

References

[1] American Psychiatric Association, "Diagnostic and statistical manual of mental disorders (5th ed.)," 2013.

[2] C. MacLeod and A. Mathews, "Cognitive bias modification approaches to anxiety," *Annual Review of Clinical Psychology*, vol. 8, no. 1, pp. 189–217, apr 2012.

[3] J. R. Beadel, A. Mathews, and B. A. Teachman, "Cognitive bias modification to enhance resilience to a panic challenge," *Cognitive Therapy and Research*, vol. 40, no. 6, pp. 799–812, 2016.

[4] H. Xiong, Y. Huang, L. E. Barnes, and M. S. Gerber, "Sensus: a cross-platform, general-purpose system for mobile crowdsensing in human-subject studies," in *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing*. ACM, 2016, pp. 415–426.

[5] A. Sano and R. W. Picard, "Stress recognition using wearable sensors and mobile phones," in *Affective Computing and Intelligent Interaction (ACII), 2013 Humaine Association Conference on*. IEEE, 2013, pp. 671–676.

[6] M. Wu, H. Cao, H.-L. Nguyen, K. Surmacz, and C. Hargrove, "Modeling perceived stress via hrv and accelerometer sensor streams," in *Engineering in Medicine and Biology Society (EMBC), 2015 37th Annual International Conference of the IEEE*. IEEE, 2015, pp. 1625–1628.

[7] T. T. Wells and C. G. Beevers, "Biased attention and dysphoria: Manipulating selective attention reduces subsequent depressive symptoms," *Cognition & Emotion*, vol. 24, no. 4, pp. 719–728, jun 2010.

[8] F.-T. Sun, C. Kuo, H.-T. Cheng, S. Buthpitiya, P. Collins, and M. Griss, "Activity-aware mental stress detection using physiological sensors," in *International Conference on Mobile Computing, Applications, and Services*. Springer, 2010, pp. 211–230.

[9] A. Mathews and B. Mackintosh, "Induced emotional interpretation bias and anxiety." *Journal of Abnormal Psychology*, vol. 109, no. 4, pp. 602–615, 2000.

[10] "Kernel density estimators," pp. 125–193.