# Stress Detection Using Smart Phone Data

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**Abstract.** In today's society, working environments are becoming more stressful. The problem of occupational stress is generally recognized as one of the major factors leading to a wide spectrum of health problems. However work should, ideally, be a source of health, pride and happiness, in the sense of enhancing motivation and strengthening personal development. In this work, we present StayActive, a system which aims to detect stress and burn-out risks by analyzing the behaviour of the users via their smartphone. The main purpose of StayActive is the use of the mobile sensor technology for detecting stress. Then a mobile service can recommend and present various relaxation activities "just in time" in order to allow users to carry out and solve everyday tasks and problems at work. In particular, we collect data from people's daily phone usage gathering information about the sleeping pattern, the social interaction and the physical activity of the user. We assign a weight factor to each of these three dimensions of wellbeing according to the user's personal perception and build a stress detection system. We evaluate our system in a real world environment with young adults and people working in the transportation company of Geneva. This paper highlights the architecture and model of this innovative stress detection system. The main innovation of this work is addressed in the fact that the way the stress level is computed is as less invasive as possible for the users.

**Keywords:** Stress detection · Smartphone · Sleeping pattern · Social interaction · Physical activity

## 1 Introduction

Stress is a mental condition that everybody experiences in his life, sometimes even daily. Today stress is omnipresent as never before and it is one of the major problems in modern society. Stress symptoms may be affecting people's health, even though they might not realize it. People may think illness is to blame for

This work was co-funded by the State Secretariat for Education, Research and Innovation of the Swiss federal government and the European Union, in the frame of the EU AAL project StayActive (aal-2013-6-126).


K. Giokas et al. (Eds.): eHealth 2016, LNICST 181, pp. 340–351, 2017.
DOI: 10.1007/978-3-319-49655-9_41

that nagging headache, their frequent insomnia or their decreased productivity at work. But stress may actually be the culprit. Due to all these negative effects, it can be assumed that early assessment of stress condition, and early suggestions on how to reduce it, may reduce its overall impact and lead to improved health state of individuals. Stress detection technology could help people better understand and relieve stress by increasing their awareness of heightened levels of stress that would otherwise go undetected [1]. Detecting stress in natural environments is beneficial to avoid developing burn-out situations and illnesses.

The most common method to quantify stress is to simply ask people about their mood using questionnaires. There are standard methods for doing so like the Perceived Stress Scale questionnaire (PSS) [2]. Questions in the PSS assess to what degree a subject feels stressed in a given situation.

Nowadays wearable devices such as mobile phones and wearable sensors are ubiquitous in our lives. Several researchers have tried to understand personality from mobile phone usage [1,10]. Our stress detection system aims to use technology to recognize stress levels using data from the devices that users always carry and wear.

Sleeping patterns, social life and physical activity are connected with the presence of stress in people's lives [3]. We take into account these three dimensions for building our stress detection system. The motivation for creating a solution based only on the daily phone usage of people is based on the idea to be as less invasive as possible for the end-user.

The rest of this paper is organized as follows. In Sect. 2, our designed stress detection system is described in detail. Experimental results using real data are reported and discussed in Sect. 3. Future work to be done on StayActive is presented in Sect. 4. Finally, a brief conclusion is drawn in Sect. 5.

## 2 System Design

The StayActive system [15] provides an Android application running on a smartphone. We have chosen the Android based solution because it is an open source framework designed for mobile devices. The Android Software Development Kit (SDK) provides the Application Programming Interface (API) libraries and developer tools necessary to build, test and debug applications for Android. We implemented the prototype in Java using the Android SDK API 23. The idea of the full StayActive system is the following. There is a combination of a mathematical model and a Machine Learning (ML) approach which work independently in order to compute the stress level of the users. The mathematical model is running on the phone of the user being a light application with minimized battery consumption. The reason is that we want to make the users able to use the application for the biggest possible amount of time without needing to recharge their phone. This application will be synchronized with the ML approach running on the server of the StayActive system. The results of the two individual models will be combined and give a final stress level to the users. In this paper the mathematical approach running on the phone is explained in detail and the ML approach and the integration procedure is introduced.

### 2.1 System Overview

In this study we aim to find physiological or behavioral markers for stress. Although there are still several open questions regarding the links between the behaviour of a person and their stress level, in StayActive we take a pragmatic approach and build an initial stress detection system which can be extended and refined. The general architecture of our stress detection system is given in Fig. 1.

