PRISM: A DATA-DRIVEN PLATFORM FOR MONITORING MENTAL HEALTH

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Neuropsychiatric disorders are the leading cause of disability worldwide and there is no gold standard currently available for the measurement of mental health. This issue is exacerbated by the fact that the information physicians use to diagnose these disorders is episodic and often subjective. Current methods to monitor mental health involve the use of subjective DSM-5 guidelines, and advances in EEG and video monitoring technologies have not been widely adopted due to invasiveness and inconvenience. Wearable technologies have surfaced as a ubiquitous and unobtrusive method for providing continuous, quantitative data about a patient. Here, we introduce PRISM — Passive, Real-time Information for Sensing Mental Health. This platform integrates motion, light and heart rate data from a smart watch application with user interactions and text insights from a web application. We have demonstrated a proof of concept by collecting preliminary data through a pilot study of 13 subjects. We have engineered appropriate features and applied both unsupervised and supervised learning to develop models that can recapitulate user-reported ratings of their emotional state. This demonstrates that the data has the potential to be useful for evaluating mental health. This platform will allow us to leverage continuous streams of passive data for early and accurate diagnosis as well as constant monitoring of patients suffering from mental disorders.

Keywords: mental health; wearables; user interactions; visualization

1. Introduction

1.1. *The current state of mental health care*

Neuropsychiatric disorders are the leading cause of disability among non-communicable diseases worldwide and are estimated to be the cause of around 10.4% of the global burden of disease.[1,2] These disorders include mood disorders (depression, unipolar and bipolar disorders), anxiety-related disorders (anorexia and other eating disorders, obsessive-compulsive disorders, panic disorders and post-traumatic stress syndrome), schizophrenia, substance- and alcohol-use disorders, dementia, as well as neurological disorders like epilepsy, Parkinson's and multiple sclerosis. Within this group, depressive disorders accounted for the most DALYs, followed by anxiety disorders.[1] Historically, major health policy decisions have been primarily informed through mortality statistics. As a result, the impact of these pervasive and disabling neuropsychiatric disorders has been undervalued in comparison to cardiovascular diseases, cancer and communicable diseases. Thus, research on these disorders has not been a priority

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and improvement in the management of mental health is lagging behind. The current standard practices for patients with such mental health disabilities, including those described in the APA's Diagnostic and Statistical Manual of Mental Disorders (DSM), rely on descriptive criteria and are often not evidence-based.[3,4] Unlike in other areas of medicine, very few objective clinical tests or medical devices are routinely used in mental health care.[5] The information physicians use to make diagnoses is not only subjective, but it is also episodic, capturing only occasional snapshots from patient visits and ignoring the finer dynamics of a patient's condition. EEG-based methods have been shown to be effective for quantitatively capturing a patients condition,[6] but they are invasive and thus do not permit continuous data collection. Other methods, such as video monitoring, have been shown to be useful for monitoring the mental health status of patients, but are extremely difficult to interpret.[7] These drawbacks have been a barrier to widespread adoption of these modern technologies. While the first EEG-based mental health evaluation tool has recently been approved for ADHD,[8] more comprehensive patient-friendly technologies and robust methods are needed to improve the state of mental health care.

1.2. *The emergence of web and wearable technologies*

Wearable products have emerged as a ubiquitous technology for passive collection of quantitative data. Over 10 million fitness trackers, smart watches and other such devices are sold each year and the market is growing rapidly.[9] Many such products have the ability to measure physiological data, environmental data, and activity data. In addition, other data, such as keystroke dynamics and eye tracking, can be collected based on the user's interaction with their wearables and other devices. Unlike in other emerging solutions discussed previously, these data can be collected in a passive manner, without affecting the day-to-day life of the user. Preliminary evidence has shown that these data can be leveraged for use in monitoring of mental health patients.[10,11] Variability in heart rate, activity, light exposure and electrodermal responses have been studied previously for screening in disorders like sleep apnea, dementia and epilepsy.[12,13] Patient-reported outcomes, as collected through social networks and citizen science approaches, serve as real-time evidence for determining emotional distress symptoms.[14,15] Performing sentiment analysis over social streams provides a better understanding of human emotions than occasional surveys.[16] Web and wearable technologies have been experimented with for unobtrusive data collection to detect seizures and mental fatigue.[10,11] However, such methods have only been applied individually in a very narrow set of test cases. We believe that the integration of these diverse passive data types will provide a robust and quantitative method for characterizing a wide range of mental health states.

