Predicting Calmness, Anxiety, and Depression using Wearable Sensors

Rajlakshmi Borthakur (✉ raji@teblux.com)

TerraBlue XT <https://orcid.org/0000-0003-0608-7242>

Natwar Sharma

Saveetha Medical College Hospital

Priya Pattanaik

TerraBlue XT

Article

Keywords:

Posted Date: January 19th, 2022

DOI: <https://doi.org/10.21203/rs.3.rs-1273712/v1>

License: © ⓘ This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Predicting Calmness, Anxiety, and Depression using Wearable Sensors

Rajlakshmi Borthakur, Natwar Sharma, Priya Ranjan Pattanaik

Abstract

One of the main reasons for the high prevalence of mental disorders is that there is no technology to aid diagnosis or to report on recovery factors like effect of therapeutic interventions and medicines. To enable faster access to screening and to measure recovery, we propose a wearables-based framework for the automatic prediction of the states of anxiety, depression and calmness in individuals. The framework called H2SEC is based on the integrated measurements of Habituation, Hypoactivity, Synchronization, Experience and Calmness (H2SEC) through a unified framework. The framework also enables the tracking of these states in realtime, showing transition from one state of consciousness to another.

To build and validate the H2SEC framework, we collected Electrodermal Activity (EDA) and Blood Volume Pulse (BVP) data, sampled at 100 Hz using a wearable device from 61 Neutral, 60 Depressed and 110 subjects with Anxiety, while they performed the experimental task. By tracking the timeseries data in centiseconds, we identified segments of time in the subjects' data where their per minute state of Sympathetic Nervous System (SNS) was lower compared to the previous minutes. Within these segments called Sympathetic Transition Points (STPs), we calculated scores related to the H2SEC parameters of Habituation, Hypoactivity, Synchronization, Experience and Calmness and compared them against similar scores from non-STP segments. We thus arrived at the physiological coordinates of the Neutral, Anxiety, and Depression groups, apart from identifying the intrinsic nature of calmness in each group.

We implemented multi-output, multi-label machine learning (ML) algorithms to predict mental states, along with the nature of calmness (Calm, Approaching Calmness and Not Calm) in each individual. We report 100% F1, along with 100% Precision and Recall in identifying both the states. Our methodology is the state-of-the-art in terms of mental health monitoring, and to the best of our knowledge we are the first to report on mental health disorders (anxiety and depression) and recovery mechanism (calmness) using an integrated methodology.

1 Introduction

An important contributing factor to the high prevalence of mental disorders like anxiety and depression is that there is no technology to aid diagnosis. Biomarkers¹ for diagnosis or assessment of outcomes with respect to mental states and “objective, continuous, ecological measurements of emotion, cognition, and behavior are not available.”² The Diagnostic and Statistical Manual of Mental Disorders (DSM-5) is the most commonly referred manual for mental health diagnosis, while the International Classification of Diseases (ICD) is its most popular alternative. Diagnosis using DSM-5 or ICD depends on a clinician’s judgement or self-reporting and the ‘ambiguous or unstated perspective’ of patients and caregivers.³ Several studies have shown that the correct diagnosis of depression and anxiety disorders is lacking in the primary care setting.^{4 5 6}

Measurement-based care is recommended as a foundation for improving the quality of mental health services.⁷ The Lancet Commission for Global Mental Health calls out for the “adoption of digital platforms to facilitate the delivery of interventions across the continuum of care.”⁸ An integrated approach for efficient delivery of mental health, which includes technology-based offerings⁹ to urgently address mental health challenges have been suggested in various studies,^{10 11 12} and it is hoped that new technologies will be invaluable in fostering mental healthcare.¹³

2 Proposed solution

By incorporating the concepts of Habituation, Hypoactivity, Synchronization, Experience and Calmness (H2SEC) into a common platform, called the H2SEC Framework, we propose to automatically and quantitatively measure the specific states of calmness, anxiety and depression in individuals. The literature that we reviewed to arrive at this framework is listed in Supplemental.

- Habituation: Refers to the reduction in response to a stimulus over repeated exposures¹⁴; it is the fundamental learning mechanism responsible for filtering the sensory environment.¹⁵ In humans, habituation can be observed via the activities of the central and autonomic nervous systems. Studies have shown that it is possible for humans to get habituated to both positive and negative stimuli.¹⁶
- Hypoactivity: Refers to the lack of arousal and inhibition of emotions in response to any stimulus. Electrodermal hypoactivity is a common feature seen in depressed individuals.^{17 18} Regular meditators were also expected to show low arousal and electrodermal hypoactivity, while people with anxiety were expected to show higher arousal and excitability.
- Synchronization: Refers to the study of the heart rate with respect to the phase of the respiratory cycle.
- Experience: Refers to an occurrence that leaves a positive or negative mental impression on participants of the event. Experience has been extensively studied as ‘valence’ in the context of the ANS.¹⁹ Electrodermal and cardiovascular responses are reported to index the activation level and the valence of emotional stimuli.²⁰
- Calmness: Refers to the state of inner tranquillity, free from negative and strong emotions. We believed calmness to be a slow, steady, hypoactive activity, where the cardiorespiratory function synchronizes and negative emotions dissipate, resulting in a tranquil and positive state of mind.

The H2SEC framework distinguishes and identifies specific states of anxiety, depression and calmness by tracking the functions of the Autonomic Nervous System (ANS) with wearable sensors. Habituation and Hypoactivity are related to sympathetic activation and can be studied by tracking arousal levels using Electrodermal Activity (EDA) sensors, while Synchronization and Experience can be studied using features of Cardiorespiratory Synchronization (CRS) and Heart Rate Variability (HRV). With the H2SEC framework, we have brought together two key aspects of mental health – (a) the ability to screen mental disorders quantitatively and (b) measurement of balanced, calmer states in individuals, using a uniform and consistent methodology.

2.1 Neuroscientific background of the H2SEC framework

The ANS consists of numerous pathways of neurons that control various organ systems in the human body, using diverse chemicals and signals.²¹ The ANS functions without conscious and voluntary control and innervates cardiac muscle, smooth muscle, and various endocrine and exocrine glands,²² playing a crucial role in maintaining homeostasis.²³ The ANS is composed of two systems, namely the Sympathetic Nervous System (SNS) and the Parasympathetic Nervous System (PNS). The SNS prepares the body for a real or perceived threat, while the PNS aids relaxation.

The Activation Arousal Theory, which describes a continuity between central mechanisms and peripheral autonomic responses, proposed that any organ influenced by the ANS could be a potential index of mind activity.²⁴ According to Pandya, the mind is defined as that which is responsible for one’s thoughts and feelings, the seat of the faculty of reason or the aspect of intellect and consciousness experienced as combinations of thought, perception, memory, emotion, will and imagination, including all unconscious cognitive processes. Furthermore, “the mind cannot be localised to particular areas within the brain, though the entire cerebral cortex and deep grey matter form important components. Consciousness, perception, behaviour, intelligence, language, motivation, drive, the urge to excel and reasoning of the most complex kind are the product of the extensive and complex linkages between the different parts of the brain. Likewise, abnormalities attributed to the mind, such

as the spectrum of disorders dealt with by psychiatrists and psychologists, are consequences of widespread abnormalities, often in the chemical processes within different parts of the brain.”²⁵

Changes in electrical properties of the skin have been used successfully to study several dimensions of mind from a long time.²⁶ It has been shown through autonomic electrophysiology that variations of pupillary responses, cardiovascular activity and electrical properties of the skin are potential markers of affective or cognitive expressions.²⁷ Electrodermal and cardiovascular responses are reported to index the activation level and the valence of emotional stimuli.²⁸ Thus, we focussed our attention to deriving insights about mental states by observing the ANS through changes in electrodermal activity and cardiovascular responses.

2.1.1 Electrodermal Activity

Electrodermal Activity (EDA) refers to the variation of the electrical properties of the skin in response to sweat secretion.²⁹ Such secretion may happen due to sympathetic innervation in response to environmental temperature, leading to thermoregulatory sweating. Activities of the central nervous system related to affective and cognitive states lead to palmar, mental or emotional sweating.^{30 31} EDA has been recognized as a reliable indicator for sympathetic arousal.³² EDA is measured to explore multiple mind-states, namely emotions, cognition,^{33 34 35} decision-making, reasoning bias,³⁶ and several behavioural adaptations.³⁷ Multiple studies on meditation, anxiety and depression³⁸ have used EDA measurements to show the effects of the ANS on mood states.