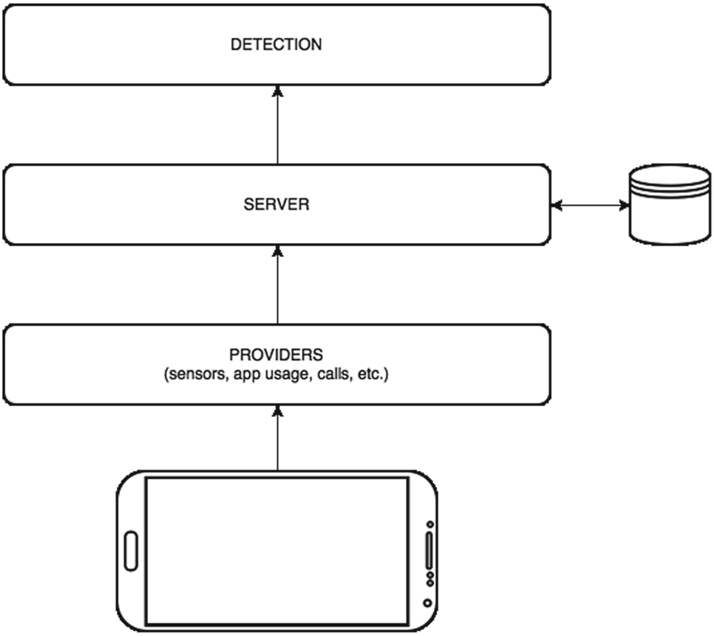


**Fig. 1.** StayActive system architecture overview.

**Providers.** The first layer is the one that collects and provides the data to upper layers. The provider module contains all the implemented data providers, which are responsible for collecting a specific type of data from the device. They are free to implement the data monitoring behaviour as they wish. The currently implemented providers collect the following type of data: type of physical activity, calls and SMS, ambient light and temperature, location, battery level, screen on/off intervals, Wi-Fi, step counter, number of screen touches and finally type of applications launched. We give some examples of the results of these providers in Figs. 2, 3, 4 and 5.

**Server.** The server module is responsible for receiving data from the mobile devices and storing it in a database. We aggregate all the data and we process