Here, we describe a novel platform, PRISM (**P**assive, **R**eal-time **I**nformation for **S**ensing **M**ental Health), which allows us to leverage passive sources of data for continuous monitoring of users' health. Not only will this provide more informative measurements to allow doctors to better assist their patients, but it also will enable early and more accurate identification of undiagnosed users. In addition, the web interface enables patients to easily access and understand their own data and thus their health condition. This system has the potential

both to generate more knowledge about which treatments work best for patients and to allow for more informed decision making in the clinic. We believe that this integrated system for collecting and analyzing quantitative information about a patient will have huge ramifications for the improvement of the care of mental health patients.
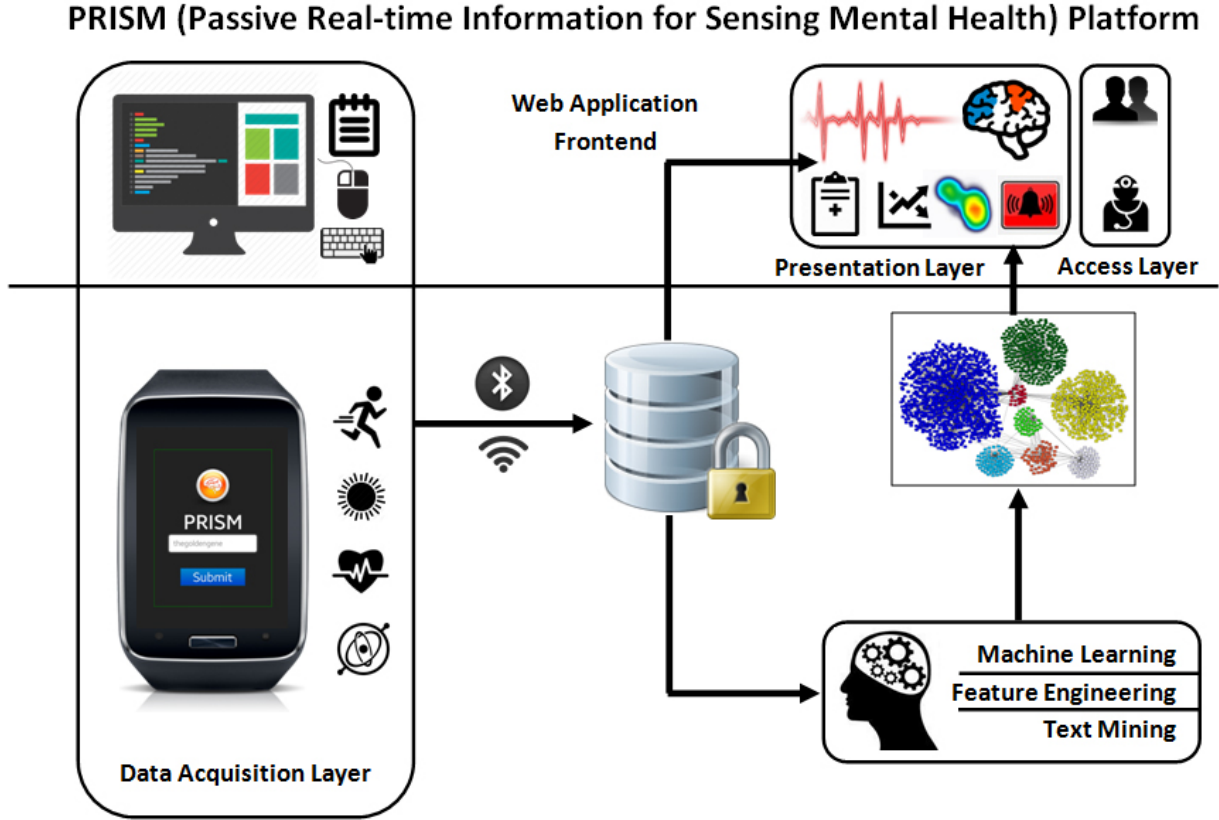

Fig. 1. The PRISM platform for data collection, integration and analysis is outlined here. Our system allows for a smooth workflow that incorporates data acquisition, data analysis and feedback to the user.

