LivNao

# Using Passive Sensor Data From Smartphones To Measure Mental Health

February 2020

Daniel Leung
LivNao Technologies

# Contents:

## Introduction:

Burnout costs companies in the United States $300B annually [1]. 77% of full-time employees report having experienced burnout at least once in their current job [2]. As one of the fastest-growing public health concerns, the World Health Organization, WHO, recently classified burnout as an occupational phenomenon in the 10th release of their International Classification of Diseases, ICD-10 [3]. Studies demonstrate strong correlations [4] [5] between elevated anxiety and depression levels with high Maslach Burnout Inventory, MBI scoring [6].

Studies have shown burnout is a leading cause and correlates strongly with poor mental health. Poor mental health has been proven to increase physical health risks by up to 6.5x [7]. Those with poor mental health can see up to a 10 to 25 year decrease in life expectancy, twice the effect smoking has on longevity [8]. Additionally, poor mental health can increase the risk of musculoskeletal pain by 201% [9] and morbidity risk by 35% in hazardous workplaces [10]. In medicine, it is estimated that 78% of malpractice claims involved a physician who reported burnout symptoms [11] and further research has shown physicians who are burnt out are 2.2x more likely to malpractice [12], costing insurers $3.12B every year in the United States alone.

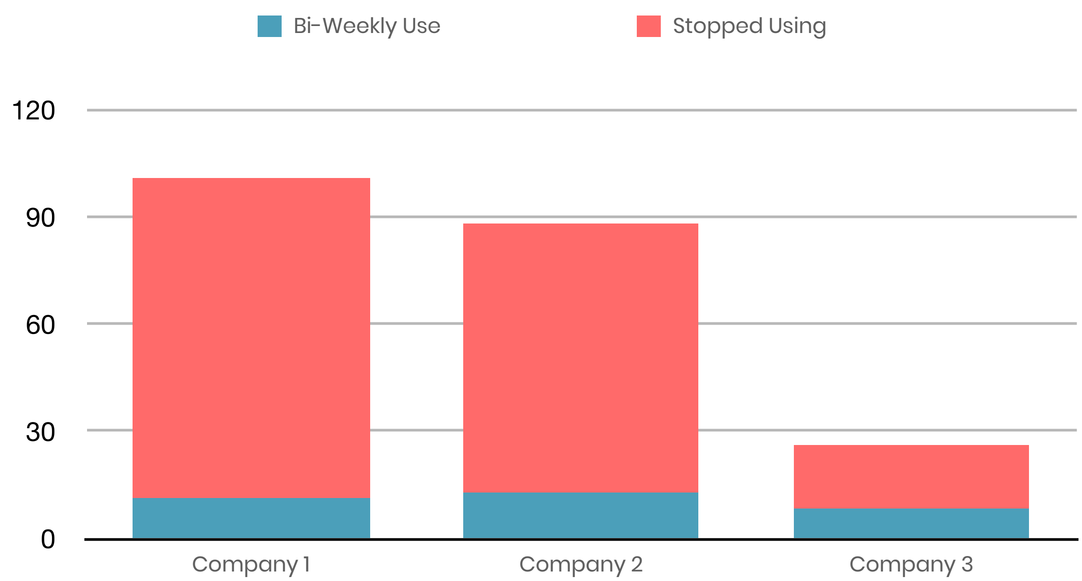
Products such as Calm [13], Headspace [14] & Happify [15] claim to alleviate mental health and burnout issues. Our previous research and user testing identified a major gap in these products' long-term efficacy. Products such as Headspace require users to regularly (1) open a mobile app, (2) search through a variety of interventions and, (3) self-select an intervention, or complete a questionnaire for a recommendation. Products such as Calm require surveying of users to identify which intervention should be delivered to the user [Figure 1].

**Figure 1: Calm App**


Existing solutions such as Calm require users to manually input their mood daily for recommendations

To better understand whether these solutions work, we conducted a series of electronic surveys in February 2019 to determine the efficacy and adoption of products such as Calm, Headspace & Happify. 215 employees from enterprises and a public healthcare system were surveyed electronically via email. The surveys indicated that 85% of users had experimented with mobile applications that claim to improve mental health at some point over the past two years, only 19% reported continued bi-weekly use [Figure 2].

**Figure 2: Electronic Survey Results**




Users were surveyed on whether they tried an app in the last two years and whether they still use it at least once bi-weekly

Additional user studies were conducted within two focus groups with select individuals from a large technology firm and public health system. Participants included 12 full-time employees with job titles L3 Engineer, Marketing Operations, Campaigns Coordinator, Sales, Emergency Room Physician, Receptionist, Paediatrics Nurse, Public Health Manager and Head of Cardiology. Feedback received from users in the focus groups included:

- “All the questions those apps ask me stress me out even more, they’re annoying”
- “Checking in every day is too much work, what’s in it for me?”
- “The suggestions they give all seem to be pretty random”
- “Opening the app is not top of mind for me every day”

Our user studies identified a gap that needed to be filled for long-term sustainability of positive outcomes to alleviate mental health & burnout issues. For a digital solution to be effective, user experience must be improved. Passive measurement and detection of mental health scores could fill this gap by removing onus on the user to seek help, but rather push the right help at the right time.