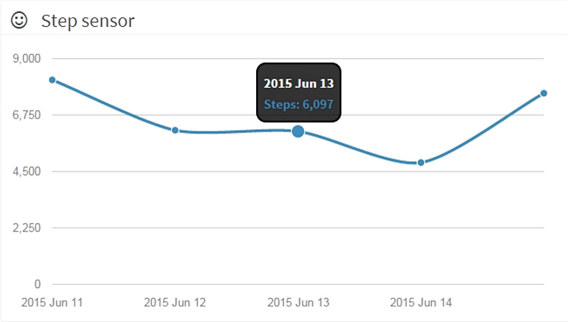


**Fig. 2.** Visualization of data from the step counter provider.

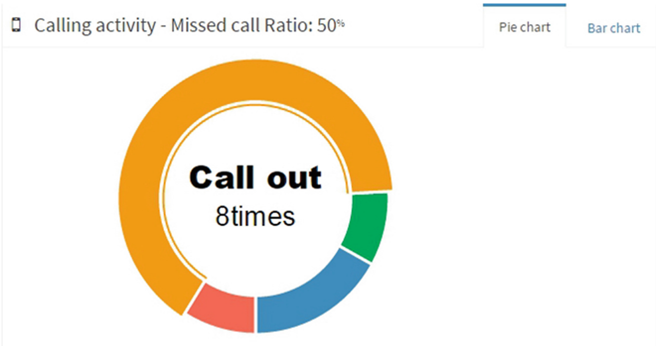


**Fig. 3.** Visualization of data from the call provider.

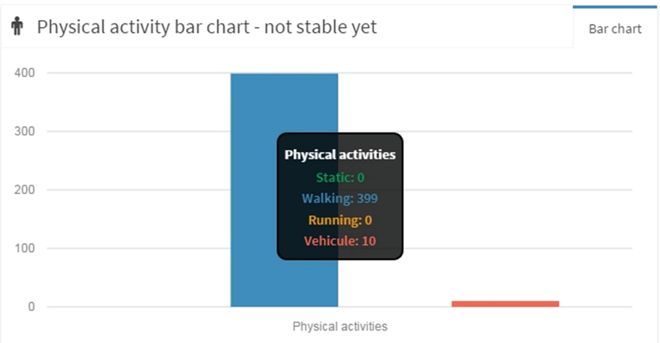


**Fig. 4.** Visualization of data from the physical activity provider.

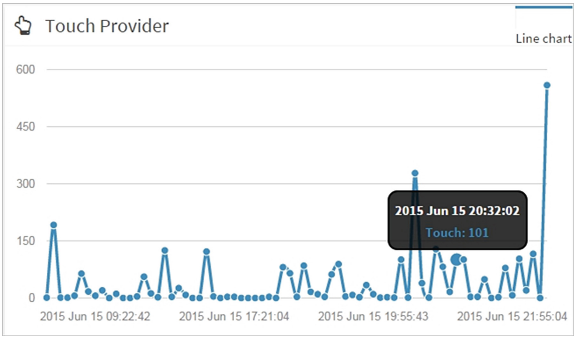


**Fig. 5.** Visualization of data from the screen touch provider.

it in order to extract a relaxation score for each user as explained in the next section. The ML approach will be implemented in this module, using features produced from providers mentioned above, and will compute a stress level.

**Detection.** This module contains analyzers for each data provider, which extract useful information and patterns from the raw data to output a partial relaxation score. The core detector module will aggregate the results of these individual analyzers and compute a final stress level, as explained in the next section.

### 2.2 Mood Inference

Aside from gathering as many data as possible from the smartphone, the system will prompt the user to fill in a questionnaire with his subjective self-perception of his mood. First we researched several validated models that psychologists have proposed to measure and describe affect and emotion, including the Positive and Negative Affect Schedule (PANAS). We concluded to use the Circumplex Model of Affect as described by James A. Russell [14]. This model consists of two dimensions: the pleasure-displeasure and the arousal-sleep dimension. On top of this we have added a third dimension, the relaxed-stressed one, as depicted in Fig. 6. We chose to use this model because it can represent a wider range of mood states and it is easy and quick to be filled by the end-users. It will be acceptable for them to fill it every day without being so invasive for their daily life.

### 2.3 Stress Detection

Simply collecting the patterns of people's behaviour is insufficient for helping them improve their personal wellbeing. It is important to use different dimensions of people's wellbeing and compute their stress level. That way, we will be able to help them by giving advice for reducing their stress level and therefore improving

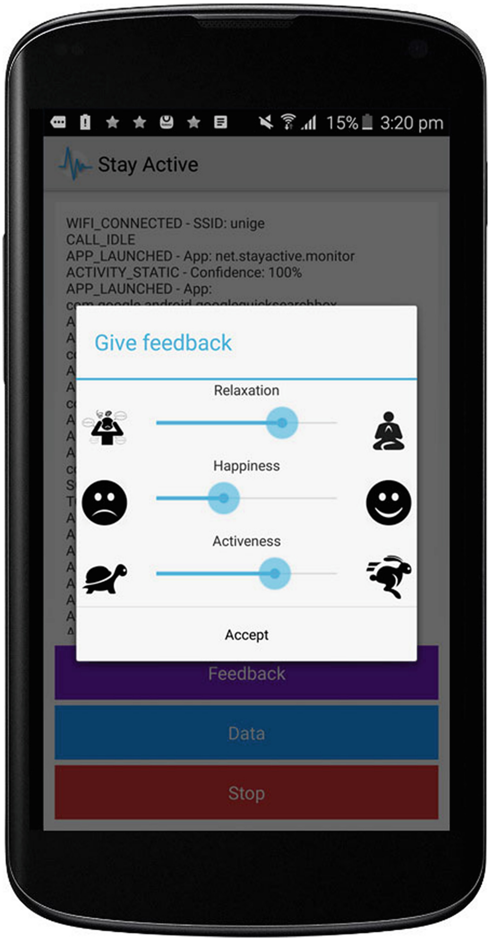


**Fig. 6.** User interface for the mood inference.

their quality of life. Our stress detection module takes into account three main dimensions of wellbeing: the sleeping pattern of the users, their social interaction and their physical activity.

