EasyBreathe: Chronic Stress Reduction Platform

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***Abstract*—Chronic psychological stress is often associated with the prevalence of mental disorders in modern healthcare, such as heart attacks, panic attacks, and substance misuse. Severe mental conditions of this scale have approximately 75% probability of settling in adults by the age 24. In order to combat these symptoms, we propose regular sessions of slow-paced breathing and mindfulness meditation as valid solutions. This pilot study introduces EasyBreathe, a chronic wearable stress reduction platform capable of administering real-time therapeutic treatment on a daily basis. The EasyBreathe system was attached to eight Imperial College students for six-hour sessions of experimentation. Our findings indicated that rhythmic breathing can potentially assist patients in managing persistent states of stress in the long-run.**

I. Introduction

An increasing concern for modern healthcare is the prevalence of mental disorders and diminished wellbeing in response to consistent levels of psychological stress. Excessive amounts of stress over long-term periods of time have demonstrated correlations with a vast range of mental illnesses and severe medical conditions. For instance, studies have linked stress with strokes, heart attacks, anxiety disorders, depression [1], asthma [2], panic attacks [3], as well as smoking and other substance misuse [4][5]. Whilst most of these examples are related to traumatic individual experiences that have subsequently induced post-traumatic stress disorder (PTSD), chronic stress generated through environmental and emotional factors is also strongly linked with these medical conditions.

Mental illnesses of this scale are leading causes of disability in young adults [6] and approximately 75% of these disorders have their onset by the age 24 [7]. Therefore, an ideal method of tackling these conditions via healthcare is to identify and prevent their negative effects prior to diagnosis. As chronic stress has a critical influence over the onset of these disorders, reducing and managing regular levels of juvenile stress fits the criteria for improvement in overall mental wellbeing of the general population.

In order to accomplish this feat, this paper proposes a wearable system as an innovative solution to help reduce persistent states of stress. Wireless healthcare is a practice whereby expert medical diagnosis, feedback and treatment may be provided to patients on a real-time basis through a portable and robust system. Furthermore, machine learning (ML) techniques are a growing trend in the field of personalised medicine, with increasing application in the domain of mobile healthcare. By applying these principles, we developed EasyBreathe for the purpose of detecting irregular stress levels in users and administering therapeutic methods to assist with chronic stress reduction. This platform incorporates two components into its architecture, an Apple Watch paired with an iPhone.

The aim of this report is to demonstrate the core functionality behind EasyBreathe, as well as discuss the results of its application on Imperial College students. Section II details the research hypotheses tested against EasyBreathe during experimentation. Following this, Section III provides a background of related work and similar systems. From a holistic design perspective, Section IV describes the platform in terms of its electronic and software mechanisms. Section V details our setup and methodology for testing the presented hypotheses, whilst Section VI discusses the experimental findings of this chronic stress reduction tool. Finally, Section VII suggests future work for this wearable platform and conclusive remarks about this research project are provided in Section VIII.

II. Hypotheses

By exposing Imperial College students to the EasyBreathe platform in an everyday setting, we assert the potential benefits of this system through the following hypotheses:

- i Setting a slow and controlled breathing pace via a rhythmic interface will incite relaxed emotional states in participants at a faster rate than without any intervention.
- ii Playing meditation music will incite relaxed emotional states in participants at a faster rate than without any intervention.

III. Background

A core feature of EasyBreathe is accurate and seamless estimation of psychological stress in tested users, for which there are various techniques ranging from objective measurements of physiological signals in patients to conducting surveys for a perceived stress evaluation. In Vrijkotte's study [8], work stress in subjects was monitored continuously using ambulatory instruments for blood pressure (BP) and heart rate (HR) readings. The results indicated that higher HR and BP variability correlated with detrimental work stress levels. Poh et al. [9] instead attached a wearable sensor to participants and their electrodermal activity (EDA) was assessed as they performed mental and physical exercises. Their findings suggested a dramatic increase in skin conductance levels following both mentally and physically straining experiments. From a survey-based approach, the Perceived Stress Scale (PSS) is a well-known instrument [10] used to measure the degree of an individual's appraisal of stress during different situations.