## Previous Work:

A systemic review of 90 academic studies [Appendix B] proved the potential for passive smartphone sensor data to be used for mental health assessment score predictions.

Studies that were included experimented with basic models such as random forest classifiers and logistic regressions to predict users' scores on the following industry-standard assessment methods:

- General Anxiety Disorder Scale GAD-7 or Hamilton Anxiety HAM-A [Appendix C]
- Patient Health Questionnaire PHQ-9 or Hamilton Depression HAM-D [Appendix D]
- Perceived Stress Scale PSS [Appendix E] scores.

Of the 90 studies reviewed, 53 met our inclusion criteria. 37 studies were disqualified due to the inputs not meeting reasonable privacy expectations as determined from user focus groups. Inputs deemed as not acceptable and too invasive included; (1) any sort of natural language processing on user communications, (2) the use of a camera or microphone to record the user, and (3) detailed user phone activity logging.

Studies included in our systemic review were able to accurately predict assessment results with an F-1 score of between 0.5 and 0.8.

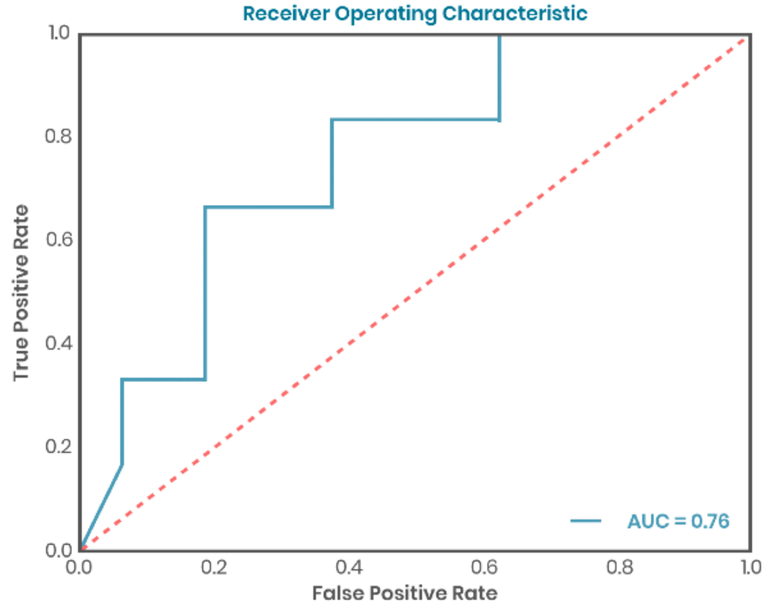
Building on raw datasets obtained from the studies included in our systemic review, we designed and deployed our first study, DC1, for 45-days in Spring 2019. A proprietary iOS app was built and deployed to 150 participants to collect pa
ssive sensor data, including accelerometer readings and physical activity information from Apple Health. Data was labeled by users through a series of daily in-app PHQ-9, GAD-7 and PSS assessments.

Additional questions on the topic of energy, focus & productivity levels were also administered daily. A total of 25M data points were collected throughout DC1.

DC1 enabled us to build an MVP validating what was done by the studies in our systemic review. Gradient-boosted decision trees and logistic regressions model technologies applied to our datasets yielded F-1 scores of between 0.70 - 0.80 when predicting for GAD-7, PHQ-9, PSS, energy, focus and productivity scores. AUC was determined to be 0.76 [Figure 3].

The addition of Heart Rate Variability from wearables yielded a marginally significant F-1 score improvement of 0.06.

**Figure 3: DC1 Results — Area Under Curve AUC**




## Objectives:

Recent technological advancements and APIs shared by Apple with developers in the release of iOS 13 in September 2019 unlocked capabilities to build improved, context-aware models.

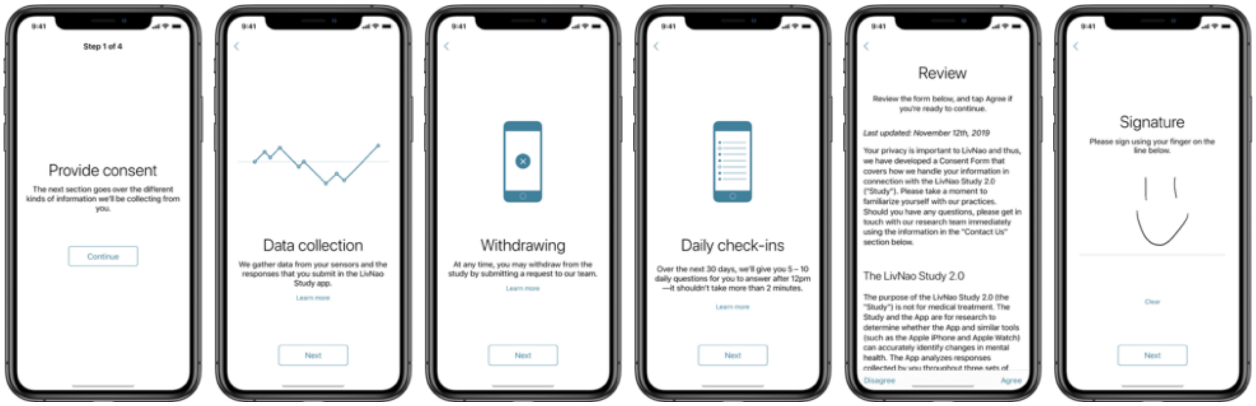
The objective of this study, DC2, is to explore the potential for usage of new indicators derived from Bluetooth Low Energy scanning and screen brightness to build more complex deep neural network models.

