Predicting Emotional States from Wearable Trackers

Mikella Green, Joaquin Menendez, Sicong Zhao

As the popularity and capability of wearable activity trackers has increased over the last 20 years, so has an interest in what data derived from their internal sensors can tell us about our overall health. Commercially available wearable fitness trackers use accelerometer and heart rate data to give users insight regarding sleep, daily activity, and heart rate which are all important variables for a healthy life. Research has shown that daily stress levels also play an important role in our overall health, with large cumulative amounts of stress being detrimental to physical, psychological, and behavioral health. Given this, integrating emotion detection and monitoring with wearable sensor technology has become of interest. **Our project examines if emotional states can be reliably recognized from data derived from a commercially available wearable fitness tracker and additional indicators including neuroimaging, personality, and demographic data.**

Background/Previous Research

To conceptualize emotional states, we use the circumplex model of affect (fig. 1) which proposes that all affective experiences are products of two fundamental neurophysiological systems, valence (positive-negative dimension) and arousal (high-low continuum)[1]. Each emotion can be thought of along these two dimensions, for example, fear is understood as a strongly negatively valenced, highly aroused state. Although our model choice was largely dictated by our dataset, the circumplex model of affect has shown to be consistent with many recent findings from cognitive neuroscience research on affect [2].

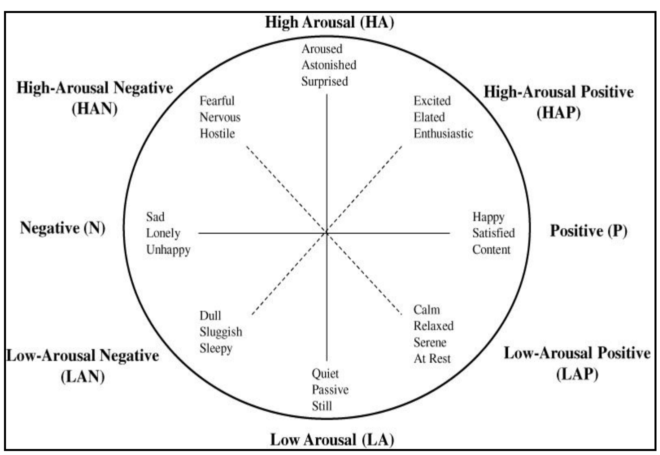

Figure 1. Affect circumplex in their octant structure[5]

Stress is generally experienced as discomfort, tension, or negative emotions[3]. For the purpose of this paper, stress is measured in terms of psychological/emotional stress and will be used interchangeably. Emotional reactivity refers to an increase in intensity of an affective state in response to an event. Stress reactivity is measured as an increase in distress as a response to challenging and stressful situations[4].

Individual characteristics and affect. In our project, individual characteristics refer to measurements of people's descriptive and relatively stable traits including personality, gender, and age. Our personality measurements of interest are neuroticism, extraversion, behavioral inhibition/activation, and ideal vs. actual affective comparisons.

Neuroticism has many different definitions, but is typically thought of as emotional instability and negativity. Higher levels of trait neuroticism are associated with greater frequency of negative affective states and higher intensity negative affective responses to stressors[5]. In contrast, people high in trait extraversion have shown to experience positive affective states more often and have higher levels of emotional reactivity to positive events than people low in trait extraversion[6].

Similarly to neuroticism and extraversion, an individual's sensitivity to punishment (behavioral inhibition; BIS) and sensitivity to reward (behavioral activation; BAS) influence affective responses to events[7]. People with higher BIS sensitivity tend to experience negative affective states more frequently and more intensively relative to people with lower BIS sensitivity. In turn, BAS sensitivity scales have shown to correlate with affective states and responses similarly to extraversion.

Personality literature has also shown that how people actually feel compared to how they would ideally like to feel plays a role in emotional response regulation. Individuals with larger differences between general and desired affect tend to be more neurotic, less extraverted, and report lower levels of life satisfaction and self-efficacy in affect regulation[8].

Functional connectivity and affect. The relationship between brain and stress has been extensively studied in neuroimaging literature. Of particular interest for our project are the functional couplings between brain regions implicated in emotion- and stress-processing, more specifically, the amygdala, medial prefrontal cortex (mPFC), and anterior cingulate cortex (ACC).