**Sleeping Pattern.** There is a large body of research work which analyzes the link between sleep hygiene and the mood of people [11,12]. People usually exchange sleep for additional working hours as a coping mechanism for busy lifestyles. In our stress detection module we take into account the user's duration of sleep. We set the number of normal sleeping hours at 8 and penalize insufficient sleep and oversleeping. We set the lower threshold of normal sleeping hours at 7 and the upper threshold at 9 h according to [4]. For any extra missing or more hours of sleep we penalize the behaviour of the user with a weight factor per

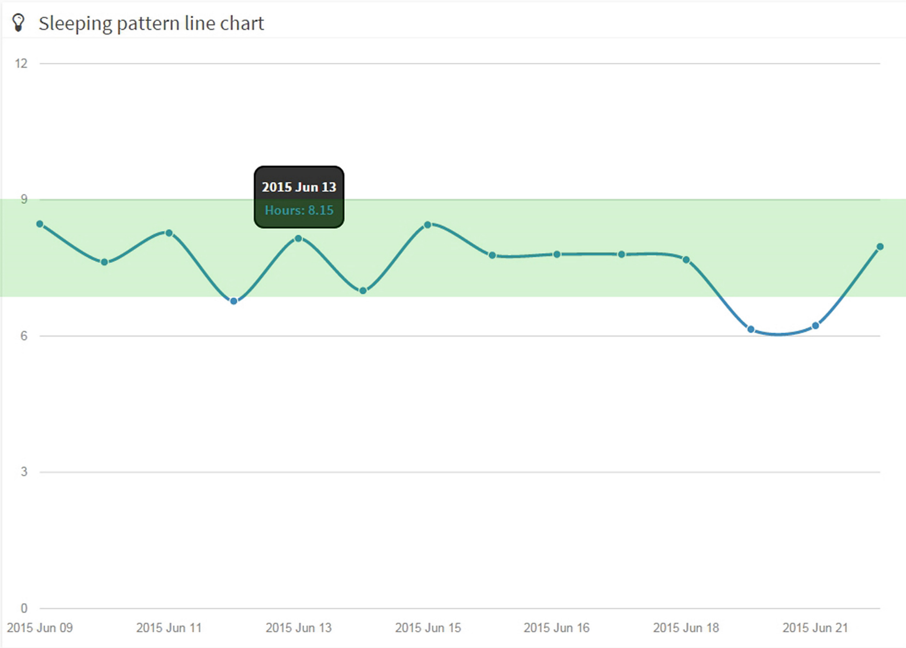


**Fig. 7.** Example of a sleeping pattern.

hour. In order to compute the sleeping pattern of the user we take into account the interaction of the user with his phone, by monitoring touches on the device's screen. Between 6 p.m. and 10 a.m. we compute the biggest time interval that the user did not touch his screen and we infer the duration of his sleep. An example of the sleeping pattern of a user for some days is depicted in Fig. 7.

**Social Interaction.** The daily social interaction of people has a serious impact on many dimensions of wellbeing [12]. People who maintain dense social connections are more likely to have resilient mental health. They tend to be able to cope with stress and often are better able to manage chronic illness.

On the other hand regarding communication, researchers are hypothesizing that perhaps people become so used to and even dependent on receiving constant messages, emails, and tweets, that the moment they do not receive one, their anxiety increases. People feel compelled to check their phone constantly, which can then lead to disappointment when there are no new messages, and increased stress about why no one is messaging them, or when the next message might come.

However, repetitive checking of mobile phones is considered a compulsive behaviour [9]. People who are highly dependent on the Internet for interaction act impulsively, avoid emotions, and fail to keep up a proper planning or time management [8]. We identify features which are relevant for detecting problematic phone usage and therefore increase the stress level of the user.

In our system we take into account the number of touches of the screen (quantifying the usage of applications on the phone), the number of calls and the number of SMSs as factors for the social interaction of the users using their smartphones. The accumulated result per day is multiplied with the corresponding weight factor and therefore it is accumulated in the total relaxation score. The accumulated result of the social interaction dimension is computed using weights. These weights of the subdimensions of the social pattern are computed by asking the users in the beginning of the experiment to prioritize the ways of social interaction. The idea of the scoring procedure is the following. We assign a weight factor to each of the three subdimensions of social interaction. This factor is based on the response of the participants to the following question which was asked in the beginning of the experiment. Which of the three subdimensions do they personally consider as the most important for their communication with other people? To the most important dimension we assign a weight of $w_1 = 0.4$ and to the rest we assign a weight of 0.3 respectively ($w_2 = w_3 = 0.3$), so that $w_1 + w_2 + w_3 = 1$.