For quantitative and precise psychological stress detection through a wearable device, EasyBreathe relies on a combination of HR variability (HRV) and body movement as input vital signals. HRV analysis is a measurement of intervals between successive heartbeats and is often used as a biomarker for stress assessment [11]. This analysis can be commonly achieved through photoplethysmography (PPG), an optical method of measuring blood oxygenation variations. However, Lu and Yang [12] presented a key limitation behind this technique by displaying the noisy effect of motion artifacts on PPG waveforms. In order to offset the impact of physical activity on physiological quantities, a study by Wu et al. [13] used two modalities of sensors by integrating HRV sensors and accelerometers in predictive stress analysis. Their results demonstrated a significant correlation between accelerometer data and HRV readings for stress estimation.

There are various mindful and calming approaches to reducing mental stress levels in a human being. A small-scale study [14] examining the effects of yoga on anxiety and stress of breast-cancer patients presented positive psychological responses after the participants implemented a recommended yoga regimen. The effectiveness of different types of music on emotional state and physiological arousal of college students was also explored by Labbé et al. [15]. Their findings signified substantial reductions in anxiety and positive increases in states of relaxation after exposing subjects to self-selected and classical music, in comparison to sitting in silence or listening to heavy metal music.

Another common relaxation technique for managing chronic stress is to alter the pace of breathing. Breathing practices constitute voluntary variations in the tempo of respiration and are classified in different forms. In the Nogawa et al. paper [16], slow-breathing techniques were investigated for their influence over hemodynamic changes in healthy volunteers. Their results suggested that slow breathing could lead to potentially significant improvements in the cardiovascular function of patients managing acute stress on a daily basis. Brown et al. [17] also conducted an examination of the effects of breathing techniques on multiple stress-related medical conditions. The paper presented numerous breathing mechanisms and outlined their effects on stress-induced mental states based off other similar research. Once again, slow-paced breathing indicated a beneficial impact in reducing symptoms of stress.

A competitive selection of ML algorithms is currently available for stress recognition in research applications similar to EasyBreathe. Karstoft et al [18][19] investigated capabilities of predicting PTSD tendencies in pre-deployed soldiers through use of ML methods. They applied a feature selection algorithm to identify the most predictive variables of PTS and used Support Vector Machines (SVMs) [20] for classification of individuals into groups of resilience or distress. SVMs are a state-of-the-art supervised learning algorithm for classification problems and have been widely applied in stress classification by using modified techniques [21][22], or by integrating with other algorithms in order to form a hybrid system [23]. Other classifiers have also been extensively used in stress recognition, such as the Naïve Bayes and Decision Tree (DT) classifiers [24]. With regard to feature extraction from stress-related sensor data, signal processing algorithms involving time or frequency analysis of the incoming signal are commonly employed methodologies [13][24].

Similar systems to EasyBreathe are currently available in the mobile healthcare application market. For example, Calm [25] is a Watch app undergoing development with the aim of performing real-time stress detection and instructing breathing exercises for patients to follow as a method of calming mental distress. Similarly, Headspace [26] applies meditation techniques through a Watch and iPhone, allowing users to perform mindfulness exercises according to this system's guidance.

IV. System Design

A. System Overview

The EasyBreathe platform is composed of two wearable hardware components: an iPhone and an Apple Watch. Sampling HR readings from the user is performed via the in-built PPG sensors of the Watch. The Watch also acquires accelerometer data from the user in order to model their mobility on a real-time basis. On the other hand, the iPhone processes the data sent from the Watch and detects elevated stress levels based purely on fluctuations in HR, whilst filtering out the influence of motion artifacts.

From a software perspective, EasyBreathe is divided into two segments: an iOS app and a watchOS app. The iOS app provides the main graphical interface to our platform and is also responsible for any bulk data processing. For secure storage of any patient-related information, Apple's HealthKit framework is used and represents the back-end of our system. Over a Bluetooth connection, the Watch app connects HR and accelerometer feeds of data to the iOS app and displays these readings through a user interface (UI). Both the iOS and watchOS apps also administer therapeutic treatment for chronic stress through their respective graphical interfaces.

A complete overview of the aforementioned software and hardware components that are integrated into the EasyBreathe system is shown in Figure 1.

B. Wearable Sensors

There are two sensors required for this system: a sensor that can measure the movement of the user, and a sensor that can measure heart activity.