These more complex models combined with circadian rhythm predictions would allow for better generalizability, higher accuracy in predictions and improved AUC.

## Methods:

Similar to DC1, delivery of this study, DC2, was done in the form of an iOS app. Users were asked to download the DC2 app through a landing page. Once downloaded, users were prompted to complete an informed consent [Figure 4] component as part of the onboarding process explaining the type of passive data collected and their expected commitment to answering questionnaires.

**Figure 4: DC2 Informed Consent Steps**




Informed consent screens were designed in accordance to Apple's Human Interface Guidelines

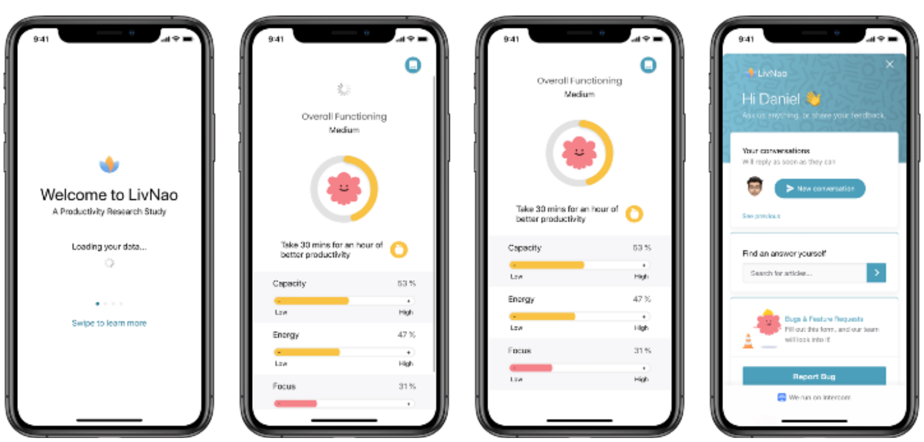
Sensor inputs included raw data from Accelerometer readings obtained via the Apple CoreMotion API, nearby Bluetooth Low Energy BLE device IDs, Wifi-based positioning methods, Wifi BSSIDs and biometric data from Apple Health when available.

User inputs included daily energy, focus, and PSS questionnaires alongside weekly GAD-7 and PHQ-9 questionnaires on Monday and Thursday respectively. Additionally, users completed a full GAD-7 and PHQ-9 questionnaire upon exit of the study at 30 days.

All data were de-identified using a randomly generated alpha-numeric participant ID before leaving the user's device. Consent documents and daily activity confirmation were reported and stored separately from user input and sensor data.

Users were allowed to read their passively calculated mental health scores from within the app as well as view historical predictions [Figure 5].

**Figure 5: DC2 Passive Mental Health Scores**



Passively calculated mental health scores were displayed to users as an encouragement to participate in DC2

## Inclusion Criteria:

To improve the generalizability of the resulting model, inclusion criteria were kept to a minimum. Participants had to meet basic criteria to; (1) provide consent and (2) provide quality data. As such, the following inclusion criteria were enforced:

1. Must be over the age of majority in their local jurisdiction
2. Must be comfortable with written English
3. Must own an iPhone 6 or later with iOS 13.2 or later
4. Must be able to connect to the internet over a Wifi or Cellular Data network daily

## Participant Recruitment:

An omnichannel approach was used for recruitment of participants including; (1) Key Opinion Leaders, (2) Social Media Networks, (3) Strategic Organization Partnerships and (4) Public Solicitation.

Key Opinion Leaders KOLs, across a variety of demographic and occupation groups were identified to recruit participants within their social circles. KOLs were incentivized using a point-based system where prizes were award to those who had the highest number of daily active user attributions.

Social Media Networks such as Blind App, Facebook Groups & Twitter were used to promote DC2. Posts directed participants to a blog post on our website containing informed consent information and instructions on how to participate in DC2.

Strategic partnerships were leveraged for the promotion of DC2 at events and over email communication. Partners included the University of Toronto Medical Society, various student clubs at the University of British Columbia, and the global Health Tech Forum.

Members of the public were solicited by study administrators at various coffee shops in Vancouver, San Francisco, Palo Alto and, Toronto to participate in DC2.

A total of 1,300 users downloaded our DC2 app and 800 users completed a full 30-day study period [Figure 6].

Ages ranged from 22 to 58 with a gender split of 56% males vs. 44% females [Figure 7]. Notable occupational populations included 55% who identified as working in a corporate or technology firm and 30% as students [Figure 8].