EDA has a tonic and a phasic component. The tonic component, also called Skin Conductance Level (SCL) is the slow-moving, spontaneous electrical fluctuations of the sweat gland activity that results from an interaction between tonic discharges of sympathetic innervation and local factors like skin temperature and hydration.³⁹ The fast-changing element of the EDA signal is referred to as the Skin Conductance Response (SCR) and are correlated with phasic sympathetic nervous discharges.⁴⁰ Another aspect of EDA is the Sudomotor Nerve Activity (SMNA), which plays a major role in thermoregulation,⁴¹ enabling sensory discrimination by the skin⁴², and providing information about emotional arousal.⁴³ Hence, with the EDA it is thus possible to estimate the time and amplitude of stimuli generated from control centres in the brain.⁴⁴

2.1.2 Heart Rate Variability and Cardiorespiratory Synchronization

The Blood Volume Pulse (BVP) signal reflects the flow of blood that occur during a cardiac cycle, and hence, it has been used as an alternative to ECG to assess the instantaneous heart rate and the RR⁴⁵ or inter-beat-interval (IBI), along with the Breathing Rate,⁴⁶ Pulse Transit Time (PTT) and peripheral vasodilatation.⁴⁷ Heart rate and rhythm are largely under the control of the autonomic nervous system.⁴⁸ Heart Rate Variability (HRV), which is the beat-to-beat alteration of heartbeats is widely used as a reliable indicator of ANS arousal. An increase in HRV denotes parasympathetic nervous system (PNS) activation, while a decrease indicates a rise in sympathetic dominance. The High Frequency (HF) component of HRV is considered a reliable measure for the assessment of parasympathetic activity.⁴⁹ Alterations in HRV are reported in people with clinical anxiety disorders⁵⁰ and anxiety disorders are also related to cardiovascular disease.^{51 52} Cardiovascular diseases are commonly seen among patients with Major Depressive Disorder(MDD),^{53 54 55} implying autonomous regulation of the heart rate as a potential pathophysiological mechanism in depression.^{56 57 58 59 60 61}

We used BVP to also study cardiorespiratory synchronization (CRS). The relationship between the cardiac and the respiratory systems have traditionally been identified through respiratory sinus arrhythmia (RSA) that accounts for the periodic variation of the heart rate within a breathing cycle.⁶² Cardiorespiratory interaction stronger than RSA is seen in CRS, with a specific number of m heartbeats per n respiration cycles (locking ratio n:m), where the heartbeats are observed for only specific phases of the respiratory cycle.⁶³ We have used the phase-synchronization method, where the RSA is represented as a continuous increase and decrease of the heart rate with respect to the phase of the respiratory cycle.⁶⁴

3 Experiment design

Our experiment was designed to objectively measure mental disorders like anxiety and depression and recovery aspects like calmness using a uniform method. We hypothesized the following:

- States of consciousness along with their transitions from one state to another can be observed through a multi-modal sensing system comprising of EDA and BVP sensors
- The physiological coordinates of calmness, anxiety and depression can be measured by tracking the activities of the ANS
- Calmness could be induced via meditative practices on subjects with anxiety and depression

3.1 Subject enrolment

For our experimental study, we collected data from 231 subjects in total (109 females and 122 males), between the ages of 18-65 years and between the period of 2017 and 2019. Data was collected from Bangalore (TerraBlue XT Lab and Heartfulness Ashram) and Hyderabad (Heartfulness Ashram), India. Of these, 61 subjects were regular meditators with greater than 5 years of meditation experience (mean 7 years). The rest had less than 5 years of meditation experience (mean 1.5 years). All the subjects signed an informed consent form before being enrolled. Standardized self-ratings were obtained before data acquisition. The regular meditators enrolled in the study scored less than 8 in GAD-7⁶⁵ and PHQ-9⁶⁶ and they were placed in the Neutral group. 110 subjects with a clinical diagnosis of anxiety and scoring greater than 12 on GAD-7 were enrolled in the Anxiety group, while 60 subjects with clinical depression, and scores greater than 12 on PHQ-9 were enrolled in the Depression group.

3.2 Experimental task

We chose relaxation and meditation as the experimental task to collect data from subjects. All subjects were trained in Sahaj Marg or Heartfulness meditation - a form of concentrative meditation technique where the focus of attention is the heart. Subjects were required to wear the data collection unit and meditate, either on the floor or on a chair, for a duration of 45 minutes, in a quiet place. Subjects were also given the flexibility to either stop their activity if they were uncomfortable or extend their session beyond the allocated time.

Generally, during studies on moods and emotions, stress is induced in subjects to elicit the appropriate sympathetic and the parasympathetic responses from them, which are then measured and reported.^{67 68} While this is standard practice, for real-world implementation, we need to be able to identify states of consciousness naturally and without the artificial inducement of stress. Hence, we decided to study the three groups of subjects without imposing any artificial stressors on them, and observe whether the groups showed statistically significant differences in features and scores.

3.3 Data acquisition and pre-processing

We used a multimodal-sensing methodology comprising of BVP and EDA sensors to track the activities of the ANS. We extracted data using devices from BioSignal Plux, along with a wearable prototype designed as per our proprietary specifications. Data was sampled at 100 Hz for both EDA and BVP, which were extracted from the distal and proximal phalanges of the non-dominant hand. We analyzed continuous, non-overlapping per 10-millisecond segments of data. During pre-processing, data was converted from raw form to their respective units, filtering and smoothening were done, along with timestamp insertion and artefact detection and removal.

Pre-processing^{69 70} and feature extraction of EDA⁷¹ and BVP⁷² were done as per standard guidelines mentioned in the literature. CRS was calculated using synchronization indices(λ) and can be visually interpreted through Synchogram⁷³

3.4 Data analysis

Data analysis to understand the intrinsic nature of the three groups under study was performed as per the steps mentioned in the following sections.

3.4.1 Step 1 - Determine range thresholds of features for each group

We performed exploratory data analysis on the groups and determined the range threshold of the features of EDA and BVP, using the Interquartile Range (IQR) technique. IQR is commonly used as statistical dispersion measure for skewed data. Mathematically, IQR can be expressed as:

$$\text{IQR} = Q_3 - Q_1, \text{ where } Q_3 \text{ and } Q_1 \text{ is upper(third) quartile and lower(first) quartile respectively.} \quad (1)$$

An interval based on lower bound and upper bound helps in identifying the outliers present in data. This can be expressed as:

$$\text{lower bound} = Q_1 - 1.5 * \text{IQR} \quad (2)$$

$$\text{upper bound} = Q_3 - 1.5 * \text{IQR} \quad (3)$$

The data points outside of the interval (lower bound, upper bound) are considered as outliers, while the data inside, encapsulated within the respective upper and lower boundaries of the required features, have been used in our study.

3.4.2 Step 2 - Determine sympathetic transition points

Secondly, we identified sympathetic transition points (STP) in each subject's time-series by using exponential moving averages (EMA).⁷⁴ Our goal was to find time segments in a subject's data where the sympathetic state showed a decrease compared to previous or elapsed periods, thus giving us hints of changing consciousness over time. We chose to track changing states of consciousness with the Sympathetic Nervous System (SNS) as the EDA sensor has been explicitly designed to track both the slow and fast-moving components of the SNS. As the experimental task progressed, we expected to see either increased or decreased sympathetic activity, depending on the disposition of each subject. If the SNS lowered at any moment during the experimental task compared to the previous time period, it would indicate that a subject is in a calmer state compared to their previous states. Figure 1 shows the concept of STPs, which are bound by a green vertical line showing the start of a segment and a red vertical line showing the end of a segment. The Non-STP segments are found on either side of an STP segment. In Figure 1, we can observe two STP segments.

Figure 1: STP and Non-STP Segments

We computed the EMA of the EDA signal using 1 minute (indicating fast-moving) and 10 minute (indicating slow-moving) windows, after which we subtracted the slow moving EMA from the fast moving EMA for every minute. We then derived the EMA of the difference of these two signals per minute forming a data stream called Signal A. We computed the EMA using 5 minutes window of Signal A, calling it Signal B. We then compared Signal A with Signal B to understand the short term and long term behavior of the tonic component of EDA. During comparisons, the points where the value of Signal B becomes greater than Signal A is referred to as the Convergence points, while the points where the value of Signal B becomes lesser than Signal A is called the Divergence points.

In terms of the tracking of the continuous consciousness state, the Convergence points indicate from when the short term EDA signal became stronger compared to its overall long term trend, while the Divergence points show when the short term behaviour of the EDA signal is in sync with its normal, long term trend. This means that if a subject is feeling calmer compared to the baseline period or any elapsed minute, then the short term EDA signal representing current time (in minutes) will become stronger the long term signal representing overall, past state of consciousness. Any feeling of internal threat, fear or worry may increase sympathetic activity and bring down the short term EDA signal below the Divergence point, merging it with its long term sympathetic trend.

There could be several Convergence and Divergence points on an EDA signal, forming blocks or segments, which we refer to as CD segments. A Divergence point is the start of a segment, while a corresponding Convergence point is the end of that particular segment. The formula for creating the DC segments is as follows:

We calculated Signal A by subtracting a 10-min exponential moving average (EMA) from a 1-min EMA, of EDA (μS). Mathematically Signal A and EMA are expressed in Eq. (1) and Eq. (2):

$$\text{Signal A} = \text{EMA}_1(\text{EDA}) - \text{EMA}_{10}(\text{EDA}) \quad (4)$$

$$\text{EMA}[n] = \alpha \text{EDA}[n] + \sum_{i=1}^n (1 - \alpha)^i \text{EMA}[n - i] \quad (5)$$

Where the smoothing factor α is defined as:

$$\alpha = \left(\frac{2}{1+m} \right) \quad (6)$$

Where m is span in minutes.

The convergence and divergence can be observed by comparing Signal A and Signal B which is a 5 min EMA of EDA. The mathematical expression of signal line expressed in Eq. (4)

$$Signal\ B = EMA_5 (EDA) \quad (7)$$

The convergence and divergence segments of EDA are identified by comparing Signal A and s Signal B sample values. The conditions for labelling the segments provided in Eq. (5) are:

$$Segment[n] = \begin{cases} converging, & \text{if } Signal\ B\ [n] > Signal\ A\ [n] \\ diverging, & \text{if } Signal\ B\ [n] \leq Signal\ A\ [n] \end{cases} \quad (8)$$

The formula for obtaining the Calmness Score is developed under the assumption that whenever a subject is within the STP segment at a particular time instant, their state of mind was calm at that instant of time, irrespective of the previous time instant.

3.4.3 Step 3 – Mathematical expression of the H2SEC framework

For subjects in each group, we measured the H2SEC Framework Scores within and outside STPs, to understand multiple aspects of their mental health. The H2SEC formula is developed under the assumption that if a subject meets all the thresholds of each aspect of the H2SEC framework within an STP segment, they have achieved absolute calmness and their ANS is in perfect balance. However, subjects may enter an STP segment, but may not meet all the thresholds of all the aspects of the H2SEC segment, implying they are approaching a state of calmness, but not in an absolute form. If a subject does not enter STP segments even once during the data collection session, the subject's mental state is not calm.