Stronger resting state amygdala-mPFC connectivity has shown to predict lower levels of trait anxiety[9]. The strength of amygdala-mPFC circuitry was also predictive of effective emotion regulation which is crucial for adaptive responses to stressors[9]. Golkar and colleagues [10] examined the relationship between work-related chronic stress and functional connectivity in emotion and stress processing brain regions in participants suffering from burnout symptoms. The study found that amygdala-ACC circuitry was correlated with the ability to down-regulate negative emotions and that individuals experiencing chronic occupational stress had weaker connectivity between amygdala and ACC regions in comparison to the non-burnout group.

The above findings highlight the roles of the amygdala, mPFC, and ACC networks for emotion and stress processing and suggest that individual differences in connectivity between these structures can moderate how people respond to stressors in their daily life.

Stress detection systems. Several studies have demonstrated the feasibility of stress detection from wearable biosensor data [11][12][13]. These previous stress detection systems have used physiological signals like heart rate variability, galvanic skin conductance, and respiration rate. One obvious limitation of previous work is that the biosensors used were designed for research purposes and are not practical. They are obstructive to daily activities, not easily wearable, and easily confounded by naturalistic environments.

Bogomolov and colleagues[14] attempted to address the shortcomings of previous research by building a daily stress recognition system from mobile phone data, weather conditions, and individual traits. Using a multifactorial approach, they designed a person-independent statistical model with 72.28% accuracy. Bogomolov's work is similar to our project in that they both use behavioral metrics (mobile phone data and fitness tracker data respectively) combined with data related to the transient environment and measurements regarding stable characteristics of individuals. Our work differs from Bogomolov and colleagues because we are not forgoing physiological measures all together and include heart rate measured unobtrusively. Our stress detection model also includes neurological data. Further, our measures of emotional state are self-reported measures of a person's current feelings at the time of the survey, rather than a reflective subjective assessment of daily stress collected at the end of the day.

A 2018 study by Lawanont[15] and colleagues used wearable activity trackers and smartphones to build a daily stress recognition system based on physical activity and heart rate data. Their recognition model used heart rate, resting heart rate, number of steps, calories burned, and sleep quality. Like Bogomolov et al.[14], stress was measured using a perceived stress scale answered at the end of the day. The main similarity between Lawanont's study and our project is that both utilize activity tracking data from Fitbits. Our project goes beyond their model by also including additional indicators about an individual, answering a limitation noted in their publication.

How solving or answering your question will be applicable to external organization or potential stakeholder

In recent decades, with the increased access to data, low-cost computing power and evolving NLP and computer vision algorithm, the machine have developed the ability to analyze human emotion. And this capability is boosting the emotion detection and recognition market.

The global emotion detection and recognition market was valued at $12.37 billion in 2018 and is expected to reach a value of USD 91.67 billion by 2024, at a CAGR of 40.46% [15]. Industries including consumer economics, marketing & advertising indicates a growing demand from both the commercial market and consumer market. [16]

From a wearable maker standpoint, equipped with emotion detection capability, their product could be more competitive in the market.

From a commercial standpoint, companies are aware that emotion detection could bring huge economic benefits. For example, through understanding the customers' emotions, companies could adjust marketing strategy accordingly to enhance conversion rates.

From a customer's perspective, with increased understanding of mental health in general, people are more aware of the influence of emotions on daily life and work. Therefore, customers would invest on emotion detection and recognition, to increase their well-being.

Within this context, the emotion detection technology we are working on has promising business value for our partner.

Firstly, backed with our emotion detection technology, Fitbit can gain extra competitiveness in the market, given the fact that all the major competitors (Apple, Xiaomi and Huawei) have not included this as a built-in feature. Admittedly, apps are running on Apple Watch could detect emotional states. However, they are mostly depending on speech, which is hard to use and can be error-prone because different people have different tones of voice. In contrast, our solution could be superior because firstly, it’s not requiring users to open an app but passively wear the device, which would lead to a comprehensive result. Secondly, we can expect our measurement to be more accurate because we have real-time phenotype data in a higher dimension, which would contain more information and seems to be more relevant to emotion than voice.

Besides, as a daily wear device, Fitbit is expected to collect the emotional states of each user during most time of the day. This comprehensive emotional data could unveil users’ overall well-being of the day, and generate an evaluation of users’ emotional intelligence level. Starting from Sep. 2019, Fitbit has announced its ‘Fitbit premium’ plan, which provides customized health and fitness guidance, advanced insights at an annual rate of $79.99. This represents that Fitbit is pivoting its strategy from device-only to device+service. With our technology, Fitbit could develop emotion-related guidance or insights, such that expand target user groups from general customers to domain experts like athletes and students, given emotion plays an important role in physical training and education.