**Figure 6: Electronic Survey Results**

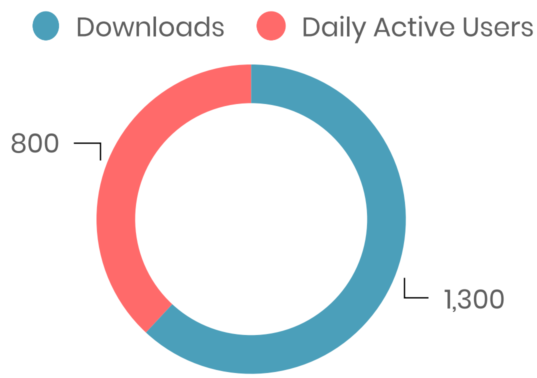



**Figure 7: Gender Distribution**

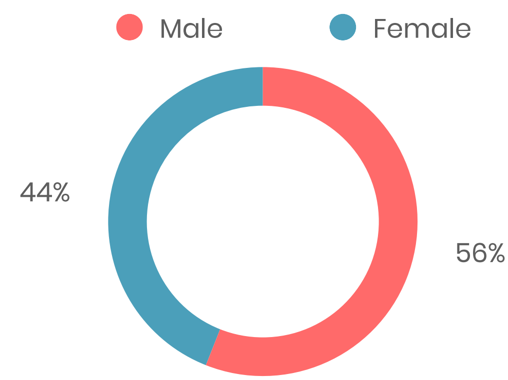
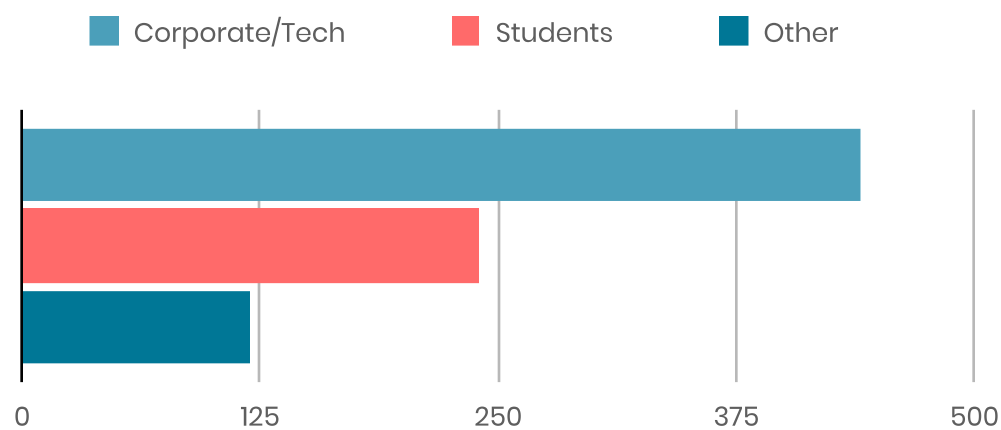



**Figure 8: Occupational Populations**




## Results:

In total, 40 million data points were collected from participants between November 2019 and February 2020. Deep neural network methods such as multi-tasked training were deployed to generate an average F-1 score of 0.95 for prediction of the correct GAD-7, PHQ-9, PSS scores.

F-1 scores using models generated post-DC2 saw an overall average improvement of 0.15 when compared to basic models developed from DC1.

Additional features allowing for controlled tradeoff of false-positive/negatives developed from DC2 resulted in an AUC of 0.9.

## Validation:

Validation was performed in side-by-side testing. 30 participants who did not participate in DC2 were selected to complete a full GAD-7, PHQ-9, and PSS assessment.

Concurrently, participants used our app running the new model created after DC2 to make predictions on their mental health assessment scores.

On average, predicted scores from our new model were matched to score categories from the traditional assessments at an accuracy of 92%.

## Future Studies:

We have decided to convert DC2 into an ongoing, continuous study with no end date to improve generalizability, allowing for accurate predictions across a wider user base. The LivNao Study application will be available for download by the general public via the Apple App Store. Future plans to develop an Android-equivalent application are in place to expand inclusion criteria.

## Appendix A — Muslach Burnout Inventory MBI:

While we would have liked to include the Muslach Burnout Inventory MBI questionnaire and scoring methods in our Appendices for publication, the MBI and MBI manual are copyrighted publications that must be obtained directly from the publisher. To obtain the survey items, scoring information, and research manual, please contact the publisher, which is a company named “Mind Garden”. The easiest way to contact the company is to go to the website: www.mindharden.com/products/mbi.