2. Materials & Methods

2.1. *Platform Development*

The first phase of our project was to develop a platform that aggregates passively recorded user data from smart watches with user interaction patterns and self-reported insights. As shown in Figure 1, our platform architecture is composed of six different layers — *i)* Data acquisition, *ii)* Text mining, *iii)* Feature Engineering, *iv)* Machine Learning, *v)* Access and *vi)* Presentation. The data acquisition layer relies on the Samsung Gear S smart watches and the Tizen APIs[17] to collect physiological, environmental and activity data of the users. A separate web application was developed that incorporates a private blog-based feature for users to disclose their own moods and self-report outcomes during a particular time of the day. User keystroke and mouse interaction patterns are captured as the user types and navigates across the web application. The web application also serves as a presentation layer that provides different visualizations through interactive widgets, allowing users to explore their own data.

A role-based access is enabled to delineate two different categories of users of our platform: *i)* General — normal users or existing patients who wish to track their mental health and/or become aware of any dormant neuropsychiatric conditions, and *ii)* Health care providers — physicians and other providers who can gain summarized access to their patients' data.

While developing the platform, we were concerned with four main concepts — *privacy*, *connectivity*, *longevity* and *storage*. Since we are dealing with personal data and insights of the users, it was imperative to store this information in a secure database in an anonymized format. To ensure HIPAA compliance,[18] we do not store any patient identifiers, such as personal information (name, date of birth, mobile or email) and GPS location information. To ensure that the data collection is not affected by the connectivity of the wearable, all the data is first written to a local file and a separate backend service stores it in our secure database using a Bluetooth-paired mobile device or a WiFi connection. The battery life of the wearable can be a rate-limiting factor to our continuous data collection process. By excluding GPS information and using a Bluetooth-paired device over a WiFi connection, we extended the battery life of our wearable to multiple days. To ensure further longevity, no data analysis is itself carried out on the wearable and the sole purpose is just to record the data. Because sensor and interactions data is voluminous, we implemented gap encoding and stored data as text blocks for disjoint periods of times to achieve efficient space utilization.

2.2. *Data Collection*

As the second phase of our project, we conducted a pilot study with anonymized participants between the ages of 19–37 years. As the participant engaged in his/her daily activities, the watch passively collected the following data with one second granularity:

(1) **Environmental:** Light intensity levels
(2) **Physiological:** Heart rate (beats per minute and R-R intervals)
(3) **Accelerometer:** Device acceleration and rotation in all three axes
(4) **Pedometer:** Cumulative distance walked, total number of walk and run steps, speed, cumulative calories burnt, and walk frequency.

Using our web application, the participants entered free form text insights about how they were feeling, as shown in Figure 2C. These were collected at approximately three hour time intervals. As the participant entered the insight and navigated our interface, we collected the following user interaction patterns:

(1) **Keystroke Patterns:** Typing speed, number of spelling errors, key press down times, interkey latencies (time taken between typing two keys), number of times 'Enter', 'Delete' (backspace), 'Ctrl+Y' (redo) and 'Ctrl+Z' (undo) are pressed.
(2) **Mouse interaction patterns:** Total number and locations of mouse clicks, mouse hover and drag positions and times, screen width and height.

All the participants were made aware of the types of data that we were collecting before registering in this pilot study, and the days they participated in our study were selected randomly. As they entered the insight, we also asked them to self-report three outcomes on our Likert scale - happiness, energy and relaxation, as depicted in Figure 2C. Finally, we asked

participants to complete a post-study survey to evaluate the usability of PRISM. We used a standard 10-question system usability scale (SUS) questionnaire.[19]

2.3. *Text mining*

We generated string tokens by parsing the subjective textual insights. We assigned each word with mean valence, arousal and dominance scores (VAD) retrieved from a database of VAD norms (1-10) for nearly 14,000 English lemmas.[20] We generated stemmed representation of words that did not have a VAD score using Snowball Stemmer.[21] We then assigned VAD scores for associated similar words, e.g. *annoy* instead of *annoyance*. We calculated weighted average VAD scores for each insight, with a greater weight attributed to emotional terms.