First find the **InSTP Score** ($\bar{F}(X) + \varphi_{in}$), when a subject is observed to be within STP (the period when the subject was in a lowered sympathetic state compared to previous time) and then subtracting the **OutSTP Score** ($\bar{G}(X) + \varphi_{out}$) from it, when the subject was not within STP (the period when the subject was in a higher sympathetic state). This subtraction would help us identify the Total Calmness Score answering the question “What was the **overall state** of mind of a subject during the experimental task - whether the subject was calm, approaching calmness or not in a calm state of mind?”

$$Total\ Calmness\ Score = (\bar{F}(X) + \varphi_{in}) - (\bar{G}(X) + \varphi_{out}) \quad (9)$$

$$\text{where } F(X) = \frac{1}{T_{in}} \sum_{t=1}^{T_{in}} f(X_1, X_2, X_3, \varepsilon_{1in}, \varepsilon_{2in}, \varepsilon_{3in}, t) = (X_{1in}, X_{2in}, X_{3in}) \quad (10)$$

$$\text{hence } \bar{F}(X) = \frac{1}{3} (X_{1in} + X_{2in} + X_{3in})$$

$$\text{and } G(X) = \frac{1}{T_{out}} \sum_{t=1}^{T_{out}} g(X_1, X_2, X_3, \varepsilon_{1out}, \varepsilon_{2out}, \varepsilon_{3out}, t) = (X_{1out}, X_{2out}, X_{3out}) \quad (11)$$

$$\text{hence } \bar{G}(X) = \frac{1}{3} (X_{1out} + X_{2out} + X_{3out})$$

F(x) denotes the score of the subject whenever they were within the STP segment, and G(X) denotes the score when the subject was outside the STP segment.

Expanding function F,

$$\begin{aligned} F(x) &= \frac{1}{T_{in}} \sum_{t=1}^{T_{in}} f(X_1, X_2, X_3, \varepsilon_{1in}, \varepsilon_{2in}, \varepsilon_{3in}, t) \\ &= \frac{1}{T_{in}} [f(X_1, X_2, X_3, \varepsilon_{1in}, \varepsilon_{2in}, \varepsilon_{3in}, t_1) + f(X_1, X_2, X_3, \varepsilon_{1in}, \varepsilon_{2in}, \varepsilon_{3in}, t_2) + \dots + f(X_1, X_2, X_3, \varepsilon_{1in}, \varepsilon_{2in}, \varepsilon_{3in}, t_{in})] \end{aligned}$$

where,

$$f(X_1, X_2, X_3, \varepsilon_{1in}, \varepsilon_{2in}, \varepsilon_{3in}, t_k) = \frac{1}{6} (\sum_{i=1}^6 x_{1i}, \sum_{i=1}^6 x_{2i}, \sum_{i=1}^6 x_{3i}) \quad (12)$$

Similarly, one can expand function G as,

$$\begin{aligned} G(x) &= \frac{1}{T_{out}} \sum_{t=1}^{T_{out}} g(X_1, X_2, X_3, \varepsilon_{1out}, \varepsilon_{2out}, \varepsilon_{3out}, t) \\ &= \frac{1}{T_{out}} [g(X_1, X_2, X_3, \varepsilon_{1out}, \varepsilon_{2out}, \varepsilon_{3out}, t_1) + \\ &g(X_1, X_2, X_3, \varepsilon_{1out}, \varepsilon_{2out}, \varepsilon_{3out}, t_2) + \dots + g(X_1, X_2, X_3, \varepsilon_{1out}, \varepsilon_{2out}, \varepsilon_{3out}, t_{out})] \end{aligned}$$

where,

$$g(X_1, X_2, X_3, \varepsilon_{1out}, \varepsilon_{2out}, \varepsilon_{3out}, t_k) = \frac{1}{6} (\sum_{i=1}^6 x_{1i}, \sum_{i=1}^6 x_{2i}, \sum_{i=1}^6 x_{3i}) \quad (13)$$

Describing each term in the function,

t : Minute value

T_{in} : Total minutes the subject was within STP

T_{out} : Total minutes the subject was outside STP

φ_{in} : Mean Synchronization score when the subject was within STP

φ_{out} : Mean Synchronization score when the subject was outside STP

Threshold description: All the thresholds described below have a general meaning and they can be interpreted for ‘within STP’ and ‘Non-STP’ data in the same way. For instance the description of ε_1 will hold true irrespective of ε_{1in} or ε_{1out} . Only the values within “($\varepsilon_{11}, \varepsilon_{12}, \varepsilon_{13}, \varepsilon_{14}, \varepsilon_{15}, \varepsilon_{16}$)” will change depending on whether the person is in STP or not. The same concept is followed for all the threshold descriptions below:

- ε_1 : Threshold values for Habituation of the parameter (Anxiety/ Depression / Neutral) whose record is passed

$\varepsilon_1 = (\varepsilon_{11}, \varepsilon_{12}, \varepsilon_{13}, \varepsilon_{14}, \varepsilon_{15}, \varepsilon_{16})$, where ε_{1i} : Threshold value for x_{1i} for the parameter (Anxiety / Depression / Neutral) whose record is passed ... where $1 \leq i \leq 6$

- ε_2 : Threshold values for Hypoactivity of the parameter (Anxiety/ Depression / Neutral) whose record is passed

$\varepsilon_2 = (\varepsilon_{21}, \varepsilon_{22}, \varepsilon_{23}, \varepsilon_{24}, \varepsilon_{25}, \varepsilon_{26})$, where ε_{2i} : Threshold value for x_{2i} for the parameter (Anxiety / Depression / Neutral) whose record is passed ... where $1 \leq i \leq 6$

- ε_3 : Threshold values for Experience of the parameter (Anxiety/ Depression / Neutral) whose record is passed

$\varepsilon_3 = (\varepsilon_{31}, \varepsilon_{32}, \varepsilon_{33}, \varepsilon_{34}, \varepsilon_{35}, \varepsilon_{36})$, where ε_{3i} : Threshold value for x_{3i} for the parameter (Anxiety / Depression / Neutral) whose record is passed ... where $1 \leq i \leq 6$

H2SEC Framework parameter (attribute) description:

X₁ : Habituation

and $X_1 = (\sigma(x_{11}), \sigma(x_{12}), \sigma(x_{13}), \sigma(x_{14}), \sigma(x_{15}), \sigma(x_{16}))$

where x_{11} : Recovery time of EDA , x_{12} : Rise time of EDA, x_{13} : EDA STD, x_{14} : Tonic STD, x_{15} : RMSSD, x_{16} : HF RoC: EDA RoC

$$\begin{aligned} \sigma(x_{1j}) &= 1 \text{ if } x_{1j} \in \varepsilon_{1j} & 1 \leq j \leq 6 \\ &= 0 \text{ otherwise} \end{aligned}$$

X₂ : Hypoactivity

and $X_2 = (\sigma(x_{21}), \sigma(x_{22}), \sigma(x_{23}), \sigma(x_{24}), \sigma(x_{25}), \sigma(x_{26}))$

where x_{21} : SMNA , x_{22} : Phasic, x_{23} :Amplitude, x_{24} : SMNA Peaks, x_{25} : RMSSD, x_{26} : HF RoC: EDA RoC

$$\begin{aligned} \sigma(x_{2j}) &= 1 \text{ if } x_{2j} \in \varepsilon_{2j} & 1 \leq j \leq 6 \\ &= 0 \text{ otherwise} \end{aligned}$$

X₃ : Experience

and $X_3 = (\sigma(x_{31}), \sigma(x_{32}), \sigma(x_{33}), \sigma(x_{34}), \sigma(x_{35}), \sigma(x_{36}))$

where x_{31} : HF, x_{32} : LF:HH, x_{33} : Tonic STD x_{34} : RMSSD, x_{36} :HF RoC: EDA RoC

$$\begin{aligned}\sigma(x_{3j}) &= 1 \text{ if } x_{3j} \in \varepsilon_{3j} & 1 \leq j \leq 6 \\ &= 0 \text{ otherwise}\end{aligned}$$

Synchronization

Let $\omega = (w_1, w_2, \dots, w_n)$ where w_i represents the Synchronization score at time instant i

$\omega_i = 1$ if subject has positive sync at time instant i

$= 0$ if subject has negative or no sync at time instant i

$$\varphi = \bar{w} \text{ i.e } \varphi = \frac{1}{n} \sum_{i=1}^n w_i$$

There will be two such synchronization scores computed for each subject.

- When the subject is in STP $\varphi_{in} = \bar{w}_{in}$
- When the subject is in Non-STP $\varphi_{out} = \bar{w}_{out}$

4 Results and statistical analysis

Complete details of scores and statistical measures are given in Supplemental. By using relevant statistical tests, we evaluated the following:

- Overall distinction between Neutral, Anxiety, and Depression groups: By performing the Shapiro-Wilk test of Normality on the H2SEC scores of the Neutral, Anxiety, and Depression groups, we ascertained that the samples are not normally distributed. Levene's test showed the samples were not homogeneous. We thus applied the nonparametric Kruskal Wallis test and found the Neutral, Anxiety, and Depression groups are significantly different from each other ($p < 0.05$). Finally, we performed Dunn's test to learn about which pair of groups are different from one another.
- Between group comparison of scores: We also examined the groups and their scores within and outside STP segments. The test of normality (Shapiro Wilk) and homogeneity of variance (Levene's) showed that our samples were not normally distributed and non-homogeneous. We thus used the Mann-Whitney U Test to compare outcomes between the STP and the Non-STP segments.
- Within group (STP and Non-STP) comparison of scores: The test of normality (Shapiro Wilk) and homogeneity of variance (Levene's) showed that our samples were not normally distributed and non-homogeneous. We performed the non-parametric Kruskal-Wallis test to find out if the H2SEC scores between Neutral, Anxiety, and Depression groups were different within the STP and Non-STP segments (respectively). Since the Kruskal-Wallis test showed that except Hypoactivity in the Non-STP segment, the three groups Neutral (N), Anxiety (A) and Depression(D) are statistically different in terms of the H2SEC scores ($p < 0.05$), we performed the Dunn's post-hoc test to find out which groups were different.