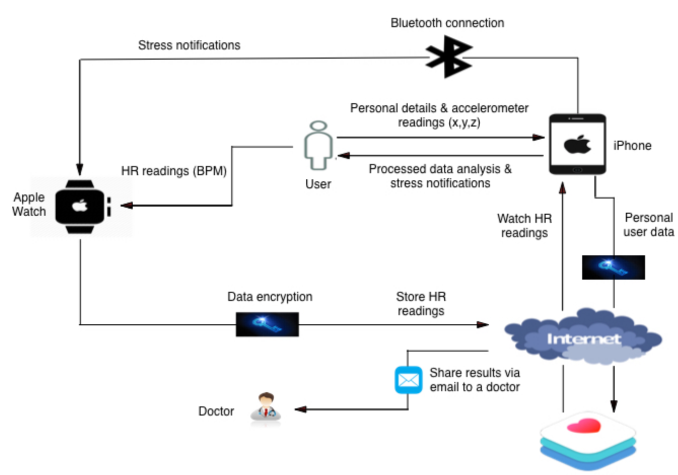

Fig. 1: EasyBreathe system architecture diagram consisting of hardware and software component interactions.

One of the preliminary system design choices made for EasyBreathe was to determine where users should wear the sensors. Forrester Research [27] presented the preferred location to be on the wrist, which inspired us to use either smartwatches or activity trackers.

Most commercial smartwatches and activity trackers use PPG to measure the HR. Unfortunately, Lu et al. [12] have shown that PPG is prone to noise and error due to movement. This drawback is offset by the fact our system measures user activity. It has been further shown that PPG is not able to accurately detect HRV [12], but performs well when measuring the mean HR. Therefore, we approximated HRV based on sampled HR readings during data processing. Other sensors that can measure the HR use ECG, however these must be worn around the chest and are hence not suitable solutions for our wearable stress reduction platform.

The most common sensor used to measure activity are accelerometers. An accelerometer measures a user's acceleration and is quantified by a three-axis system. By calculating the values of the variables of the system, it is possible to estimate a patient's mobility at runtime.

Since the majority of activity trackers and smartwatches use similar hardware sensors, PPG monitors and accelerometers, our final choice of electronic wearable was an Apple Watch.

1) Main Functions: The Watch has five main functions, three active and two passive. Active functions consist of collecting HR data, collecting accelerometer data, and sending the data to the iPhone. Whilst notifying the user and displaying a breathing exercise are considered passive functions.

In order to access the HR sensors of a Watch, we first need to initiate a workout session. The Watch normally measures the HR every 10 minutes, which is too slow for any real-time stress monitoring of a user. Nevertheless, HR can be measured at five second intervals by running a workout session. This frequency is fixed due to the limitations of PPG [28]. After probing the user for permission to store stress-related data in HealthKit, HR streams begin to be measured at a real-time rate. These HR readings are written as a string to a data array.

With regard to accessing the accelerometer data, the CoreMotion framework of Apple is necessary. The Watch collects accelerometer data instantaneously, which quickly becomes an overwhelming memory storage expense. We therefore deploy a timer that collects the accelerometer data every second. The values of three variables, X, Y, and Z, are written to a string. These string values are then aggregated together with a corresponding timestamp, and concatenated to the HR array.

The WatchConnectivity framework offers several methods to send data to the phone. Our system requires continuous streams of data to the phone for processing purposes. The most appropriate method to accomplish this feat is interactive messaging. If the phone is reachable, this method sends a message or an array together with a key to the phone. The phone receives the array by identifying this key. Through this method, data is sent via the array every two seconds.

In order not to overload memory of the phone and to simplify the computation, we sample all incoming data every minute by copying the data array into a sample array.

As described in Section III, breathing exercises are an effective method to reduce stress. Following from this notion, the Watch uses a circular animation to set a rhythmic pace for the user to follow during respiration. An animated ring is used as the majority of Watch interface features are circular. The animation was acquired from an online image generator [29].

2) Comparison: We compared the accuracy of the Watch's PPG sensor against the readings obtained from a Polar H7, which uses ECG to measure HR. Our resulting signals are shown in Figure 2. The test interval was over 15 minutes and illustrates a strong correlation between the two sensors. This confirms that the Watch is a suitable sensor for continuously measuring HR.