2.4. *Feature engineering*

All data was grouped by 1 hour-long time periods, each treated as a separate training example for our analysis. All features used are described in Table 1. For each period, each smart watch data type was composed into a time series with appropriate timestamps. Accelerometer data was converted into spherical coordinates for this analysis in order to capture more natural descriptors of the movements. For each time series, three summary statistics — mean, standard deviation, and dominant frequency — were computed. The dominant frequency was derived from a discrete Fourier Transform of the time series. For user interaction data types, the majority of features, including counts of typing errors and mouse move and drag information, were used directly. Key press times and interkey latencies were stratified by unigrams and bigrams, respectively, and captured as separate summary statistics for each distribution. This resulted in a total of 1658 features, 1591 of which are key press and latency statistics.

Table 1. This table summarizes all of the features extracted from both the smart watch and user interaction data.

Data Type(s)	Feature(s) used
all smart watch data	mean, standard deviation, dominant frequency
pedometer data	cumulative sums
key press times, interkey latencies	mean, standard deviation
undo/redo, spelling errors, enters, backspaces	raw counts
mouse moves and drags	average distance & velocity, proportion of total time
number of clicks	total counts scaled by total time

2.5. *Machine learning*

For unsupervised learning, data was scaled and centered for each feature. Hierarchical clustering of both features and training examples was performed using complete linkage with a Euclidean distance metric.

For supervised learning analysis, all missing data, composed mostly of keystroke dynamics data types, was imputed by filling in the median value of the feature. Model selection, including tuning of model parameters, was performed using cross validation, where all examples

associated with one text insight were left out for each round of training and testing. This ensures that training and testing are not performed on redundant datasets. Model types and parameters altered are described in Table 2. Performance was evaluated using an independent 20% evaluation dataset to avoid bias in model selection.

Table 2.   This table summarizes all of the models tested, along with the parameters tuned for each.

Model	Parameters
random forest	number of trees, number of features considered
gradient boosted regressor tree	learning rate, number of boosting stages
lasso, ridge, elastic net	regularization parameter
support vector machine	kernel type
k nearest neighbors	number of neighbors

2.6. *Resources*

The PRISM platform can be accessed at `http://54.200.211.229/BrainHealth/`. The wearable application can be downloaded from the platform itself. Source code for the platform can be found at `https://github.com/wuami/PRISM`.

3. Results

3.1. *PRISM Platform*

Users can register with the PRISM platform, by providing a username, year of birth and a desired password. After installation of our application on the Samsung Gear S smart watch, the username can be entered in the GUI of the application screen (Fig. 2A). The applications then starts to collect light, heart rate, accelerometer and pedometer data passively (Fig. 2B). Users have the option to stop data collection anytime by clicking on the 'Stop Collecting' button. If a Bluetooth-paired mobile device or a WiFi network is available, the wearable data is automatically uploaded to our database. They can authenticate with our web application and self-report their subjective mood insights in a textual format and their happiness, energy and relaxation outcomes on the quantitative scales (Fig. 2C, 3A). A log of users'
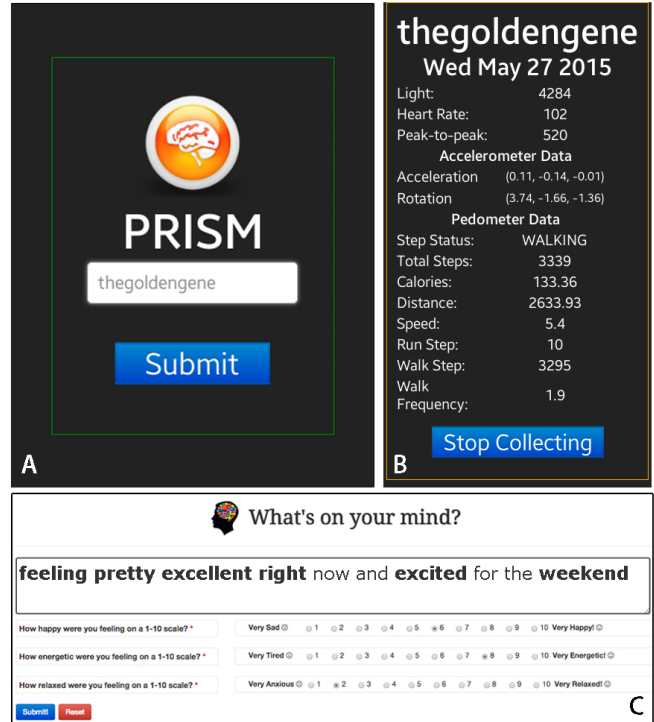

Fig. 2. PRISM data collection: (A) The Samsung Gear S wearable application welcome screen for username input. (B) The light, heart rate, accelerometer and pedometer data collected passively at every second. (C) The subjective textual insight and marked tokens.

past insights is accessible through the web application.