Furthermore, equipped with our technology, Fitbit could even develop new business in marketing. The business works in this way, Fitbit could build a data service for the marketing industry to provide reports of the deidentified emotional states of a specific group of people at a specific location. For example, Microsoft’s marketing team is advertising on the latest Surface Pro laptop in 110 billboards in the US at some time. To evaluate the effectiveness of this marketing strategy, Microsoft could purchase this service, requiring Fitbit users’ emotional situation in those 110 billboards' locations during the period when the advertisement showed. With this new dimension of information, Microsoft’s marketing team would benefit from but not limited to gaining extra precision in evaluating the public's reaction to their marketing strategies, comparing the effectiveness of different billboards and conducting marketing AB test.

Data Description
The data is composed of two datasets from different experiments (‘DNN’ and ‘R00’) recollected by researchers from the Motivated Cognition and Aging Brain Lab (Mikella's Laboratory).
226 different subjects participated in the experiment (122 subjects in one (DNN) and 104 (R00))

Every dataset is a collection of four different types of data:

- Experience sampling data
- Self-report survey data
- Activity tracking (Fitbit) data
- Neuroimaging data (not available yet)

Survey data. In both experiments, subjects answered several surveys about different psychological traits and behaviors.

- SWLS (Satisfaction With Life Scale) [17]
- TPQ-NS (Trait Dimension Personality Questionnaire - Novelty Seeking) [18]
- FTP (Future time perspective) [19]
- NEO-C (Five Factor Inventory - Conscientiousness) [20]
- NEO-E (Five Factor Inventory - Extraversion) [20]
- NEO-N (Five Factor Inventory - Neuroticism) [20]
- AVI (Affect Valuation Index) [21]
- BIS (Barratt Impulsiveness Scale) [22]
- BISBAS (Behavioral Activation/Inhibition) [23]
- Medical Screening

References for every instrument could be consulted on the project Gitlab’s ‘Reference’ section

Also both experiments share basic demographic data in common:

- Age
- Sex
- Race and Ethnicity
- Weight and Height
- Education
- Income
- Medical history (medication)

Experiencing Sample data. In both experiments, subjects were followed for a period of 10 days.The subjects completed a survey three times a day, at random times (between walking up time and sleeping time), about how they were feeling at that moment. The instrument used was the same for both experiments, but the scaled selected was different (for R00 from 1-5 and 0-4 for R00)

Subjects's emotions were punctuated in different subscales:

- Positive valence (pos)

- Negative valence (neg)
- Low arousal (low_arousal)
- High Arousal (high_arousal)
- Low arousal positive (low_arousal_pos)
- High arousal positive (high_arousal_pos)
- High arousal negative (high_arousal_neg)
- Low arousal negative (low_aroudal_neg)

Fitbit data. All the subjects used a Fitbit Charge HR device to measure physiological, motor, and behavioral metrics. The data can be divided into three categories:

Activity metrics (daily summaries)
- Date
- Calories Burned
- Steps (real time register and daily summary)
- Distance
- Floors
- Minutes Sedentary
- Minutes Lightly Active
- Minutes Fairly Active
- Minutes Very Active
- Activity Calories

Sleeping metrics (daily summaries)
- Date
- Minutes Asleep
- Minutes Awake
- Number of Awakenings
- Time in Bed

Heart Rate metrics (real time register)
- Heart Rate (HR) [sampling rate varied depending on the state of the subjects. While sleeping the sampling rate was every minute When the subjects were awake the sampling rate was every 5 seconds]

Data cleaning
R00. We explored the R00 dataset in order to evaluate for missing values and data anomalies. From the initial 104 subjects, we only have `Fitbit data` for 37 subjects.
From these 37 subjects, we needed to discard one subject [1016] given that it has not any `survey data` values. Subjects [1029, 1039] have one missing value each (over more than 500 survey features), so we decided to include them in the final analysis.
`experience sampling data` presented 38 subjects, we needed to discard one subject because we did not have `fitbit data` of this subject [1055].