3) Limitations: Despite the Apple Watch's prevalent suitability as our primary wearable sensor for EasyBreathe, there are some limitations. One of the built-in features of this sensor is that the screen turns off when lowering the wrist, which occurs deliberately to save power. However, once the screen turns off, the activities of the watchOS app in the foreground are suspended. This means that whenever the user's wrist is lowered, the app will stop writing accelerometer data to the array and sending it to the mobile phone. On average the Watch more often than not turns on whenever the wrist is raised, nonetheless there are still inconsistencies over incoming data.

Whenever the Watch measures HR, it automatically writes these values to HealthKit. So even if the screen is turned off, HR values are written to HealthKit every five seconds. By querying HealthKit from the phone and receiving HR streams directly, we are able to circumvent the problem of receiving inconsistent data. At the moment HealthKit does not have a class for accelerometer data and thus we cannot modify the classes within HealthKit. Therefore it is impossible to store accelerometer readings in HealthKit and query from the phone directly. In the near future, it may be possible if Apple develops a property to hold accelerometer axes variables. As an ad hoc solution, we are using the iPhone's accelerometer sensor.

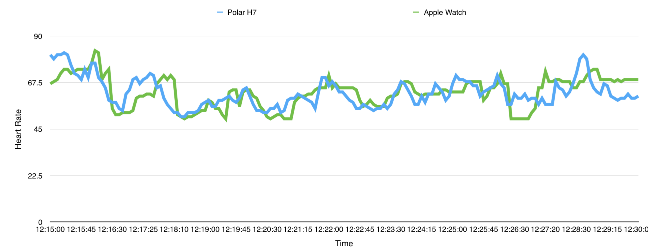

Fig. 2: Signal comparison between the Polar H7 and Apple Watch hardware sensors.

C. iOS Application

In software engineering, a platform consists of the presentation layer (Front-End) and the data access layer (Back-End). Designing and implementing the UI is part of the Front-End process. The Back-End of an application is responsible for offering services to the Front-End.

HealthKit was selected to support the Back-End of our system. Whilst HR data is stored in HealthKit every second, accelerometer data acquired from the Watch is stored locally. Storage and data privacy is further discussed in Section IV-C5.

Following the decision made for the Back-End, the main features of our EasyBreathe prototype's UI are listed here: (a) Breathing Control, (b) Meditation-Mindfulness Exercise, (c) Historical Data presentation, (d) Interventions, (e) Sharing information via email, and (f) Stress Testing.

1) User Interface: The start-up and home page of EasyBreathe are presented in Figure 3. On the left hand side, the start-up page displays a message that explains the purpose of this app. On the right of the starting page is the home page which provides a list of application operations.

Fig. 3: Starting from left to right: Start-up, home, breathing exercise, and a rhythmic settings pages.

The Breathing Control page is also available in Figure 3 next to the home page. The purpose of this function is to assist the individual in setting a slow rhythmic pace for breathing. Inhaling time is represented during ascension of the empty bar and the descent corresponds to exhaling time. Inhaling and exhaling times can be changed in the settings page according to the user's preferences.

Another method for aiding the user in stress reduction is through mindfulness meditation. It is practised by having the patient sit with their eyes closed, cross-legged on a cushion or chair, and having their back straight. This kind of meditation helps the individual focus on breathing and calming their mind. A 10-minute mindfulness guide is available to EasyBreathe, with the page illustrated in Figure 4.

Fig. 4: Starting from left to right: Historical data, meditation, and stress test pages.

2) Historical Data: Another functionality of the iOS application is that for any given week, it will record time-periods of elevated stress levels in an individual on a daily basis. EasyBreathe displays this information in the form of graph as shown in Figure 4. This page also displays the duration of total distress for a user.

The capability to extract this information and share it via email is also included in the mobile application. Sharing data with your physician or anyone whom you believe could provide medical advice is an essential characteristic for a mobile healthcare application.

3) Stress Test: In addition to the above, the iOS application enables the user to perform a Stress Test. The basic idea behind this is to allow the user to check every minute whether he is stressed or not. The outcome of this test is updated every minute since all ML processing is conducted on a minute-by-minute basis. The interface of the Stress Test page is also available in Figure 4.