User data can be visualized by clicking on the 'Explore' tab in the navigation toolbar. For a selected day, the heart rate, light intensity, net device acceleration and rotation can be viewed as line charts and walking and running steps per minute as stacked area charts. These plots are aligned to an interactive scrollable timeline (Fig. 3D). Keystroke patterns are shown as a heatmap superimposed on the actual keys pressed. The radius indicates the number of times a key is pressed and the color scale indicates the average time on the key. Interkey latencies can be visualized as a network chart where the nodes represent the keys and thickness of the edges represent the average time (Fig. 3B). A similar heatmap, superimposed over the user screen, is generated for the mouse interaction patterns, where a single dot, a blurred region or a line indicates mouse click, move or drag patterns respectively (Fig. 3A). An 'Emotion Cuboid' visualizes the average VAD scores for each insight as a scatter plot in a 3D space (Fig. 3C). Hovering over any point shows the insight with tokens and average VAD scores.

3.2. *Pilot study*

We conducted a pilot study with 13 healthy participants between 19 and 37 years of age. Each participant wore the smart watch for at least 6 hours and entered at least three insights over the course of a single day. In addition, one participant (aged 25) wore the watch for 10 days in order to collect longitudinal data. Participants walked an average of 6800 steps per day and were exposed to an average of 1050 lux. Reported happiness levels ranged from 2 to 10, forming a roughly normal distribution with a mean of 6.6 out of 10. Reported energy and relaxation levels spanned the full range from 1 to 10, in a roughly uniform distribution with means of 6.8 and 4.5, respectively. Energy levels were skewed to the left, while relaxation levels were slightly skewed to the right. VAD analysis revealed that the content of the text was indicative of reported outcomes, suggesting that mining of passive sources of text data, like Twitter feeds, could replace the blogging feature. Happiness levels and estimated valence were correlated with a Pearson's correlation of 0.48. Energy level and estimated arousal had a correlation of 0.23.

The SUS questionnaire revealed a generally positive reaction to PRISM, with an average score of 74 out of 100. Participants reported that they found the system generally easy to use, without require much knowledge or training, but reported a lack of desire to use the system frequently. This may be a result of our study population consisting of healthy individuals who do not have a strong incentive to understand their mental health.