## Appendix B — Systemic Review of Studies:

| Study Name | Input | Output |
|---|---|---|
| Assessing Social Anxiety using GPS Trajectories and Point-Of-Interest Data | Geo, Mobility | Anxiety, SIAS |
| Automatic Stress Detection in Working Environments From Smartphones' Accelerometer Data: A First Step | Mobility | Stress, B-Change |
| Behavioral Indicators on a Mobilityile Sensing Platform Predict Clinically Validated Psychiatric Symptoms of Mood and Anxiety Disorders. | Geo, SMS | Anxiety, Depression, PHQ, PTSD |
| BeWell: A Smartphone Application to Monitor, Model and Promote Wellbeing | Geo, Mobility | B-Change |
| Can Smartphones Detect Stress-Related Changes in the Behaviour of Individuals? | BLE | Stress, PSS |
| CASP: Context-Aware Stress Prediction System | BLE | Stress, PSS |
| Cloud based mental state monitoring system for suicide risk reconnaissance using wearable bio-sensors | Bio | Anxiety, Depression, Stress, PSS |
| Comparison of Machine Learning Techniques for Psychophysiological Stress Detection | Geo, SMS | PHQ, Depression, Stress, PSS |
| Continuous Stress Detection Using a Wrist Device - In Laboratory and Real Life | Mobility | B-Change, Stress |
| Correlations Between Objective Behaviour Features Collected From Mobilityile & Wearable Devices & Depressive Mood Symptoms In Patients With Affective Disorders: a Systematic Review: | Mobility, SMS | Depression, PHQ |
| Daily Mood Assessment Based on Mobilityile Phone sensing | Mobility, Geo, SMS | B-Change, Mood |
| DeepMood: Modeling Mobilityile Phone Typing Dynamics for MoodDetection | Mobility | Depression |
| deStress: Mobilityile and Remote Stress Monitoring Alleviation, and Management Platform | Mobility | Stress, PSS |
| Harnessing Context Sension to Develop a Mobilityile Intervention for Depression | Geo, Mobility | PHQ |
| How to use smartphones for less obtrusive ambulatory mood assessment and mood recognition | Geo, Mobility, SMS | Stress, PSS |
| Identifying Behavioral Phenotypes of Loneliness and Social Isolation with Passive Sensing: Statistical Analysis, Data Mining and Machine Learning of Smartphone and Fitbit Data | BLE, Geo, Use, SMS | Anxiety, Depression, Loneliness |
| Identifying Objective Physiological Markers and Modifiable Behaviors for Self-Reported Stress and Mental Health Status Using Wearable Sensors and Mobilityile Phones: Observational Study. | Geo, SMS | Anxiety, Depression, PHQ, Stress |
| Leveraging Routine Behavior and Contextually-Filtered Features for Depression Detection among College Students | Geo, BLE, Mobility, SMS, Use | Depression, BDI-II |
| Machine Learning in Mental Health - A systematic scoping review of methods and applications | Met | Anxiety, Depression, Stress |
| Mining Smartphone Data to Classify Life-Facets of Social Relationships | Geo, SMS, BLE | SIAS |
| Mobilityile Phone & Wearable Sensor-Bsaed mHealth Approach for Psychiatric Disorders and Symptoms: Systematic Review and Link to the m-RESIST Project | Geo, SMS, Mobility | PHQ, Anxiety, Depression, Stress, SIAS |
| Mobilityile Phone Detection of Semantic Location and its Relationships to Depression and Anxiety | Geo, Mobility, SMS | Anxiety, Depression, PHQ |
| Mobilityile Phone Sensor Correlates of Depressive Symptom Severity in Daily-Life Behavior: An Exploratory Study | Geo | Depression, PHQ |
| Mobilityile phones as medical devices in mental disorder treatment: an overview | Geo, Mobility, SMS, BLE, Bio | Depression, B-Change, Stress, Mood |