4) Interventions: Mobile interventions also have beneficial effects on the healthcare delivery process. In the work of Free et al. [30], their results demonstrated a positive impact of application intervention in provision of healthcare. Text-messaging, notifications or phone call reminders are some of the techniques they used in this study.

EasyBreathe is responsible for predicting chronic stress situations. When stress is detected, the application intervenes by aiming to reducing further elevation of this mental state. Interventions are triggered through the iPhone and Apple Watch. In particular, the mobile phone intervention is in the form of a notification that advises the user to relax and perform a suggested medication program. An example of this intervention is shown in Figure 5.

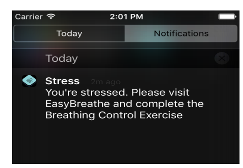

Fig. 5: Mobile phone intervention via notification.

5) Data Privacy & HealthKit: One of the most significant aspects that must be taken into consideration when designing and developing a healthcare system is data privacy. Data concerning an individual's health can be a very sensitive subject. Threats to sensitive data have reached a critical point over the last few years, with an escalation in sophistication and frequency of cyberattacks. It is imperative that healthcare organisations implement security solutions that will not only protect important data assets, but also satisfy the compliance mandates for which they are held accountable [31].

HealthKit grants users control over their data by providing fine-grain manipulation over the information that mobile applications share. The user must explicitly grant each app permission to read and write data to the HealthKit store. Users can grant or deny permission separately for each type of data. For example, a user could let your app read the step count but prevent it from reading the blood glucose level. To prevent possible information leaks, an app does not know whether permission to read data is denied. From the app's point of view, permission denial means no data of that type exists [32].

Moreover, the HealthKit information is only kept locally to the user's device. For security purposes, the HealthKit store is encrypted when the device is unlocked and it can only be accessed by an authorised app. Since authorisation is needed in order to access this signal data, our EasyBreathe platform initially requires the user to press the HealthKit authorisation button available in the home page (Figure 3). The HealthKit authorisation icon provides our application with access to any stored user HealthKit data.

6) Limitations: Power consumption is a critical challenge for many mobile applications and this is no exception for EasyBreathe. ML data analytics require the application to remain in foreground status during execution, as background mode will cause this process to stall. This proves to be an extremely costly outcome for battery life, which is a major drawback for a chronic stress reduction platform.

D. Stress Classification

A fundamental characteristic of EasyBreathe is timely detection of elevated psychological stress levels in young adults. In order to achieve this target, our mobile platform incorporates a stress recognition module into its system design that is capable of identifying persistent peaks of distress in users based on incoming wearable sensor data. Stress inference is a typical classification problem and a variety of supervised ML algorithms can be applied in the context of stress detection. This section of the report describes the learning component of EasyBreathe and discusses its capability in distinguishing between user states of relaxation or distress.

Given the requirements for supervised learning methodologies, gathering labelled data for the purpose of training ML models was an initial concern in developing this stress classification module. Although an ideal approach would have been to resort to online datasets that contained labels for healthy volunteers undergoing chronic stress, the additional requirement of HR and accelerometer sensor readings presented challenges in locating such a source of data. Training data was therefore collected from 10 Imperial College students over varying time periods and environmental settings. The final dataset amounted to approximately 27 hours of raw signal data.

In the pre-processing stage of our learning component, feature extraction is performed over the incoming signal data derived from the 10 subjects and sampled at rates varying between 1-10 Hz. Feature extraction is primarily implemented in our system to reduce dimensionality of input data, which is a well-known issue of operating prediction algorithms over real-time signals due to the computational intractability and worsened classification performance. Moreover, the consequences of high-dimensional data have significant impact on the power consumption of mobile applications.

Since stress-related HR and accelerometer data are continuous time-series readings, the features extracted from these input feeds are time-domain and frequency-domain signal properties. Table I provides a complete list of the core features extracted during the pre-processing phase of the EasyBreathe stress recognition component. Following from analogous research into chronic stress recognition [13] and activity-based stress detection [33], input signals were segmented into data windows of 1-minute intervals during feature extraction. As a result, daily monitoring would require 1440 data windows $w_1 \dots w_{1440}$ for full coverage. Each window has a corresponding feature vector $f_i(j)$, where *i* is the window index and *j* is a stress-related feature. According to a similar predictive stress application [33], psychological stress is accurately classified from most HRV features computed within a minute.