5 Discussion

Using our experimental approach, we were able to see distinction in the physiology of subjects in Neutral, Anxiety, and Depression groups. The highlights are as follows:

- Multiple reports describes the ability of meditators to have strong control over their emotions as well as autonomic system. Reports of ‘Samadhi’ - thoughtless awareness and the highest form of internal balance have also been described in various literature, implying that meditators may have the ability to achieve extreme levels of serenity. Hence, this group was the natural choice to measure the physiological coordinates of calmness in people. In our analysis, we found that subjects in this group achieved a calmer state sooner than the other groups. This group showed the highest increase in HF Power and the lowest decrease in LF Power among the other groups. The Neutral group also had the best rate of positive cardiorespiratory synchronization. These observations indicate that the Neutral group achieved better ANS balance compared to the Anxious and Depression groups. This behavior during the experimental phase could be the result of the long term meditation practiced by subjects in the Neutral group.
- Evidence suggest that people with anxiety find it difficult to relax. Thus, we felt meditation could be an effective method to understand the physiological coordinates of anxiety as this group is known to demonstrate elevated ‘baseline startle’, implying the presence of anxious thoughts in the absence of threat. Individuals with GAD also typically show hypervigilant physiological arousal at baseline and demonstrate an exaggerated reactivity to threat. Therefore when asked to meditate, which is a non-threatening tasks, it was hypothesized that this group could demonstrate some of the classic signs of sympathetic arousal like increased heart rate, sweating and flushing. To our surprise, 9 subjects from the Anxiety group achieved an ‘absolute calm’ state, and showed prefect ANS balance. Majority of the subjects in this group approached a calming state as evidenced from their entry into STP segments. However, in the Non-STP segments, subjects in this group showed heightened arousal and decreased CRS, reflecting the characteristic features of anxiety disorder.
- Based on a study of 58328 subjects on ‘mood homeostasis’ or the ability to stabilise one’s mood via mood-modifying activities, it was found that mood homeostasis is impaired in people with low mood, and completely absent in people with depression.⁷⁵ Meditation could be considered a mood-modifying activity and thus it was assumed that during the experimental task, subjects with depression may show classic signs of self-focus^{76 77 78} and fixation on negative thoughts,⁷⁹ resulting in abnormal changes in their autonomic tone. We found 6 individuals from the Depressed group entered the absolute calm state, achieving all the threshold of all scores in the H2SEC framework. However, majority of the subjects in this group were found to be ‘not calm.’

Table 1 shows the mean and standard deviation (STD) of the commonly features used to calculate the H2SEC parameter scores for the Anxiety (A), Depression (D), and Neutral (N) groups.

Table 1: Mean and STD of Features used in H2SEC Scores

	Overall			Within STP segment			Outside STP		
Feature	A	D	N	A	D	N	A	D	N
EDA (μ S)	1.96 $\pm$	0.35 $\pm$	0.38 $\pm$	2.0 $\pm$	0.31 $\pm$	0.40 $\pm$	1.90 $\pm$	0.38 $\pm$	0.36 $\pm$
	2.36	0.82	0.28	2.37	0.22	0.30	2.35	1.05	0.27
	0.13 $\sim$ $\pm$	0.0 $\sim$ $\pm$	0.0 $\sim$ $\pm$	0.11 $\sim$ $\pm$	0.0 $\sim$ $\pm$	0.0 $\sim$ $\pm$	0.15 $\sim$ $\pm$	0.0 $\sim$ $\pm$	0.0 $\sim$ $\pm$
EDA SD	0.23	0.0	0.0	0.2	0.0	0.0	0.26	0.0	0.0
	1.88 $\pm$	0.35 $\pm$	0.38 $\pm$	1.94 $\pm$	0.31 $\pm$	0.40 $\pm$	1.82 $\pm$	0.38 $\pm$	0.36 $\pm$
	2.24	0.82	0.28	2.27	0.22	0.30	2.21	1.05	0.27
Tonic (μ S)	4.73 $\pm$	0.19 $\pm$	0.09 $\pm$	4.23 $\pm$	0.16 $\pm$	0.11 $\pm$	5.35 $\pm$	0.21 $\pm$	0.07 $\pm$
	3.66	0.56	0.40	3.76	0.52	0.45	3.44	0.59	0.32
	0.08 $\pm$	0.0 $\pm$	0.0 $\pm$	0.07 $\pm$	0.0 $\pm$	0.0 $\pm$	0.09 $\pm$	0.0 $\pm$	0.0 $\pm$
Amplitude (μ S)	0.18	0.0	0.0	0.16	0.0	0.0	0.19	0.0	0.0
	1578.72	91.14	64.67	1447.57	73.82	81.17	1737.97	103.26	46.06
	$\pm$	$\pm$	$\pm$	$\pm$	$\pm$	$\pm$	$\pm$	$\pm$	$\pm$
SMNA Peaks (Count)	1080.31	188.19	164.60	1100.02	173.12	184.76	1034.09	197.24	136.11
	1.43 $\pm$	0.70 $\pm$	0.57 $\pm$	1.28 $\pm$	0.66 $\pm$	0.58 $\pm$	1.61 $\pm$	0.73 $\pm$	0.56 $\pm$
	0.72	0.26	0.21	0.70	0.23	0.23	0.71	0.27	0.18
Rise Time (Sec)	3.77 $\pm$	0.81 $\pm$	0.87 $\pm$	4.24 $\pm$	0.85 $\pm$	0.95 $\pm$	3.20 $\pm$	0.79 $\pm$	0.78 $\pm$
	3.34	0.53	0.54	3.91	0.60	0.61	2.36	0.47	0.44
	777.80 $\pm$	795.42 $\pm$	799.02 $\pm$	777.76 $\pm$	797.11 $\pm$	789.35 $\pm$	777.86 $\pm$	794.24 $\pm$	809.92 $\pm$
Inter Beat Interval (ms)	90.72	97.10	91.55	90.86	103.67	89.92	90.59	92.27	92.19

	Overall			Within STP segment			Outside STP		
Feature	A	D	N	A	D	N	A	D	N
Heart Rate (BPM)	78.85 ± 8.69	77.16 ± 9.10	76.66 ± 8.62	78.81 ± 8.73	77.10 ± 9.69	77.63 ± 8.56	78.90 ± 8.64	77.20 ± 8.68	75.57 ± 8.56
RMSSD (ms)	70.37 ± 64.62	74.94 ± 72.18	77.81 ± 61.69	67.54 ± 62.10	70.34 ± 74.04	81.57 ± 63.58	73.8 ± 67.40	78.17 ± 70.72	73.57 ± 59.22
PNN50 (%)	24.57 ± 26.65	24.82 ± 26.73	28.36 ± 26.09	23.87 ± 26.12	22.33 ± 26.80	29.81 ± 26.44	25.42 ± 27.25	26.57 ± 26.55	26.71 ± 25.61
SDNN (ms)	65.85 ± 40.96	60.76 ± 43.78	61.48 ± 38.37	62.89 ± 39.87	57.04 ± 45.05	64.05 ± 39.63	69.46 ± 41.98	63.36 ± 42.71	58.58 ± 36.71
LF :HF (%)	1.65 ± 2.17	1.17 ± 1.72	0.89 ± 1.45	1.58 ± 2.18	1.28 ± 1.94	1.0 ± 1.76	1.74 ± 2.16	1.09 ± 1.54	0.76 ± 0.97
	3581.60	3017.77	3046.61	3312.27	2791.78	3291.03	3908.62	3175.78	2770.92
Total Power (ms ²)	± 4076.51	± 3926.22	± 3607.41	± 3838.87	± 3934.20	± 3843.13	± 4326.31	± 3915.07	± 3302.03
	1938.93	1930.04	2024.89	1799.19	1805.39	2201.47	2108.60	2017.20	1825.71
HF Power (ms ²)	± 3005.70	± 3024.53	± 2748.79	± 2819.84	± 2995.67	± 2936.53	± 3209.66	± 3043.18	± 2507.06
	1346.96	910.04	875.49	1251.77	837.07	955.05	1462.54	961.06	785.76
LF Power (ms ²)	± 1856.12	± 1392.83	± 1217.43	± 1755.94	± 1347.34	± 1336.37	± 1965.27	± 1422.30	± 1061.09
	295.71 ± 579.20	177.69 ± 432.20	146.22 ± 434.76	261.31 ± 507.52	149.33 ± 267.56	134.50 ± 298.27	337.48 ± 653.50	197.52 ± 516.31	159.44 ± 549.33
VLF Power (ms ²)	49.76 ± 52.99	52.99 ± 55.02	55.02 ± 47.76	47.76 ± 49.73	49.73 ± 57.68	57.68 ± 52.19	52.19 ± 55.27	55.27 ± 52.02	52.02 ± 41.88
SD1 (ms)	45.69 ± 75.80	51.04 ± 64.79	43.62 ± 65.12	43.91 ± 72.29	52.35 ± 60.84	44.96 ± 67.61	47.66 ± 80.06	50.00 ± 67.55	41.88 ± 62.30
SD2 (ms)	41.48 ± 0.61	40.09 ± 0.73	36.52 ± 0.78	40.67 ± 0.61	40.64 ± 0.71	37.77 ± 0.78	42.06 ± 0.59	39.48 ± 0.74	34.87 ± 0.77
SD1:SD2 (%)	0.32 ± 19.39	0.38 ± 17.59	0.35 ± 17.44	0.32 ± 19.25	0.38 ± 17.60	0.35 ± 17.32	0.32 ± 19.55	0.38 ± 17.58	0.35 ± 17.58
Respiration	5.89 ± 0.85	4.83 ± 0.85	5.26 ± 0.85	5.79 ± 0.87	4.26 ± 0.85	4.99 ± 0.83	6.01 ± 0.84	5.20 ± 0.85	5.55 ± 0.87
Lambda	0.19 ± 0.0	0.21 ± 0.0	0.20 ± 0.0	0.18 ± 0.0	0.21 ± 0.0	0.21 ± 0.0	0.20 ± 0.0	0.20 ± 0.0	0.19 ± 0.0
Slope	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

5.1 Physiological coordinates of Neutral, Anxiety, and Depression

The H2SEC framework helped to understand the intrinsic nature of calmness, anxiety and depression.