## Appendix B — Systemic Review of Studies (Cont'd):

| Study Name | Input | Output |
|---|---|---|
| Monitoring Physical Activity and Mental Stress | Geo, Mobility | Stress, PSS |
| MoodScope: Building a Mood Sensor from Smartphone Usage Patterns | Geo, SMS, Mobility | B-Change |
| Multi-view Bi-clustering to Identify Smartphone Sensing Features Indicative of Depression | Geo, Mobility | PHQ, Depression, Stress, B-Change |
| Next-Generation Psychiatric Assessment: Using Smartphone Sensors to Monitor Behaviour and Mental Health | Geo, Mobility | B-Change, Depression, PHQ, Stress |
| Passive & In-situ Assessment of Mental & Physical Well-being using Mobilityile Sensors | Mobility | Depression, Mood, B-Change |
| Personal Sensing: Understanding Mental Health Using Ubiquitious Sensors and Machine Learning | BLE, Geo, Mobility, SMS, Bio | Anxiety, B-Change, Depression, PHQ, Stress, Mood |
| Physical activity, screen time and self-rated health and mental health in Canadian adolescents. | Mobility | Depression, Anxiety, Stress, B-Change |
| PRISM: A Data-Driven Platform For Monitoring Mental Health | Mobility | Anxiety |
| Recognizing Academic Performance, Sleep Quality, Stress Level & Mental Health Using Personality Traits, Wearable Sensors & Mobilityile Phones | Mobility, SMS | Mood, Stress |
| Role of physical and sedentary activities in the development of depressive symptoms in early adolescence | Mobility | B-Change, Stress, Depression, Mood |
| Sensing Behavioral Symptoms of Mental Health & Delivering Personalized Interventions Using Mobilityile Technologies | Geo, Mobility | Anxiety, B-Change, Depression, PHQ |
| Sensing Technologies for Monitoring Serious Mental Illnesses | BLE, Mobility, Geo | Depression, PHQ, B-Change |
| SmartGPA: How Smartphones Can Assess and Predict Academic Performance of College Students | Mobility, Geo | B-Change, Depression, Mood, PHQ, Stress |
| Smartphone App Usage As Predictor Of Perceived Stress Levels At Workplace | Use | Stress, B-Change |
| Smartphone Based Stress Prediction | Use | Stress, PSS |
| Smartphone-Based Monitoring of Objective and Subjective Data in Affective Disorders: Where Are We Going and Where Are We Going? Systematic Review | BLE, Geo, Mobility, Use | Anxiety, Depression, PHQ, HAM |
| Smartphones in Mental Health: Detecting Depressive and Manic Episodes | Mobility, Use | Depression, HAM |
| Stress Detection Using Wearable Physiological Sensors | Bio | Stress, PSS |
| Stress Modelling and Prediction in Presence of Scarce Data | Geo, Mobility, Use | Stress, PSS |
| Stress Recognition Using Wearable Sensors & Mobilityile Phones | Use, Bio | Stress, PSS |
| Systematic review of smartphone-based passive sensing for health and wellbeing | Mobility, BLE | Stress, PHQ, Depression |
| Tackling Mental Health by Integrating Unobtrusive Multimodal Sensing | Bio, Ext | Depression, Stress |
| Tell me your apps and I will tell you your mood: correlation of apps usage with bipolar disorder state | Use | BPD |
| The associations between sedentary behaviour and mental health among adolescents: a systematic review | Mobility, Use | Stress, Depression, Anxiety |
| The Diagnosis of Mental Stress by Using Data Mining Technologies | Bio | Stress, PSS |
| The Relationship Between Mobilityile Phone Location Sensor Data & Depressive Symptom Severity | Geo | Depression, B-Change |
| Towards Measuring Stress with Smartphones and Wearable Devices During Workday and Sleep | Bio | Stress, PSS |
| Towards Personalised Ambient Monitofing of Mental Health via Mobilityile Technologies | Geo, BLE | BPD, B-Change, Depression |

## Appendix B — Systemic Review of Studies (Cont'd):

| Study Name | Input | Output |
|---|---|---|
| **Trajectories of Depression: Unobstructive Monitoring of Depressive States by means of Smartphone Mobilityility Traces Analysis** | Geo, SMS, BLE, Mobility | Depression, PHQ, Stress |
| **Using Intermediate Models and Knowledge Learning to Improve Stress Prediction** | SMS, BLE, Geo | Stress, B-Change |
| **Using Mobilityile Phone Sensor Technology for Mental Health Research: Integrated Analysis to Identify Hidden Challenges and Potential Solutions** | BLE, Mobility | B-Change, Depression |
| **Using Smart Phone Mobilityility Traces For The Diagnosis of Depressive and Manic Episodes in Bipolar Patients** | Geo | BPD, Depression |
| **Using Smartphones to Monitor Bipolar Disorder Symptoms: A Pilot Study** | Geo, Mobility, Use | Depression, BPD |
| **Well-Being Tracking via Smartphone-Measured Activity and Sleep: Cohort Study** | Mobility, Geo | Depression, B-Change |

## Appendix C — General Anxiety Disorder GAD-7

### GAD-7 Questionnaire

| Over the last 2 weeks, how often have you been bothered by the following problems? | Not at all sure | Several days | Over half the days | Nearly every day |
|---|---|---|---|---|
| 1. Feeling nervous, anxious or on edge | 0 | 1 | 2 | 3 |
| 2. Not being able to stop or control worrying | 0 | 1 | 2 | 3 |
| 3. Worrying too much about different things | 0 | 1 | 2 | 3 |
| 4. Trouble relaxing | 0 | 1 | 2 | 3 |
| 5. Being so restless that it's hard to sit still | 0 | 1 | 2 | 3 |
| 6. Becoming easily annoyed or irritable | 0 | 1 | 2 | 3 |
| 7. Feeling afraid as if something awful might happen | 0 | 1 | 2 | 3 |
| **Add the score for each column** | + | + | + | |
| **Total Score *(add your column scores)* =** | | | | |

### GAD-7 Scoring

This is calculated by assigning scores of 0, 1, 2, and 3 to the response categories, respectively, of "not at all," "several days," "more than half the days," and "nearly every day."