**Physical Activity.** Physical activity plays a key role in the control of neuroendocrine, autonomic, and behavioral responses to physical and phychosocial stress. Physical activity is commonly regarded as beneficial to both physical and psychological health, and is seen as an effective preventive measure and treatment for stress-related diseases. Physically active people show reduced reactivity to physical stressors as well as reduced susceptibility to the adverse influences of life stress [13]. Several studies have linked exercise to improved depression, self-esteem and stress [5,6]. Our system monitors the physical activity of the user, making the distinction between the type of activity (e.g. walking, running, bicycling). We have also implemented a step counter which gives us the opportunity to find the number of steps that each user took per day. The American Heart Association uses the 10,000 steps metric as a guideline to follow for improving health and decreasing risk of heart disease, the leading cause of death in America. 10,000 steps a day is a rough equivalent to the Surgeon Generals recommendation to accumulate 30 min of activity most days of the week.

At first, in our model we assign the maximum value of wellbeing, and therefore the lowest stress level, when reaching the goal of 10,000 steps per day. If someone reaches less than this number we penalize (decrease relaxation score) with a weight factor per 1,000 steps. After the reception of the data for one month and based on the answers of the users to the Circumplex Model of Affect, we extract the pattern between the ideal physical activity of each individual user and his daily steps. Therefore extracting the personal pattern of the user we assign this value to the maximum value of wellbeing for this user. Then the comparison and the behavior of the user is compared with this personalized new value.

## 3 Evaluation with Real Data

For the evaluation of our data, we followed an empirical mathematical model. We monitored the behaviour of the user in the above mentioned three dimensions (sleeping pattern, social interaction and physical activity) collecting data for a month. Therefore we take this data as the basis for extracting the personalized stress level of each individual user that uses the StayActive application.

### 3.1 Relaxation Score

At first we compute a relaxation score for each individual user for every day of the monitoring month. The relaxation score is in the scale of [0–10] where the more stressed you are, the lower your score will be (so the more relaxed you are the higher your relaxation score). The idea of the scoring procedure is the same with the score assignment of the subdimensions of the social interaction. We assign a weight factor to each of the three dimensions of wellbeing that we have taken into account in our study. This factor is based on the response of the participants to the following question which was asked in the beginning of the experiment. Which of the three dimensions do they personally consider as the most important for their wellbeing? To the most important dimension we assign a weight of $w_1 = 0.4$ and to the rest we assign a weight of 0.3 respectively ($w_2 = w_3 = 0.3$), so that $w_1 + w_2 + w_3 = 1$. Based on these factors we are able to calculate the per day relaxation level of each person as depicted in Figs. 8 and 9 according to the Eqs. 1 and 2. Therefore we compute a result per dimension and adding them we calculate the final daily relaxation score of the user. For each of the three dimensions we normalize the results in the scale of [0–10] and then multiply each of them with the respective factor. Adding the three results per user, per day we extract the daily relaxation level of each user.

We should highlight that the values of the three dimensions are in three different scales. Therefore, in order to compute the result in one common scale we respect the following procedure:

1. Firstly we compute the standardized values of the items. This value is also called the normal deviate and it represents the distance of one data point from the mean, divided by the standard deviation of the distribution.

$$std\_vl = (unstd\_vl - mean)/\sigma \tag{1}$$

   where $std\_vl$ is the standardized value and $\sigma$ is the standard deviation.
2. Secondly we use factor weights to compute the unstandardized score.

$$unstd\_sc = w_1 * dm_1 + w_2 * dm_2 + w_3 * dm_3 \tag{2}$$

   where $unstd\_sc$ is the unstandardized score, $w_i$ is the weight score of the item $i$ and $dm_i$ is the standardized value of the item $i$.