Habituation: For Habituation, which is indicative of the functioning of the sympathetic skin response⁸⁰, from the post-hoc Dunn’s tests, we found that subjects in the Anxiety and Depression groups showed no significant difference among themselves in general (Table 2 – Supplemental) and also within and outside the STP segments ((Table 5 – Supplemental). This implies that the nature of habituation, which is known to be slow and impaired for Anxiety⁸¹ and Depression⁸², is similar for both, and showed similar characteristics throughout the experimental observations. On the other hand, subjects in the Neutral category had markedly different habituation scores in both the STP segments when compared to the Anxiety and the Depression groups independently. To illustrate this point, the Rise Time of EDA is a good measure of habituation and we notice that for the Neutral group it was 0.58 seconds (secs) (SD ± 0.23 secs) in the STP group and 0.56 secs (SD ± 0.18 secs) in the Non-STP group. On the other hand, it stood at 1.28 secs (SD ± 0.7 secs) in STP and 1.61 secs (SD ± 0.71 secs) outside STP for the Anxiety group and 0.66 secs (SD ± 0.23 secs) in STP and 0.79 secs (SD ± 0.47 secs) outside STP for the Depression group. Thus, our study confirms faster habituation in the Neutral group compared to the Anxiety and the Depression groups. Rapid habituation implies safety and familiarity, while delayed habituation to neutral stimuli may trigger feelings of uncertainty or unfamiliarity.^{83 84 85} While rapid habituation is adaptive, inability to habituate quickly is maladaptive, as processing resources get inappropriately allocated to neutral, safe stimuli, potentially leading to inappropriate fear and anxiety even in safe situations.⁸⁶

Hypoactivity: Hypoactivity can be considered an index of arousal in the SNS. During the general comparison of the three groups (Table 2 – Supplemental), we observed no difference in Hypoactivity scores between the Anxiety and Depression pairs as well as the Neutral and the Depression pairs. The Anxiety and Neutral groups, however, were significantly different from each other. Within the STP segment (Table 2 – Supplemental), Anxiety and Depression were significantly different from each other, but no differences were observed between Anxiety and Neutral pairs and Depression and Neutral pairs. Outside the STP segment, no statistically significant differences were observed between the three groups. A key feature we used to calculate arousal in

the Hypoactivity score is the Sudomotor Nerve Activity (SMNA) from EDA, and we found that the Neutral group had the least arousal in general (mean 64.67, SD $\pm$ 164.60) and in the Non-STP segment (mean 46.06, SD $\pm$ 136.11), suggesting that this group could be the least aroused of the three during the task. The Neutral group was also made up of long-term meditators, and the ability to keep arousal at a minimum in a non-meditative state (Non-STP) could be the result of their practice. Within the STP segment, the least arousal was however seen in the Depression group (mean 73.82, SD $\pm$ 173.12). The Anxiety group was the most highly aroused throughout the experimental task (mean 1578.72, SD $\pm$ 1080.31), showing the same increase in STP (mean 1447.57, SD $\pm$ 1100.02) and outside of STP segment (mean 1737.97, SD $\pm$ 1034.09) in Non-STP.

Synchronization: In Synchronization, which indicates the behavior of the PNS, we observed that subjects in the Neutral, Depression and Anxiety groups showed distinguishing characteristics, except for the Depression and Neutral pairs during general comparison of groups (Table 2 – Supplemental). This was evident from the Dunn’s test applied on the three groups ((Table 2 – Supplemental) and also within STP and Non-STP segments (Table 5 – Supplemental). Heart rate and respiratory rate can show synchronization at lower heart rates as well as higher heart rates, where synchronization at lower heart rates (BPM < 72) signifies healthier physical and mental state. We categorized synchronisation as follows:

- If $\lambda_{\text{mean}(1\text{min})} > 0.7$ and heart rate < 72, synchronization is positive (Positive sync)
- If $\lambda_{\text{mean}(1\text{min})} > 0.7$ and heart rate > 72, synchronization is negative (Negative sync)
- If $\lambda_{\text{mean}(1\text{min})} < 0.7$ there is no synchronization (No sync)

We observed that for Positive sync, HR and respiratory rate lie between normal acceptable ranges, while for negative it falls in a wider range with higher standard deviation of both HR and respiration. For No sync, both HR and respiration are arbitrary with highest standard deviation. Neutral subjects showed higher positive (29%) and Nosync (22%), but least Negative (49%) among the three groups. Better control of cardiorespiratory synchronization by the Neutral group can be attributed to their regular meditation practice. Negative synchronization (56%) was higher in the Anxiety group compared to the Depression group (21%), while no-synchronization was the highest in the Anxiety group (51%), followed by the Neutral (28%) and Depression group (20%).

Figure 2 shows Ψ (Psi) and λ (Lambda) plots for specific individuals in each group. Figure 2A is for a Neutral subject, where we can observe distinct horizontal phase bands in Ψ plot and high lambda ($\lambda \geq 0.7$) values consistently. Figure 2B is of a depressed subject and Figure 2C is for an anxious subject with lower lambda values where we can’t observe distinct horizontal phase bands.

Figure 2: Psi and Lambda Plots

Experience: Using the Experience measure, we expected to see increased PNS activity under the influence of the experimental task. Overall, the Experience scores between the three groups were statistically different (Table 2 – Supplemental). When the three groups were compared in STP and Non-STP segments (Table 5 – Supplemental), we found Experience scores to be similar between Anxiety and Depression, while significant differences were seen between Anxiety and Neutral and Depression and Neutral within the STP segment. On the other hand, the Experience scores between all the three groups showed statistical significance in difference outside the STP segment. The HRV indices of Power have long been used to describe experience. In our study population, overall 127 subjects (Anxiety 66, Depression 30 and Neutral 31) out of 231 total subjects exceeded their HF Power (which is a known indicator of heightened PNS) during the experimental task, compared to their baseline (mean of HF Power of first three minutes in the experimental task) measures, within the STP segment. We report the following values: Rate of change of HF Power in the Anxiety group was 65.80% (Baseline HF – mean 1169.72 ± 1625.22 , Task HF mean 1939.35 ± 2782.06), Depression group was 97.35%, (Baseline HF – mean 1211.34 ± 1574.87 , Task HF mean 2391.24 ± 2708.15) and Neutral group was 38.83% (Baseline HF mean 2211.55 ± 2419.03 , Task HF mean 3070.31 ± 3057.39). Figure shows mean plots for Total Power (TP), HF Power, LF Power and ratio of LF to HF of Anxiety (A), Neutral (N) and Depression (D). As can be seen in Figure 3, HF Power is the highest in the Neutral group, while LF Power is also at the lowest in the Neutral group, indicating better ANS balance in the Neutral group.

Figure 3: HRV Frequency Power Plots

104 subjects (Anxiety 42, Depression 32 and Neutral 30) showed a decrease in HF Power compared to the baseline HF. The reasons for such decreased parasympathetic function can be suggestive of underlying health problems, including heart failure,⁸⁷ cardiac autonomic neuropathy in diabetes mellitus,⁸⁸ pure autonomic failure, idiopathic orthostatic hypotension, and multiple system atrophy.⁸⁹ Contradictorily, it has also been mentioned that sometimes if the HF band decreases or disappears, it may not mean a withdrawal of cardiac vagal activity or cardiac vagal dysfunction. This could happen when the respiration frequency is out of the HF band, such as slow breathing < 0.15 Hz (9 breath/min) like during deep breathing, or fast breathing > 0.4 Hz (24 breath/min) during exercise.⁹⁰

Trend: Apart from the H2SEC measures, we observed that subjects in Neutral, Depression and Anxiety groups have a distinct trend, most visible in the measurements of EDA.

Figure 4: Distinct EDA Trends in Neutral, Anxiety & Depression

Figure 4 (A) shows the typical EDA plots of three different subjects in Anxiety, Depression and Neutral groups. Figure 4 (B) shows the direction of the trend in the Neutral, Anxiety, and Depression groups, where the X-axis shows the mean slope of the EDA signal for each 1-minute (6000 samples) interval for each of the groups, while the Y-axis shows the scaled EDA values (0,1) in Microsiemens. A regression line was fitted for every 6000 samples of EDA in the entire sample of each group, and the slope and intercept of each regression line were stored in a groupwise manner. To determine the overall trend of each group, the mean of slope and intercept were calculated across each group and the resultant color-coded lines have been plotted. In the study population, the Neutral group showed a sharp downward trend in the data (Slope mean -0.000078, SD 0.000079), while the Depression group showed an uptrend (Slope mean 0.000031, SD 0.000095) and the Anxiety group also showed a downtrend (Slope mean -0.000015, SD 0.000116) but not as sharp as the Neutral group. This simple, yet important insight means that EDA could be used as a measure to distinguish between Calm, Anxious and Depressed state by using an inexpensive, low-powered, commonly available sensor without sophisticated equipment.

5.2 Viewing mental state transitions with STP segments

Dividing a subject's timeseries data into STP and Non-STP segments provided a reliable method to understand transition between different states of consciousness. The Maan Whitney U Test (Table 4 – Supplemental) showed while Synchronization and Calmness scores are statistically different between STP and Non-STP segments, Habituation, Hypoactivity and Experience scores are similar between the two groups. However, within STP and Non-STP segments, the scores of the H2SEC parameters were statistically different (Table 5 – Supplemental).