3.3. *Model development*

We began with unsupervised learning analysis in order to gain an understanding of any structure present within our data. For this analysis, we used only the 22 features where there was no missing data. As shown in Figure 4A, the data points seem to cluster somewhat according to the associated relaxation level. The top section of the heatmap shows the most variation in relaxation levels, but this is consistent with the longer branch lengths in the dendrogram, suggesting that the training examples are not as similar as in the other clusters. Watch acceleration and rotation data as well as keyboard data seemed to be the most variable across
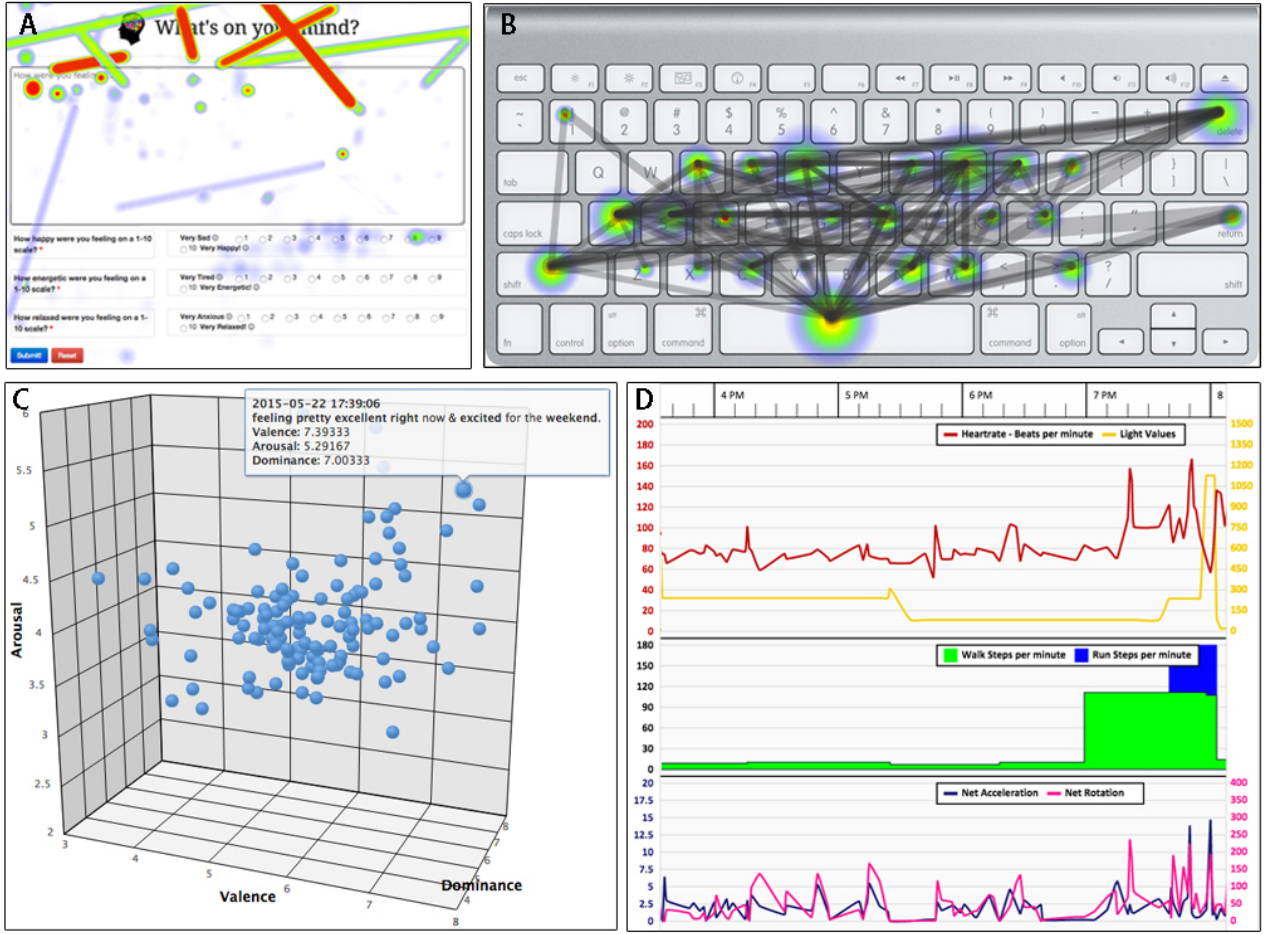
Fig. 3. PRISM Web Application: (A) The private blog-based workflow for users to input subjective mood insights. A mouse interactions heatmap is superimposed over this screen. (B) Keystroke interactions heatmap and network visualizations. (C) A 3D-scatter plot (Emotion Cuboid) for visualization of average VAD scores of insights. (D) Timeline-scrollable, exploratory interface for visualization of wearable data — [1] heart rate (beats per minute), [2] light intensity values, [3] net device acceleration, and [4] rotation, as line charts, and [5] walk steps per minute and [6] run steps per minute, as stacked area charts.

users and are the most informative for this clustering. This may have to do with the relatively high reliability of these data compared to most of the watch data types.

In the supervised learning phase, we used machine learning techniques to develop models for predicting the user-reported response variables from the smart watch and user interaction data. We evaluated a variety of methods, including decision tree-based models, generalized linear models and non-parametric models. We found that tree-based models, including random forests and gradient boosted regressor trees, resulted in the highest performance. A random forest model explained about 51% of the variance in our data, suggesting that our data does capture information about the user's emotional state. Top features were derived primarily from user interactions and included interkey latency mean values, number of backspaces and number of mouse clicks. The selection of the interkey latency features may be an artifact of the sparsity of those features, as some bigrams may be present only in a single insight. However,

the number of backspaces and mouse clicks are more likely to reflect true changes in the user's style of interaction with their computer when they are more anxious or more relaxed.