Wearable Sensors	Core Features
Heart Rate *Time Domain*	Mean & Std. HR Mean & Std. RR interval RMSSD RR50
Accelerometer *Time Domain*	Mean & Std. XY signals Activity Index
Accelerometer *Frequency Domain*	Spectral Energy over XY

TABLE I: Core features chosen for extraction from the time-domain and frequency-domain properties of the HR and accelerometer signals. Largely influenced by the work of other research applications [13][33].

Pre-processing of input data was coordinated in a Matlab environment due to the versatility of its data analytics tools. In particular, the Classification Learner App available within the Statistics and ML Toolbox is a powerful program that enables exploration and comparison of different ML models. After extracting any relevant features from the raw data collected, a total of 1579 training examples were loaded into the Classification Learner App to train stress classifiers. By comparing performance of numerous supervised ML models based off of their confusion matrices, the complex DT and cubic SVM algorithms were selected. The resulting confusion matrices of these algorithms are presented in Figure 6, with the DT and SVM models obtaining overall classification accuracies of 81.3% and 80.5% respectively.

The iPhone component of EasyBreathe executes the bulk of runtime processing required for our stress classification model using the open-source C++ OpenCV library. In order to operate the ML libraries contained within OpenCV through the mobile device, a C bridge is set up to interface this C++ package with the iOS development environment programmed using Swift. As a result of the establishment of this connection between the two software frameworks, our iOS application is able to translate inward sensor data into the cv::Mat format for matrices. These matrix structures hold 1-minute samples of vital readings and are condensed into a 1D array of features

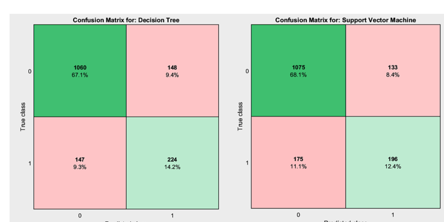

Fig. 6: Confusion matrices for the complex DT (left) and cubic SVM (right) classification algorithms.

representing a single input prepared for stress prediction.

As the iOS app requires access to the selected DT and SVM classifiers at runtime, both these ML models are trained internally to the mobile device using the OpenCV framework. After retrieving the .csv file generated from the Matlab script for feature extraction, the ML algorithms are instantiated and parameterised before undergoing training using the provided dataset. The resulting models are then stored within the iOS bundle as XML resource files that are accessible to EasyBreathe at runtime. These pre-trained classifiers are loaded from an XML format during operation and used to predict stress over the abovementioned array of features, which are calculated on a minute-by-minute basis. The final Boolean output is returned to the iOS interface indicating whether the user endured elevated stress levels or not in the past minute.

Throughout development of this stress recognition module, a fundamental limitation for classification accuracy was due to the inconsistencies present within the training dataset. Unfortunately, the 10 students that provided labelled data found classifying their own stress levels an abstract and imprecise task on a day-to-day basis. Without any specific event leading to a heightened state of stress, the process of pinpointing the exact minute intervals of elevated mental stress proved to be an imperfect method of supervised learning. However, by applying the knowledge gained from modelling stress detection algorithms in Matlab, parameterising the trained classifiers in a systematic manner avoided significantly inaccurate classification. For example, the complex DT model was visualised graphically in Matlab prior to assigning a maximum depth parameter value of eight in the OpenCV training framework.

Upon deployment of EasyBreathe, the DT algorithm was finally configured as the default model for stress classification. This selection was due to the vast difference in classification accuracy after evaluating both the SVM and DT models on a simulated testing dataset. It is also worth noting that overfitting was prevented during the training of these algorithms by employing 10-fold cross-validation as an in-built OpenCV library setting. The results of our stress classification component during experimentation are presented in Section VI.