211 subjects out of 231 entered the STP segment at least once during the experimental task. The entry into an STP segment shows a sympathetic decline, indicating that a subject is calmer compared to their previous state

of mind. On an average, it took subjects in the Neutral group 1 minutes (SD 1.06 minutes), Anxiety group 2 minutes (SD 3.0 minutes) and Depression group 5 minutes (SD 3.65 minutes) to transition into an STP segment for the first time. As can be seen in Figure 5, the time spent by subjects within the STP segment had a proportional relationship with the Total Calmness Score – the more time spent within the STP segment, the more is the Total Calmness Score. On an average, subjects in the Neutral group sustained a calmer state (stayed within the STP segment) for 9 minutes (SD 2 minutes, minimum 4 minutes and maximum 19 minutes), subjects in the Anxiety group stayed for 9 minutes (SD 3 minutes, minimum 4 minutes and maximum 19 minutes) and those in Depression stayed 10 minutes (SD 6 minutes, minimum 6 minutes and maximum 29 minutes), during the task. Our analysis showed that subjects from the Anxiety and the Depression groups not only entered a calmer state, but were able to sustain a calm state at par (Anxiety) with the Neutral group and even exceeded it (Depression).

Figure 5: Regression Plot Showing Relationship between Total Calmness Score and Time Spent in STP Segments

5.3 Measuring the overall state of calmness

We found the Total Calmness score to vary between -1 and 0.8. Table 2 summarizes the performance of each group during the experimental task.

Table 2: Calmness Scores Across Groups

Score	Time In STP (% of total time)	Time Non- STP (% of total time)	Interpretation	Neutral	Anxious	Depressed	Total Subjects
Score ≥ 0.2	54.54	45.46	Calm	5	9	6	20
$-0.2 < \text{Score} < 0.2$	52.29	47.71	Approaching calmness	51	95	45	191
Score ≤ -0.2	36.47	63.53	Not Calm	5	4	11	20

- Calmness score ≥ 0.2** : The subject's mental state is *absolutely* calm, meeting all thresholds of all the parameters and attributes of the H2SEC framework. All these subjects reported feeling 'content' and 'blissful' after their experimental task. Such a state of mental tranquillity and autonomic balance has been described as the 'Turyatit' or the 'Samadhi' state in the yogic literature of India. There were 20 such subjects observed. Typically, meditation benefits physical and mental health via down-regulation of the hypothalamic-pituitary-adrenal (HPA).^{91 92 93} The state of parasympathodominance - increased concentration, higher alpha and theta brain activity and reduction in metabolic stress parameters, can be considered as physiological markers of a deep state of relaxation, tranquillity, higher brain efficiency and positive health in the subjects rather than just the absence of the disorder.^{94 95 96} However, in our study, the state of Samadhi was not expected from subjects from the Anxiety and Depression groups, though we expected a degree of calmness in all study participants due to the nature of the experimental task. We thus conclude that meditation could have an overwhelmingly positive impact on certain subjects with anxiety and depression.

- $-0.2 < \text{Calmness score} < 0.2$: The subject's mental state *is approaching* a calmer state, indicating that subjects are meeting a few threshold parameters and attributes of the H2SEC framework. There were 191 such subjects observed.
- $\text{Calmness score} \leq -0.2$: The subject's mental state has *not moved into a calmer state*, indicating subjects have not met any threshold parameters within the H2SEC framework, during the experimental task. There were 20 such subjects observed.

Since the majority of the subjects were in the Approaching Calm tier, we further segregated the scores and subjects by Levels based on the number of H2SEC criteria they fulfilled within the STP segment. As shown in Figure 6, we see that subjects that have met all four H2SEC thresholds and their attributes in the STP segments (Level 4) have the highest scores across Neutral, Anxiety, and Depression groups, while the ones that have not entered the STP segment even once have the lowest scores (Level 0). We observed that the most common threshold that has been missed by subjects is that of Synchronization, followed by Hypoactivity.

Figure 6: Total Calmness Scores by Groups & Levels

6 Automatic prediction of mental and calmness states

Based on the insights derived about the nature of the three groups under study, we applied a chain-based multi-label⁹⁷ machine learning technique as shown in Figure 7 to classify subjects into Neutral, Anxious or Depressed and then to predict whether they are Calm, Approaching Calm, or Not Calm. Features mentioned in Table 1, were first computed per centisecond of EDA and BVP data for each subject, after which per-minute mean of features were obtained to form the initial dataset. A key part of data preparation was dividing the data into STP and Non-STP segments before using ML. The features were fed into five different types of algorithms for classification of subjects into Neutral, Anxiety and Depression groups. Post classification of subjects into groups, we computed their Total Calmness Scores and levels. These variables, along with the aggregate time within and outside STP of every subject, and their predicted label from the first model were fed into the same set of classifiers to classify whether subjects were Calm, Approaching Calmness or Not Calm. We report the highest F1 score of 1 or 100%, with 100% precision and recall in detecting both mental states and calm states.

Figure 7: Machine Learning Flow for Simultaneous Prediction of Mental & Calm States

For performance evaluation, both the datasets were divided into two subsets - training set and test set, using a split of 70:30. After splitting, we scaled the data using standard scaler and executed the models by passing tuned hyper-parameters. After tuning, we performed 5-fold cross validation and applied the performance metrics, namely Accuracy, Precision, Recall, F1, and Matthews correlation coefficient (MCC), implemented via the SKLearn library in Python. To address the issue of class imbalance seen in the dataset, we oversampled the training set using the Synthetic Minority Oversampling Technique (SMOTE) found in the ‘imblearn’ library in Python. Table 3 shows the performance of the ML models in identifying various states, along with the hyperparameters used. Random Forest, Extreme Gradient Boost and Ada Boost showed the best performance among the five classifiers.

Table 3: Machine Learning Performance for Predicting Mental States – Model 1

Classifier	Accuracy	Precision	Recall	F1	MCC	Hyperparameters
Random Forest	1	1	1	1	1	{'n_estimators': 1000, 'min_samples_split': 10, 'min_samples_leaf': 1, 'max_features': 'auto', 'max_depth': 20, 'bootstrap': True}
Extreme Gradient Boost	1	1	1	1	1	{'colsample_bytree': 0.3, 'learning_rate': 0.01, 'max_depth': 3, 'n_estimators': 100}
Ada Boost	1	1	1	1	1	{'base_estimator': DecisionTreeClassifier(max_depth=1), 'learning_rate': 0.0001, 'n_estimators': 500}
LightGBM	0.99	0.95	0.99	0.97	0.95	{'learning_rate': 0.05, 'max_depth': -1, 'min_child_samples': 15, 'num_leaves': 20, 'reg_alpha': 0.01}
Decision Tree	0.91	0.87134503	0.839599	0.82488038	0.73654391	{'criterion': 'gini', 'max_depth': 10, 'max_features': 'auto', 'min_samples_leaf': 2, 'min_samples_split': 2}

7 Conclusion

A simple, yet, reliable and quantitative methodology to measure mental states is long overdue. Our proposed methodology provides an unbiased and quantitative mechanism to efficiently predict mental states without human bias. Through our experimental study, we were not only able to identify specific aspects of calmness, anxiety and depression, but also view transitions between these mental states using a unified methodology, with

low-powered and affordable wearables. Our unified framework may make it possible to provide recovery-focused screening solutions leading to faster diagnosis, followed by timely guidance, tailored cognitive behavioral therapy and tracking of both stressors as well as calmness-inducing factors in the day-to-day lives of patients. We hope our work will help foster further exploration in the area and very soon pave the way for diagnostics in the mental health space.

8 Limitations of our work

Though promising in its inceptual form, there are several limitations of our work. Further experimentation and thorough investigation is required to establish the validity of our work for real-world use. Secondly, our experiment was conducted in India with subjects trained in a particular form of meditation. Application of our methodology in other groups and geographies will confirm if our findings apply to the general population. Thirdly, the selection of mental aspects used in the H2SEC framework could be debated as there are other varied aspects of mental health that could be better at discriminating between calmness, anxiety and depression. While we acknowledge the shortcomings of our solution, we believe we have laid the foundation to similar studies in the area.

9 Acknowledgement

We would like to extend our sincere gratitude to Shri Kamlesh Patel, Spiritual Head of The Heartfulness Institute for enabling us to carry out our scientific research. We are grateful to Sanjay Sehgal, Babu Gurram, Hari Thota, Snehal Deshpande, Faru Arora, Nikhila, Vineet Ranawat and other volunteers of Heartfulness for their support and cooperation in getting access to study participants. We would like to thank the past and the present staff of TerraBlue XT that worked on the project for their outstanding support and dedication towards the work.

10 Conflict of interest

This project was funded by TerraBlue XT. TerraBlue XT is responsible for the project design, and collection and analysis of the data. The authors, except for Natwar Sharma, are TerraBlue XT employees, and they were responsible for data interpretation, revising the manuscript for intellectual content, and approving of the manuscript for submission.