In order to understand person-to-person variation, we also trained a user-specific model for the participant for which we collected longitudinal data. However, we found that this did not result in a significant improvement over the generalized model (data not shown). This suggests that the variation across time points in a single individual are comparable than that between individuals.
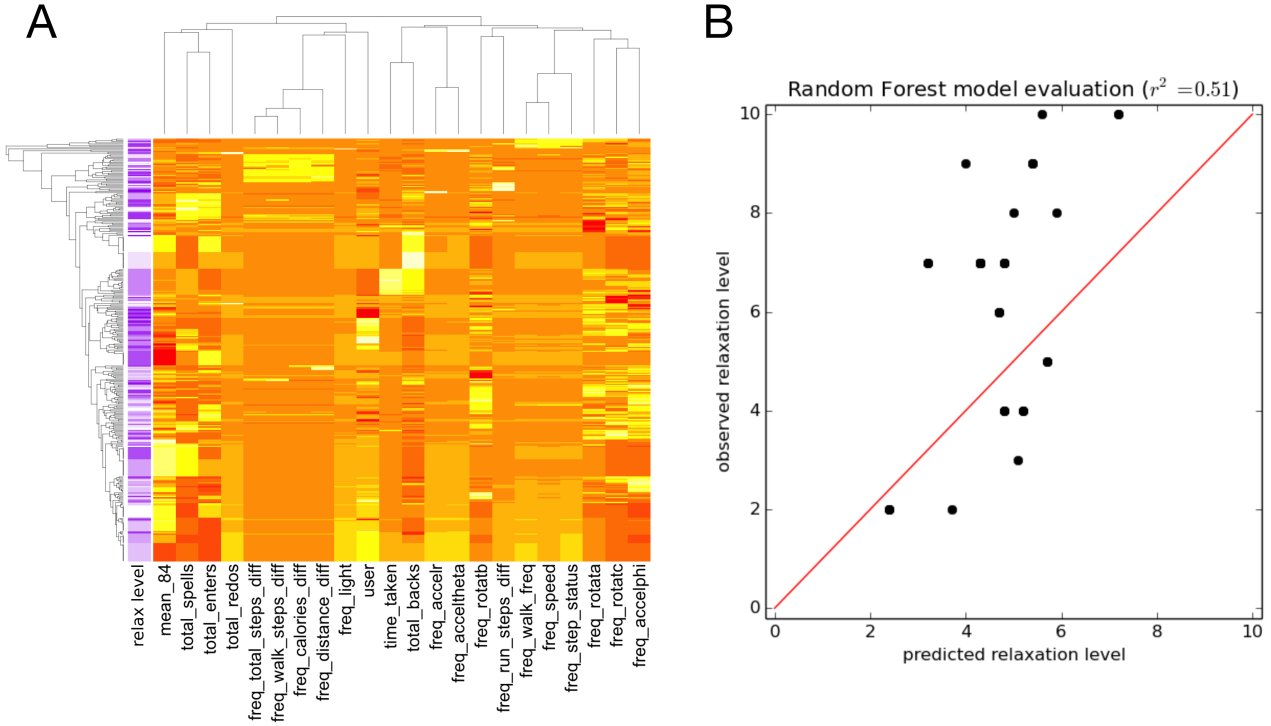

Fig. 4. Our results from machine learning analysis are shown here. (A) This heatmap shows hierarchical clustering of a subset of features, where labels beginning with "freq" indicate major frequencies and labels ending in "diff" indicate differences between time points. The associated relaxation levels, shown in purple, do cluster with the data. (B) A random forest model explains 51% of the variance in reported relaxation levels.

4. Discussion

We have designed, created, and tested the PRISM platform for the collection and analysis of smart watch and user interaction data. Based on our pilot study, we have shown that it is effective from both a usability and data analysis perspective.