GAD-7 total score for the seven items ranges from 0 to 21.

| Total Score: | Result |
|---|---|
| 0 to 4 | Minimal Anxiety |
| 5 to 9 | Mild Anxiety |
| 10 to 14 | Moderate Anxiety |
| 15 to 21 | Severe Anxiety |

## Appendix D — Patient Health Questionnaire PHQ-9

### PHQ-9 Questionnaire

| Over the last 2 weeks, how often have you been bothered by any of the following problems? | Not at all sure | Several days | Over half the days | Nearly every day |
|---|---|---|---|---|
| 1. Little interest or pleasure in doing things | 0 | 1 | 2 | 3 |
| 2. Feeling down, depressed, or hopeless | 0 | 1 | 2 | 3 |
| 3. Trouble falling or staying asleep, or sleeping too much | 0 | 1 | 2 | 3 |
| 4. Feeling tired or having little energy | 0 | 1 | 2 | 3 |
| 5. Poor appetite or overeating | 0 | 1 | 2 | 3 |
| 6. Feeling bad about yourself — or if that you are a failure or have let yourself or your family down | 0 | 1 | 2 | 3 |
| 7. Trouble concentrating on things, such as reading the newspaper or watching television | 0 | 1 | 2 | 3 |
| 8. Moving or speaking so slowly that other people could have noticed. Or the opposite — being so fidgety or restless that you have been moving around a lot more than usual | 0 | 1 | 2 | 3 |
| 9. Thoughts that you would be better off dead, or of hurting yourself | 0 | 1 | 2 | 3 |
| **Add the score for each column** | + | + | + | |

**Total Score** ***(add your column scores)*** **=**

### PHQ-9 Scoring

For initial diagnosis:

1. Patient completes PHQ-9 Quick Depression Assessment
2. If there are at least 4 answers in the shaded section, consider a depressive disorder. Add score to determine severity.

Consider Major Depressive Disorder:

- If there are at least 5 answers in the shaded section

Consider Other Depressive Disorder:

- If there are 2-4 answers in the shaded section

Note: Since the questionnaire relies on patient self-report, all responses should be verified by the clinician, and a definitive diagnosis is made on clinical grounds taking into account how well the patient understood the questionnaire, as well as other relevant information from the patient.

## Appendix D — Patient Health Questionnaire PHQ-9 (Cont'd)

**PHQ-9 Scoring (Cont'd)**

Diagnoses of Major Depression Disorder or Other Depressive Disorder also require impairment of social, occupational, or other important areas of functioning (Q10) and ruling out normal bereavement, a history of Manic Episode (Bipolar Disorder), and a physical disorder, medication, or other drug as the biological cause of depressive symptoms.

To monitor severity over time for newly diagnosed patients or patients in current treatment for depression:

1. Patients may complete questionnaires at baseline and at regular intervals (i.e. every 2 weeks) at home and bring them in at their next appointment for scoring or they may compete the questionnaire during each scheduled appointment.
2. Add up answers by column.
3. Add together column scores to get a Total Score
4. Refer to the accompanying PHQ-9 Scoring Box to interpret the Total score
5. Results may be included in patient files to assist you in setting up a treatment goal, determining degree of response, as well as guiding treatment intervention

PHQ-9 total score for the nine items ranges from 0 to 27.

| Total Score: | Result |
|---|---|
| 1 to 4 | Minimal depression |
| 5 to 9 | Mild depression |
| 10 to 14 | Moderate depression |
| 15 to 19 | Moderately severe depression |
| 20 to 27 | Severe depression |

## Appendix E — Perceived Stress Scale PSS

**PSS Questionnaire**

| In the last month, how often have you: | Never | Almost Never | Some Times | Fairly Often | Very Often |
|---|---|---|---|---|---|
| 1. Been upset because something that happened unexpectedly? | 0 | 1 | 2 | 3 | 4 |
| 2. Felt that you were unable to control the important things in life? | 0 | 1 | 2 | 3 | 4 |
| 3. Felt nervous and "stressed"? | 0 | 1 | 2 | 3 | 4 |
| 4. Felt confident about your ability to handle your personal problems? | 0 | 1 | 2 | 3 | 4 |
| 5. Felt that things were going your way? | 0 | 1 | 2 | 3 | 4 |
| 6. Found that you could not cope with all the things you had to do? | 0 | 1 | 2 | 3 | 4 |
| 7. Been able to control irritations in your life? | 0 | 1 | 2 | 3 | 4 |
| 8. Felt that you were on top of things? | 0 | 1 | 2 | 3 | 4 |
| 9. Been angered because of things outside of your control? | | | | | 4 |
| 10. Felt difficulties were piling so high. you could not overcome them? | 0 | 1 | 2 | 3 | 4 |

**PSS Scoring**

The Perceived Stress Scale PSS is the most widely used psychological instrument for measuring the perception of stress. It is a measure of the degree to which situations in one's life are appraised as stressful. Items were designed to tap how unpredictable, uncontrollable, and overloaded respondents find their lives. The scale also includes a number of direct queries about current levels of experienced stress. The PSS was designed for use in community samples with at least a junior high school education. The items are easy to understand and the responses alternatives are simple to grasp. Moreover, the questions are of a general nature and hence are relatively free of content specific to any subpopulation group. The questions in the PSS ask about feelings and thoughts during the last month. In each case, respondents are asked how often they felt a certain way.

Evidence for Validity — Higher PSS scores were associated with for example:

1. Failure to quit smoking
2. Failure among diabetics to control blood sugar levels
3. Greater vulnerability to stressful life-event-elicited depressive symptoms
4. More colds

Health Status Relationship To PSS — Cohen et al. (1988) shows correlations with PSS and Stress Measures, Self-Reported Health and Health Services Measures, health Behaviour Measures, Smoking Status, Help Seeking Behaviour.