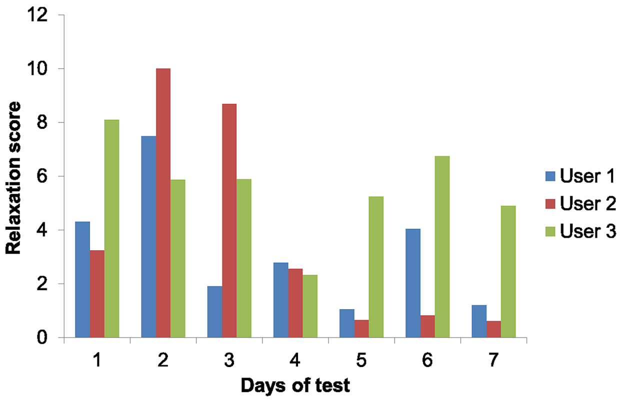


**Fig. 8.** Relaxation score evolution for three users.

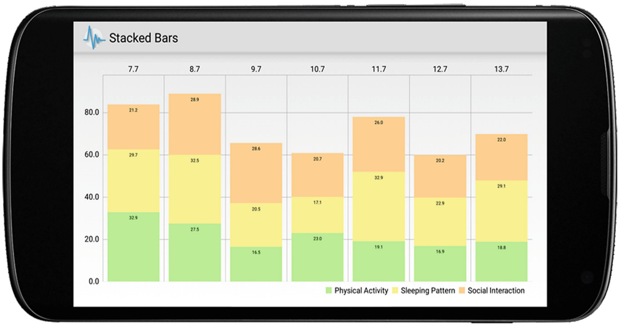


**Fig. 9.** Relaxation score as represented by each dimension.

3. We find the minimum and the maximum of the scores and accordingly we translate everything in the scale of [0–10] by normalizing the results. Following the above mentioned procedure even if we have dimensions which are measured in different scales we produce a relaxation score in the scale of [0–10].

### 3.2 Preliminary Results

The five participants of our tests were young adult members from our research group. The evaluation of the results takes place by asking the people who participated in the experiment how they felt on each day corresponding to the monitoring month when data was collected, without knowing the outcome. Then, we compare their personal perception with the relaxation score that we have computed using the StayActive application for each individual day. The more score you have the less stressed you are. This is the first step of evaluating the accuracy of the relaxation score that we produced through our empirical model.

Secondly, we extract a pattern for the behaviour of the user based on the data that we collected during the testing month and then we compare this pattern with the average daily activity of the user for this month. We calculate the deviation from the normal behaviour that we have extracted from the one-month experiment and based on that we characterize the user as stressed or not. We also calculate the mean of the stress factor for each person during a month in order to have more relevant information.

## 4 Future Work

This is a first model of our stress detection system. We are still enhancing and improving it. The immediate steps after the work that has been presented are the following. Further use of the application collecting data for a month from people outside our lab. We have already started the trials with the transportation company of Geneva and factory workers in Bucharest and the collected results will be more representative for real life working scenarios. In the long term, we are targeting a final ML approach which will take more features into account in order to improve the accuracy of stress detection. Having collected a set of initial data, these will be processed in the statistical software R in order to build a workflow with the aim to acquire a first understanding of the data as well as prepare them as much as possible for the initial modeling phase. Having concluded to the best model under the given dataset, this along with the data preprocessing workflow, will be employed on the Spark framework on the server side, so as to take advantage of the real time data assessment modules along with the Big Data processing capabilities. For the improvement of our algorithm we will analyze data from biosensors like the heart rate and the heart rate variability of the user adding them as extra dimensions to our system. The long term idea of StayActive is to provide adults with a personalized, adaptable tool which can also monitor some changes to biological signals like skin conductance and heart rate, using wearable sensors and link them to a low relaxation score (increased stress level). Then it will recommend and present various relaxation activities just-in-time in order to allow the users to carry out and solve everyday tasks and problems at work.

## 5 Conclusions

Stress detection is a research field that can have a big impact on the improvement of people's daily life. In this paper we presented a stress detection system which takes into account three main dimensions of wellbeing. The sleeping pattern, the physical activity of the users and their social interaction were accumulated with different weight factors and give an estimation of the daily stress level of the user. To the best of our knowledge, this is the first system that computes a stress score based on different dimensions of human wellbeing. The main innovation of this work is addressed in the fact that the way the stress level is computed is as less invasive as possible. Our solution relies only on the daily phone usage of people. Also we acquire the ground truth for the importance of each dimension of wellbeing for each individual by asking the users. This leads us to a personalized model which focuses on the personality of each individual user.

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