4.1. *Usability and User Experience*

A mental health monitoring system can achieve maximum usability only if it can seamlessly integrate into the user's and physician's daily workflow. Developing an application for a smart watch wearable allows us to achieve passive, non-invasive data collection without the need for any manual intervention. We informally asked our pilot study participants regarding their

experience of wearing the smart watch during their daily work hours, and while most users had been skeptical at the start of the study, everyone was very interested and felt comfortable wearing the watch on a daily basis. While a new blog-based feature might not be appealing to the users at first, the methods developed here can easily be combined with a Wordpress-based blog or a Twitter plugin. Both of these networks have been established for user engagement and have also been used as a data source of subjective insights for early diagnosis of neuropsychiatric conditions.[22] As it is cumbersome to enter the username in the wearable screen without a stylus, we wish to remove that requirement in the subsequent versions of the wearable application. As each Samsung Gear S smart watch can be identified with a unique International Mobile Station Equipment Identity (IMEI) key, we can ask the user to provide the IMEI key during registration with our platform and link a watch with single user. Providing interactive visualizations to the user for exploring the data that we collect helps increase user engagement and build trust. In the future, we will also provide a panel to present our inferred insights, and also map mental activity to a 3D Brain Browser visualization. We plan to extend our platform to provide feedback and recommendations to our users through the visualization panels or as notifications in the smart watch. In light of the rapid advances in this domain with the introduction of Apple Research Kit and Samsung Simband wearables, it will be interesting to develop solutions that are interoperable across different wearable platforms.

4.2. *Data Quality*

In the process of testing our watch and web applications, we observed several factors contributing to poor data quality. Many of the watch sensors are extremely sensitive to the tightness of the strap and the placement on the wrist. In particular, heart rate data is not collected properly when the sensor is not directly in contact with the skin. Further, even when the watch was fastened tightly, the measurement varied by 10 bpm or more as compared to a direct pulse measurement and was not consistent when placed on different wrists. The heart rate is derived using photoplethysmography, or optical measurements of blood volume changes at the surface of the skin. While this has been shown to be effective for heart rate monitoring in wearables,[23] it is clear that either the Gear S hardware or the algorithms used by the Tizen API are failing to capture the true signal. Similarly, pedometer data is very sensitive to hand placement. Activities like cycling or treadmill walking, where hands are often gripping a stable handle, are omitted. Additionally, pedometer data was observed to update sporadically rather than continuously, affecting our time series analysis. These factors are introducing significant noise into our data and significantly impacting our ability to create predictive models.

While there is potential for upgrading to more advanced wearables like the Samsung Simband, we will no doubt need to develop smarter ways to handle noisy data and to distinguish between true and artifactual features of the data. This will require the collection of larger datasets that will give us the power to identify predictive variation over chance variation in the data. Bigger data would also allow us to take advantage of tools like `softImpute`,[24] which take advantage of low rank structure in data to impute missing values. Similar methods, like generalized low rank models,[25] could also use this structure to smooth over noise in the data. In the future, we also plan to carry out sentiment analysis by generating a term-insight matrix

composed of VAD-weighted term frequencies and using a Naive Bayes or an SVM classifier.

4.3. *Further Applications*

We believe that PRISM has the potential to dramatically change the way that mental health is diagnosed, monitored and treated. In order to fully realize this potential, further studies with neuropsychiatric patients will be necessary to validate the utility of the data. Our system can be seamlessly integrated into a patient's daily life; however, introduction into a physician's workflow may require integration with existing EMR systems. Visualizations will enable clinicians to process both raw data and analytics rapidly in order to assist decision making, while our models will allow for the triggering of alerts to the physician when their patients are in an unstable mental state. In addition, the patient studies will enable us to link our data with actual outcomes, allowing both physicians and analytic models to learn how physiology affects treatment response.

5. Conclusions

Physiological and exogenous data (behavioral, social, environmental) is overwhelming to capture and analyze, but makes up a large portion of health determinants. In this work, we have developed the PRISM platform that can leverage heterogeneous, continuous streams of data, collected in a passive, non-invasive fashion to monitor mental health. We have shown the potential of such a platform by developing models that can recapitulate users' reported emotional states. While developing the platform, we have ensured that the privacy and anonymity of our users is maintained, and that data collection is not hindered by the rate-limiting factors of device connectivity and longevity. We have also developed interactive visualization panels that allow users to explore and understand their own data, and can also serve as mechanisms through which feedback can be provided.

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