Appendix - References

- ¹ Singh, Ilina, and Nikolas Rose. "Biomarkers in psychiatry." *Nature* 460.7252 (2009): 202-207.
- ² Hirschtritt, Mathew E., and Thomas R. Insel. "Digital technologies in psychiatry: present and future." *Focus* 16.3 (2018): 251-258.
- ³ Allsopp, Kate, et al. "Heterogeneity in psychiatric diagnostic classification." *Psychiatry research* 279 (2019): 15-22.
- ⁴ Lecrubier Y. Comorbidity in social anxiety disorder: impact on disease burden and management. *J Clin Psychiatry*. 1998;59(suppl 17):33–38.
- ⁵ Van Os TW.D.P, Van den Brink RHS, Van der Meer K, et al. The care provided by general practitioners for persistent depression. *Eur Psychiatry*. 2006;21(2):87–92.
- ⁶ Alonso J, Liu Z, Evans-Lacko S, et al. Treatment gap for anxiety disorders is global: Results of the World Mental Health Surveys in 21 countries. *Depress Anxiety*. 2018;35(3):195–208. doi:10.1002/da.22711
- ⁷ Fortney, John C., et al. "A tipping point for measurement-based care." *Psychiatric Services* 68.2 (2017): 179-188.
- ⁸ Firth J Siddiqi N Koyanagi Aet al., The Lancet Psychiatry Commission: a blueprint for protecting physical health in people with mental illness., *Lancet Psychiatry*. 2019; 6: 675-712
- ⁹ Donker T, Petrie K, Proudfoot J, Clarke J, Birch MR, Christensen H. Smartphones for smarter delivery of mental health programs: a systematic review. *J Med Internet Res*. 2013;15(11):e247. Published 2013 Nov 15. doi:10.2196/jmir.2791
- ¹⁰ Firth J Siddiqi N Koyanagi Aet al., The Lancet Psychiatry Commission: a blueprint for protecting physical health in people with mental illness., *Lancet Psychiatry*. 2019; 6: 675-712
- ^z Dandona R, Mind and body go together: the need for integrated care. *Lancet Psychiatry*. 2019; 6: 638-639
- ¹² Lund C Tomlinson M Patel V, Integration of mental health into primary care in low- and middle-income countries: the PRIME mental healthcare plans. *Br J Psychiatry*. 2016; 208: s1-s3
- ¹³ Roberts, L., Chan, S. & Torous, J. New tests, new tools: mobile and connected technologies in advancing psychiatric diagnosis. *npj Digital Med* 1, 20176 (2018). <https://doi.org/10.1038/s41746-017-0006-0>
- ¹⁴ Leventhal, Adam M., et al. "Investigating the dynamics of affect: Psychological mechanisms of affective habituation to pleasurable stimuli." *Motivation and Emotion* 31.2 (2007): 145-157.
- ¹⁵ Ramaswami M. (2014). Network plasticity in adaptive filtering and behavioral habituation . *Neuron* , 82 , 1216 – 29 .
- ¹⁶ Wright, Christopher I., et al. "Differential prefrontal cortex and amygdala habituation to repeatedly presented emotional stimuli." *Neuroreport* 12.2 (2001): 379-383.
- ¹⁷ Iacono, William G., et al. "Electrodermal activity in euthymic unipolar and bipolar affective disorders: A possible marker for depression." *Archives of General Psychiatry* 40.5 (1983): 557-565.

-
- ¹⁸ Sarchiapone, Marco, et al. "The association between electrodermal activity (EDA), depression and suicidal behaviour: A systematic review and narrative synthesis." *BMC psychiatry* 18.1 (2018): 1-27.
- ¹⁹ Ghiasi, Shadi, et al. "Assessing autonomic function from electrodermal activity and heart rate variability during cold-pressor test and emotional challenge." *Scientific reports* 10.1 (2020): 1-13.
- ²⁰ Bradley, M.M., Lang, P.J., 2000. Measuring emotion: behavior, feeling and physiology. In: Lane, R.D., Nadel, L. (Eds.), *Cognitive Neuroscience of Emotion*. Oxford University Press, Oxford, pp. 242–276.
- ²¹ LeBouef, Tyler, Zachary Yaker, and Lacey Whited. "Physiology, Autonomic Nervous System." *StatPearls* [Internet] (2020).
- ²² McCorry, Laurie Kelly. "Physiology of the autonomic nervous system." *American journal of pharmaceutical education* 71.4 (2007).
- ²³ McCorry, Laurie Kelly. "Physiology of the autonomic nervous system." *American journal of pharmaceutical education* 71.4 (2007).
- ²⁴ Lindsley, D.B., 1951. Emotion. In: Stevens, S.S. (Ed.), *Handbook of Experimental Psychology*. Wiley, New York, pp. 473–516.
- ²⁵ Pandya, Sunil K. "Understanding brain, mind and soul: Contributions from neurology and neurosurgery." *Mens sana monographs* 9.1 (2011): 129.
- ²⁶ Boucsein, W., 1992. *Electrodermal Activity*. Plenum, New York. 456 pp.
- ²⁷ Kutas, M., Federmeier, K.D., 1998. Minding the body. *Psychophysiology* 35, 135–150. Lacey, B.C., Lacey, J.I., 1978. Two way communication between the heart and the brain. *Am. Psychol.* 33, 99–113.
- ²⁸ Bradley, M.M., Lang, P.J., 2000. Measuring emotion: behavior, feeling and physiology. In: Lane, R.D., Nadel, L. (Eds.), *Cognitive Neuroscience of Emotion*. Oxford University Press, Oxford, pp. 242–276.
- ²⁹ Benedek, Mathias & Kaernbach, Christian. (2010). A continuous measure of phasic electrodermal activity. *Journal of neuroscience methods*. 190. 80-91. 10.1016/j.jneumeth.2010.04.028.
- ³⁰ Gunnar Wallin B, Fagius J. The sympathetic nervous system in man — aspects derived from microelectrode recordings. *Trends Neurosci.* 1986;9: 63–7. [https://doi.org/10.1016/0166-2236\(86\)90024-X](https://doi.org/10.1016/0166-2236(86)90024-X).
- ³¹ Asahina M, Suzuki A, Mori M, Kanesaka T, Hattori T. Emotional sweating response in a patient with bilateral amygdala damage. *Int J Psychophysiol.* 2003;47(1):87–93.
- ³² Boucsein W. *Electrodermal activity*. 2nd ed. New York ; London: Springer; 2012.
- ³³ Critchley, H.D., 2002. Electrodermal responses: what happens in the brain. *Neuroscientist* 8, 132–142.
- ³⁴ Tranel, D., Damasio, A.R., 1985. Knowledge without awareness: an automatic index of facial recognition by prosopagnosics. *Science* 228, 1453–1454.
- ³⁵ Williams, L.M., Brown, K.J., Das, P., Boucsein, W., Sokolov, E.N., Brammer, M.J., Olivieri, G., Peduto, A., Gordon, E., 2004. The dynamics of cortico-amygdala and autonomic activity over the experimental time course of fear perception. *Cogn. Brain Res.* 21, 114–123.

-
- ³⁶ Carbonnell, L., Vidal, F., Sequeira, H., Caverni, J.P., 2006. A reasoning bias revealed by electrodermal activity. *Psychophysiology* 43, 387–393.
- ³⁷ Edelberg, R., 1973. In: Stellar, E., Sprague, J.M. (Eds.), *Mechanisms of electrodermal adaptations for locomotion, manipulation, or defense*. . Progress in Physiological Psychology, vol. 5. Academic Press, New York, pp. 155–209.
- ³⁸ A. Greco, G. Valenza, A. Lanata, G. Rota and E. P. Scilingo, "Electrodermal Activity in Bipolar Patients during Affective Elicitation," in *IEEE Journal of Biomedical and Health Informatics*, vol. 18, no. 6, pp. 1865-1873, Nov. 2014, doi: 10.1109/JBHI.2014.2300940.
- ³⁹ Macefield, V.G., Wallin, B.G., 1996. The discharge behaviour of single sympathetic neurones supplying human sweat glands. *J. Auton. Nerv. Syst.* 61, 277–286.
- ⁴⁰ Lidberg, L., Wallin, B.G., 1981. Sympathetic skin nerve in relation to amplitude of skin resistance responses. *Psychophysiology* 18, 268–270.
- ⁴¹ Wenger CB. Thermoregulation. In: Freedberg IM, Eisen AZ, Wolff K, Austen KF, Goldsmith LA, Katz SI, editors. *Dermatology in general medicine*, 1. New York: McGraw-Hill; 2003. p.119–27.
- ⁴² Jänig W. The integrative action of the autonomic nervous system. *Neurobiology of homeostasis*. Cambridge: University Press; 2006.
- ⁴³ Boucsein W. *Electrodermal activity*. 2nd ed. New York ; London: Springer; 2012.
- ⁴⁴ Andreassi, John L. *Psychophysiology: Human behavior and physiological response*. Psychology Press, 2010.
- ⁴⁵ Medeiros, J., et al. "Blood Volume Pulse peak detector with a double adaptive threshold." *Technology and Medical Sciences-TMSi* 2010 (2011): 345-347.
- ⁴⁶ Nemati, S., Malhotra, A. & Clifford, G.D. Data Fusion for Improved Respiration Rate Estimation. *EURASIP J. Adv. Signal Process.* 2010, 926305 (2010)
- ⁴⁷ Reisner, A. et al., 2008. Utility of the Photoplethysmogram in Circulatory Monitoring. *Anesthesiology*, 108(5), 950-958
- ⁴⁸ Jalife J, Michaels DC. Neural control of sinoatrial pacemaker activity. In: Levy MN, Schwartz PJ, eds. *Vagal Control of the Heart: Experimental Basis and Clinical Implications*. Armonk, NY: Futura; 1994:173-205.
- ⁴⁹ Reinsberger C, Sarkis R, Papadelis C, et al. Autonomic changes in psychogenic nonepileptic seizures: toward a potential diagnostic biomarker?. *Clin EEG Neurosci.* 2015;46(1):16-25. doi:10.1177/1550059414567739
- ⁵⁰ Friedman, B.H., Thayer, J.F., 1998. Autonomic balance revisited: panic anxiety and heart rate variability. *J. Psychosom. Res.* 44, 133–151.
- ⁵¹ Anxiety and risk of incident coronary heart disease: a meta-analysis. Roest AM, Martens EJ, de Jonge P, Denollet J *J Am Coll Cardiol.* 2010 Jun 29; 56(1):38-46.
- ⁵² Davies SJC, Allgulander C. Anxiety and cardiovascular disease. In: Baldwin DS, Lennard BE, editors. *Modern trends in pharmacopsychiatry: anxiety disorders*. Vol. 29. Basel, Switzerland: Karger Publishers; 2013. pp. 85–97.