V. Experimental Setup

In order to test our hypotheses asserting the benefits of the EasyBreathe platform for chronic stress reduction, a set of experiments on eight users took place. All of the users involved in these experiments were selected Imperial College students, with no prior case of mental disorder. These mixed gender volunteers aged 20-24 withstand persistent levels of stress throughout the year in the high-pressure environment of Imperial College. Each of the users wore our wearable system for a period of six hours in an arbitrary day-to-day setting. For this duration, the participants were asked to simply perform their daily tasks and apply either of the EasyBreathe stress relief functions upon experiencing stress. The participants were also asked to refrain from using EasyBreathe during one of the stress intervals, so that a baseline rate for declining stress can be captured without intervention.

A flexible experiment protocol with no standard methodology or fixed environment setting was deemed a suitable setup for evaluating EasyBreathe against the many sources of stress among university students [34]. Taking into account the nature of chronic stress relief, our wearable platform required testing on users performing various tasks in different locations. As a result, volunteers were set up with our system in numerous environments ranging from university to their own homes, and on multiple days of the week, including the weekend.

However, there were various unavoidable limitations associated with our experimental setup. First and foremost, these experiments were all held around the Easter holiday period at the end of spring term. Consequently, the majority of students participating in these experiments had no inclination to be stressed and were enjoying their break from university. Secondly, the time constraints of this project limited experimentation to be held on a single day per volunteer. Ideally, chronic stress is best monitored over weeks of readings and is a long-term healthcare concern. Finally, the number of evaluated users suggests that EasyBreathe requires further evaluation before a statistically relevant conclusion can be drawn from the tested research hypotheses.

VI. Evaluation & Results

A. System Evaluation

The results of our experimentation with EasyBreathe have been summarised in Table II. Unfortunately due to the small sample of users and lengthy time requirements for monitoring chronic stress, these results lack statistical significance. Consequently, this evaluation will act as an introductory setting for future research involving the EasyBreathe platform.

Table II demonstrates the stress prediction output of EasyBreathe and the corresponding user labels categorised as true or false. In cases 2,4,5,6, the samples were all classified as not stressed during the six hour experiment and 100% accuracy was achieved. Similarly, stress detection over User 1 had a high predictive accuracy. During the stress period of the session for User 1, the subject indicated that they performed the slow-paced breathing exercise every five minutes. In their opinion, this therapeutic method assisted them in managing their stress during this interval. Users 1, 7, and 8 have also successfully achieved high accuracy results during their periods of distress.

With regard to User 3, there was a low classification accuracy for detecting situations at a relaxed mental state. By investigating this further, it was observed that User 3 has an average resting HR of 102 beats per minute (BPM), which is

	EasyBreathe Results		User's Results			
	Stress Intervals (min)	Not Stress (min)	Stress Intervals (min)	Not Stress (min)	Stress Prediction (%)	Not Stress Prediction (%)
User 1	31-202	1-30 , 203-360	26-185	1-25, 186-360	96.80	87.94
User 2	0	1-360	0	1-360	0	100
User 3	18-36, 49-277	37-48,277-360	101-198	1-100, 199-360	100	36.02
User 4	0	1-360	0	1-360	0	100
User 5	0	1-360	0	1-360	0	100
User 6	0	1-360	0	1-360	0	100
User 7	14-37	1-13,38-360	10-37	1-10,38-360	85.18	100
User 8	118-351	1-117,352-360	105-345	1-104 , 346-360	94.58	94.91

TABLE II: Stress monitoring results for eight volunteers.

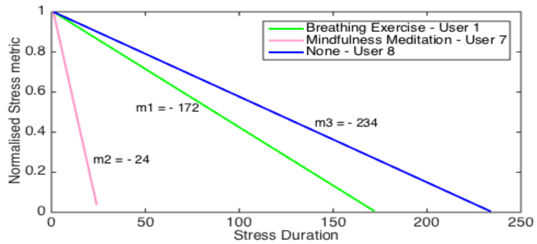

Fig. 7: Stress reduction rates for the breathing exercise, mindfulness meditation, and no intervention.

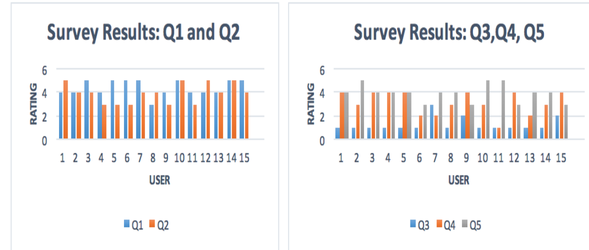

Fig. 8: Survey results evaluating the EasyBreathe UI.

above the normal range. This may have affected our results due to the fact that the training dataset was not expansive enough to capture this exceptional scenario. User 3 also indicated that the breathing exercise was helpful during stress intervals.