## Appendix E — Perceived Stress Scale PSS (Cont'd)

### PSS Scoring (Cont'd)

Temporal Nature — Because levels of appraised stress should be influenced by daily hassles, major events, and changes in coping resources, predictive validity of the PSS is expected to fall off rapidly after four to eight weeks.

Scoring — PSS scores are obtained by reversing responses (i.e. 0 = 4, 1 = 3, 2 = 2, 3 = 1, 4 = 0) to the four positively stated items (items 4, 5, 7, 8) and then summing across all scale items. A short 4 item scale can be made from questions 2, 4, 5, and 10 of the PSS 10 item scale.

Norm Groups — L. Harris Poll gathered information on 2,387 respondents in the U.S.

| Category | N | Mean | S.D. |
|---|---|---|---|
| **Gender** | | | |
| Male | 926 | 12.1 | 5.9 |
| Female | 1406 | 13.7 | 6.6 |
| **Age** | | | |
| 18 to 29 | 645 | 14.2 | 6.2 |
| 30 to 44 | 750 | 13.0 | 6.2 |
| 45 to 54 | 285 | 12.6 | 6.1 |
| 55 to 64 | 282 | 11.9 | 6.9 |
| 65 & older | 296 | 12.0 | 6.3 |
| **Race** | | | |
| White | 1924 | 12.8 | 6.2 |
| Hispanic | 98 | 14.0 | 6.9 |
| Black | 176 | 14.7 | 7.2 |
| Other | 50 | 14.1 | 5 |

## Citations


[1] N. Stelter, "Workplace Stress — The $300B business problem that's only getting worse", 2019. [Online]. Available: https://business.kaiserpermanente.org/insights/mental-health-workplace/workplace-stress-business-problem-getting-worse. [Accessed: Feb-2020]

[2] J. Fisher, "Workplace Burnout Survey", Deloitte, 2019. [Online]. Available: https://www2.deloitte.com/us/en/pages/about-deloitte/articles/burnout-survey.html. [Accessed: Feb-2020]

[3] World Health Organization, *International Statistical Classification of Diseases and Related Health problems*, 10th ed. Geneva: World Health Organization, 2009. [Accessed: Feb-2020]

[4] Y. Choi, B. Choi, T. Park, J. Uhm, D. Lee, S. Chang and S. Kim, "A study on the characteristics of Maslach Burnout Inventory-General Survey (MBI-GS) of workers in one electronics company", Annals of Occupational and Environmental Medicine, vol. 31, no. 1, 2019.

[5] B. Choi, J. Kim, D. Lee, J. Paik, B. Lee, J. Lee, H. Lee and H. Lee, "Factors Associated with Emotional Exhaustion in South Korean Nurses: A Cross-Sectional Study", Psychiatry Investigation, vol. 15, no. 7, pp. 670-676, 2018.

[6] A. Coker and P. Omoluabi, "Validation Of Maslach Burnout Inventory", IFE Psychology, vol. 17, no. 1, 2009.

[7] J. Burton, "WHO healthy workplace framework and model: background and supporting literature and practices", World Health Organization, Geneva, 2010 [Online]. Available: http://www.who.int/iris/handle/10665/113144. [Accessed: Feb-2020]

[8] World Health Organization, "Premature death among people with severe mental disorders", 2014. [Online]. Available: https://www.who.int/mental_health/management/info_sheet.pdf. [Accessed: Feb-2020]

[9] E. Lanballe, S. Innstrand, K. Hagtvet, E. Falkum and O. Gjerløw Aasland, "The relationship between burnout and musculoskeletal pain in seven Norwegian occupational groups", Work, vol. 32, no. 2, pp. 179-188, 2009 [Online]. Available: https://content.iospress.com/articles/work/wor00804. [Accessed: Feb-2020]

[10] K. Ahola, A. Väänänen, A. Koskinen, A. Kouvonen and A. Shirom, "Burnout as a predictor of all-cause mortality among industrial employees: A 10-year prospective register-linkage study", Journal of Psychosomatic Research, vol. 69, no. 1, pp. 51-57, 2010 [Online]. Available: https://doi.org/10.1016/j.jpsychores.2010.01.002. [Accessed: Feb-2020]

[11] T. Reith, "Burnout in United States Healthcare Professionals: A Narrative Review", Cureus, 2018. [Accessed: Feb-2020]

[12] J. Huberty, "Calm Science", Calm Blog, 2020. [Online]. Available: https://blog.calm.com/calm-science. [Accessed: Feb-2020]

[13]A. Motluk, "Do doctors experiencing burnout make more errors?", Canadian Medical Association Journal, vol. 190, no. 40, pp. E1216-E1217, 2018.

[14] A. Rooney, "Headspace: Burnt out? Try this.", 2020. [Online]. Available: https://www.headspace.com/blog/2016/11/21/burnt-out-try-this/. [Accessed: Feb-2020]

[15] D. Levey, "Happify: Is Your Team Suffering from Burnout? Here's How to Help", 2020. [Online]. Available: https://www.happify.com/hd/is-your-team-suffering-from-burnout-here-is-how-to-help/. [Accessed: Feb-2020]