-
- ⁵³ Hare DL, Toukhsati SR, Johansson P, and Jaarsma T. Depression and cardiovascular disease: a clinical review. *Euro Heart J.* (2014) 35:1365–72. doi: 10.1093/eurheartj/eh462
- ⁵⁴ Carney RM, Freedland KE. Depression in patients with coronary heart disease. *Am J Med.* (2008) 121:20–7. doi: 10.1016/j.amjmed.2008.08.006
- ⁵⁵ Stapelberg NJ, Hamilton-Craig I, Neumann DL, Shum DH, McConnell H. Mind and heart: heart rate variability in major depressive disorder and coronary heart disease-a review and recommendations. *Aust N Z J Psychiatry* (2012) 46:946–57. doi: 10.1177/0004867412444624
- ⁵⁶ Carney RM, Freedland KE. Depression and coronary heart disease. *Nat Rev Cardiol.* (2017) 14:145–55. doi: 10.1038/nrcardio.2016.181
- ⁵⁷ Bassett, D. A literature review of heart rate variability in depressive and bipolar disorders. *Aust N Z J Psychiatry* (2016) 50:511–9. doi: 10.1177/0004867415622689
- ⁵⁸ Sgoifo A, Carnevali, L, Pico Alfonso MD, Amore M. Autonomic dysfunction and heart rate variability in depression. *Stress* (2015) 18:343–52. doi: 10.3109/10253890.2015.1045868
- ⁵⁹ Davydov DM, Shapiro D, Cook IA, Goldstein I. Baroreflex mechanisms in major depression. *Prog Psychopharmacol Biol Psychiatry* (2007) 31:164–77. doi: 10.1016/j.pnpbp.2006.08.015
- ⁶⁰ Carney RM, Freedland KE, Miller GE, Jaffe AS. Depression as a risk factor for cardiac mortality and morbidity: a review of potential mechanisms. *J Psychosom Res.* (2002) 53:897–902. doi: 10.1016/S0022-3999(02)00311-2
- ⁶¹ Jandackova VK, Britton A, Malik M, Steptoe A. Heart rate variability and depressive symptoms: a cross-lagged analysis over a 10 year period in the Whitehall II study. *Psychol Med.* (2016) 46:2121–31. doi: 10.1017/S003329171600060X
- ⁶² Ren, Yumiao, and Jianbao Zhang. "Increased cardiorespiratory synchronization evoked by a breath controller based on heartbeat detection." *Biomedical engineering online* 18.1 (2019): 1-13.
- ⁶³ Perry, Sean, Natasha A. Khovanova, and Igor A. Khovanov. "Control of heart rate through guided high-rate breathing." *Scientific reports* 9.1 (2019): 1-10.
- ⁶⁴ Penzel, T. et al. Modulations of heart rate, ECG, and cardio-respiratory coupling observed in polysomnography. *Front. Physiol.* vol. 7, 460 (2016).
- ⁶⁵ Spitzer, Robert L., et al. "A brief measure for assessing generalized anxiety disorder: the GAD-7." *Archives of internal medicine* 166.10 (2006): 1092-1097.
- ⁶⁶ Kroenke, Kurt, Robert L. Spitzer, and Janet BW Williams. "The PHQ-9: validity of a brief depression severity measure." *Journal of general internal medicine* 16.9 (2001): 606-613.
- ⁶⁷ Larradet, Fanny, et al. "Toward emotion recognition from physiological signals in the wild: approaching the methodological issues in real-life data collection." *Frontiers in psychology* 11 (2020): 1111.
- ⁶⁸ Vahey, Róisín, and Rodrigo Becerra. "Galvanic skin response in mood disorders: A critical review." (2015).
- ⁶⁹ https://biosignalsplux.com/learn/notebooks/Categories/Other/eda_analysis_rev.php
- ⁷⁰ https://biosignalsplux.com/learn/notebooks/Categories/Other/bvp_analysis_rev.php

-
- ⁷¹ Greco, Alberto, et al. "cvxEDA: A convex optimization approach to electrodermal activity processing." *IEEE Transactions on Biomedical Engineering* 63.4 (2015): 797-804.
- ⁷² Elgendi, Mohamed. "On the analysis of fingertip photoplethysmogram signals." *Current cardiology reviews* 8.1 (2012): 14-25.
- ⁷³ Perry, Sean, Natasha A. Khovanova, and Igor A. Khovanov. "Control of heart rate through guided high-rate breathing." *Scientific reports* 9.1 (2019): 1-10.
- ⁷⁴ Gerald Appel, E. D. "Understanding MACD (Moving Average Convergence Divergence). 2008." (2008).
- ⁷⁵ Taquet, Maxime, et al. "Mood homeostasis, low mood, and history of depression in 2 large population samples." *JAMA psychiatry* 77.9 (2020): 944-951.
- ⁷⁶ Nolen-Hoeksema S, Wisco BE, and Lyubomirsky S (2008) Rethinking rumination. *Perspect Psychol Sci* 3:400–424.
- ⁷⁷ Hamilton JP, Farmer M, Fogelman P, and Gotlib IH (2015) Depressive rumination, the default-mode network, and the dark matter of clinical neuroscience. *Biol Psychiatry* 78:224–230.
- ⁷⁸ Whisman MA, du Pont A, and Butterworth P (2020) Longitudinal associations between rumination and depressive symptoms in a probability sample of adults. *J Affect Disord* 260:680–686.
- ⁷⁹ Harrington MO, Pennington K, and Durrant SJ (2017) The 'affect tagging and consolidation' (ATaC) model of depression vulnerability. *Neurobiol Learn Mem* 140:43–51.
- ⁸⁰ Cariga, P., et al. "Characteristics of habituation of the sympathetic skin response to repeated electrical stimuli in man." *Clinical neurophysiology* 112.10 (2001): 1875-1880.
- ⁸¹ Benito, Kristen G., and Michael Walther. "Therapeutic process during exposure: Habituation model." *Journal of obsessive-compulsive and related disorders* 6 (2015): 147-157.
- ⁸² Miquel, Marta, et al. "Habituation and sensitization processes in depressive disorders." *Psychopathology* 32.1 (1999): 35-42.
- ⁸³ Fried I. MacDonald K.A. Wilson C.L. (1997). Single neuron activity in human hippocampus and amygdala during recognition of faces and objects . *Neuron* , 18 , 753 – 65 .
- ⁸⁴ Dubois S. Rossion B. Schiltz C. , et al. . (1999). Effect of familiarity on the processing of human faces . *NeuroImage* , 9 , 278 – 89 .
- ⁸⁵ Wright C.I. Fischer H. Whalen P.J. McNerney S.C. Shin L.M. Rauch S.L. (2001). Differential prefrontal cortex and amygdala habituation to repeatedly presented emotional stimuli . *Neuroreport* , 12 , 379 – 83 .
- ⁸⁶ Avery, Suzanne N., and Jennifer Urbano Blackford. "Slow to warm up: the role of habituation in social fear." *Social cognitive and affective neuroscience* 11.11 (2016): 1832-1840.
- ⁸⁷ Olshansky, Brian, et al. "Parasympathetic nervous system and heart failure: pathophysiology and potential implications for therapy." *Circulation* 118.8 (2008): 863-871.
- ⁸⁸ Pop-Busui, Rodica. "Cardiac autonomic neuropathy in diabetes: a clinical perspective." *Diabetes care* 33.2 (2010): 434-441.

⁸⁹ Consensus Committee of the American Autonomic Society and the American Academy of Neurology. "Consensus statement on the definition of orthostatic hypotension, pure autonomic failure, and multiple system atrophy." *Neurology* 46.5 (1996): 1470-1470.

⁹⁰ Hayano, Junichiro, and Emi Yuda. "Pitfalls of assessment of autonomic function by heart rate variability." *Journal of physiological anthropology* 38.1 (2019): 1-8.

⁹¹ Tang YY, Lu Q, Geng X, Stein EA, Yang Y, Posner MI. Short-term meditation induces white matter changes in the anterior cingulate. *Proc Natl Acad Sci U S A*. 2010; 107(35): 15649-52. doi: 10.1073/pnas.1011043107. Epub 2010 Aug 16.

⁹² Xue S, Tang YY, Posner MI. Short-term meditation increases network efficiency of the anterior cingulate cortex. *Neuroreport*. 2011 Aug 24;22(12):570-4. doi: 10.1097/WNR.0b013e328348c750.

⁹³ Taren AA, Gianaros PJ, Greco CM, Lindsay EK, Fairgrieve A, Brown KW, Rosen RK, Ferris JL, Julson E, Marsland AL, Bursley JK, Ramsburg J, David Creswell J. Mindfulness meditation training alters stress-related amygdala resting state functional connectivity: a randomized controlled trial. *Soc Cogn Affect Neurosci*. 2015 Jun 5. pii: nsv066. [Epub ahead of print]

⁹⁴ Ratanasiripong P, Park JF, Ratanasiripong N, Kathalae D. Stress and Anxiety Management in Nursing Students: Biofeedback and Mindfulness Meditation. *J Nurs Educ*. 2015 Sep 1; 54(9):520-4. doi: 10.3928/01484834-20150814-07.

⁹⁵ Song Y, Lindquist R. Effects of mindfulness-based stress reduction on depression, anxiety, stress and mindfulness in Korean nursing students. *Nurse Educ Today*. 2015 Jan;35(1):86-90. doi: 10.1016/j.nedt.2014.06.010. Epub 2014 Jul 9.

⁹⁶ Hou RJ, Wong SY, Yip BH, Hung AT, Lo HH, Chan PH, Lo CS, Kwok TC, Tang WK, Mak WW, Mercer SW, Ma SH. The effects of mindfulness-based stress reduction program on the mental health of family caregivers: a randomized controlled trial. *Psychother Psychosom*. 2014;83(1):45-53. doi: 10.1159/000353278. Epub 2013 Nov 19.

⁹⁷ Read, Jesse, et al. "Classifier chains for multi-label classification." *Machine learning* 85.3 (2011): 333-359.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [PredictingCalmnessAnxietyandDepressionusingWearableSensorsSupplementalFinal.pdf](#)