In accordance with our hypotheses, the stress reduction rates for Users 1, 7, and 8 are presented in Figure 7. Our results for User 3 are not presented due to the aforementioned low classification accuracy. In this plot, User 1 applied the breathing control exercise, whereas User 7 followed the mindfulness meditation guide. User 8 performed no therapeutic exercises.

Overall, our findings indicate that the therapeutic methods had positive effects on the two tested users based off of their steeper gradients. Instead, User 8 remained stressed throughout the entirety of their stress-inducing activity. However after further examination, the three users experienced different stress-inducing situations. Firstly, User 1 undertook a three hour test for a job, in which they mentioned that the breathing exercise assisted with their anxiety. On the other hand, User 7 was classified as stressed during a group meeting and performed mindfulness meditation in the five minutes following this meeting. This user noted that there was an immediate effect on their mental state. Finally, User 8 was experiencing stress during the hours before their deadline submission. Therefore, our results conclude through steeper gradient values of -24 and -172 that both stress relief methods aided in managing chronic stress. Nonetheless, states of distress are largely dependent on the situation and individual undergoing experimentation.

B. *User Interface Evaluation*

In this section, we discuss the EasyBreathe interface evaluation results, which are displayed in Figure 8. For the purpose of UI evaluation, a short survey was provided to all participants of the experiment and an additional selection of students that solely evaluated the front-end of the system. The following questions were asked to 15 volunteers with answers in the form of a rating from 1-5 (5 positive and 1 negative):

i Were all application interfaces easy to navigate?
ii Do you believe that the breathing exercise was helpful?
iii Would you use mindfulness meditation to calm yourself in a stressful state?
iv Would you generally use an application to track your stress?
v Did you find the graphical illustration of your data useful?

The survey showed that overall our interface received positive feedback in terms of usability. This is reinforced by the fact that all 15 participants rated the application with 4 and 5, averaging out to 4.4. With regard to our therapeutic methods, although most people assessed the paced breathing exercise as useful in a scenario of distress, most test subjects stated that they would not use mindfulness meditation in practice.

VII. Future Work

Future work with EasyBreathe might include a number of potential improvements. First of all, it is not currently possible to add any classes to HealthKit, so all the user data collected regarding stress levels is currently stored locally to the iPhone. To ensure data security over this information, an external database should be integrated into the EasyBreathe design.

Secondly, all ML processing at the moment relies on labelled training examples. Ideally we would like to deploy a semi-supervised learning approach, where the user can provide feedback to the system at runtime. For example, this could involve the user confirming whether they are stressed or not upon receiving a notification from EasyBreathe. Given the user's response and their corresponding sensor streams of data, the ML algorithm could be enhanced to have better prediction performance.

The stress classification module is currently limited by two aspects: a relatively small training dataset and lack of consideration for intra-day stress factors. Whilst future implementations would simply gather more data to training the algorithms, a more complex change would have to be taken into account for intra-day differences of user stress levels. That is to say, a patient's location and the time of day should be included as variables for improving the classification algorithms.

Finally, the user can tailor the breathing exercise to their preferences but are unaware of an ideal pace to follow. An optimisation to our platform would be to predict a personal setting for each user, depending on their mental state.

VIII. Conclusion

In this report, we highlighted our aim to develop a chronic stress management system capable of reducing the onset of mental disorders in young adults, which is often correlated with consistent states of stress. Each of the constituent hardware and software components of the EasyBreathe platform was analysed from a system design perspective. Our hypotheses for chronic stress relief were also tested against a small sample of Imperial College students. Despite a statistically insignificant number of trial users, our findings were inclined towards verifying the therapy hypotheses. In particular, slow-paced breathing demonstrated a potential solution for managing elevated stress levels in the long term. However, we also note that our methodology for experimentation was limited for a chronic stress trial setting and requires further investigation to validate our results. Finally, we proposed a set of future implementations for EasyBreathe as a follow-up on the research presented in this pilot study.

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