In summary, we count on 36 subjects from the R00 dataset with complete data for `experience sampling data`,`fitbit data` and `survey data`

DND. `experience sampling data’ have 76 subjects. We needed to discard two subjects [001, 002] because they did not have any survey completed.
We do have missing data in some questions. We should discuss how we are going to solve this.
One subject was discarded because we do not have `fitbit data` for this subject [058].
The `experience sampling data` ended with a total of 73 subjects.

We need to continue cleaning the DND dataset. Most precisely, we need to clean the `survey data` , the detailed `fitbit data` and the daily `fitbit data`. We also need to clean the daily ‘fitbit data` from R00.Once we finish doing this we would integrate the data from both experiments into a dataset (as we had done with the `experience sampling data` from R00 and the `experience sampling data` from DND into a single curated database table).

Preliminary analysis
Experience sampling. When we observe the frequency distribution for the different emotional states reported by the subjects we could observe an assimetry depending on the emotional state. States like High Arousal, High Arousal Negative and Negative shown small values. In other words, the subjects report not feeling ‘Amuse’, ‘Nervous’ or ’Sad’, over the course of a typical week.
This trend could be observed as a trend indenpendently of factors as the age or sex of the subjects (Figure 2).

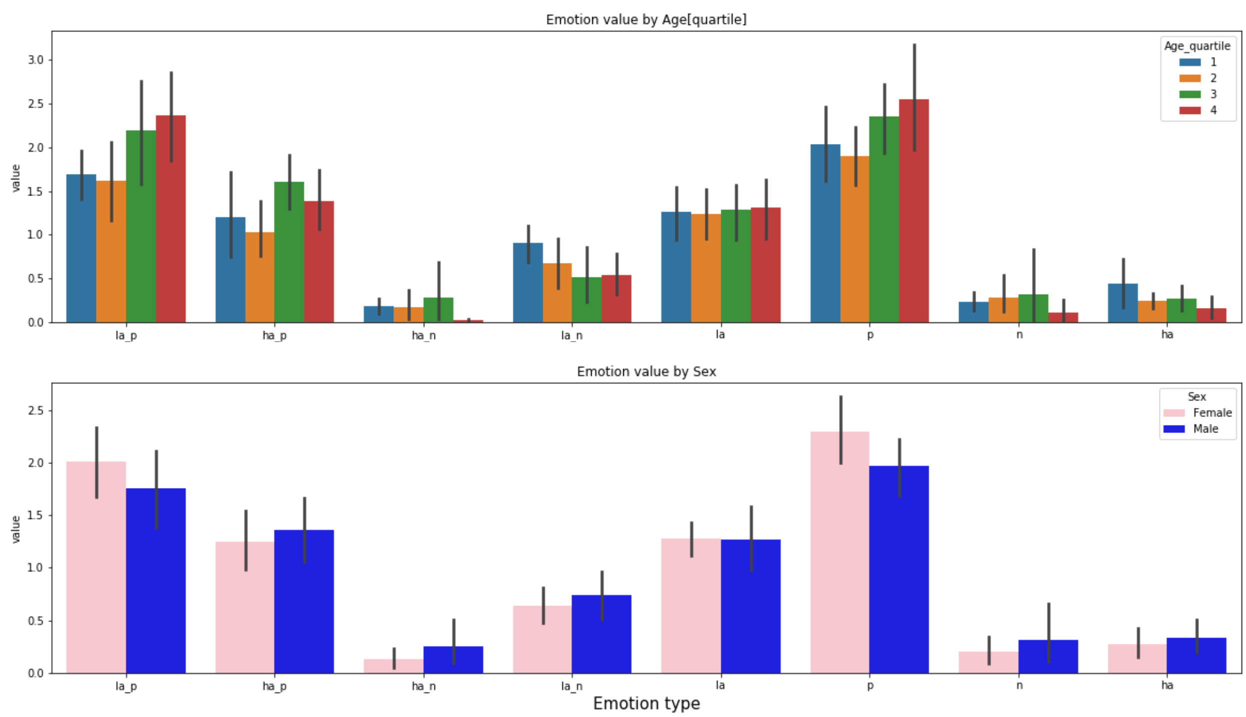

Figure 2. Average Emotional state value reported by the subjects of the R00 experiment. The graph shows the average for all the surveys of all subjects. The error bars show a 95% CI.

We wanted to see if there was an effect of time of day on the emotional states. We performed an exploratory analysis and the data does not support that theory (Figure 3).

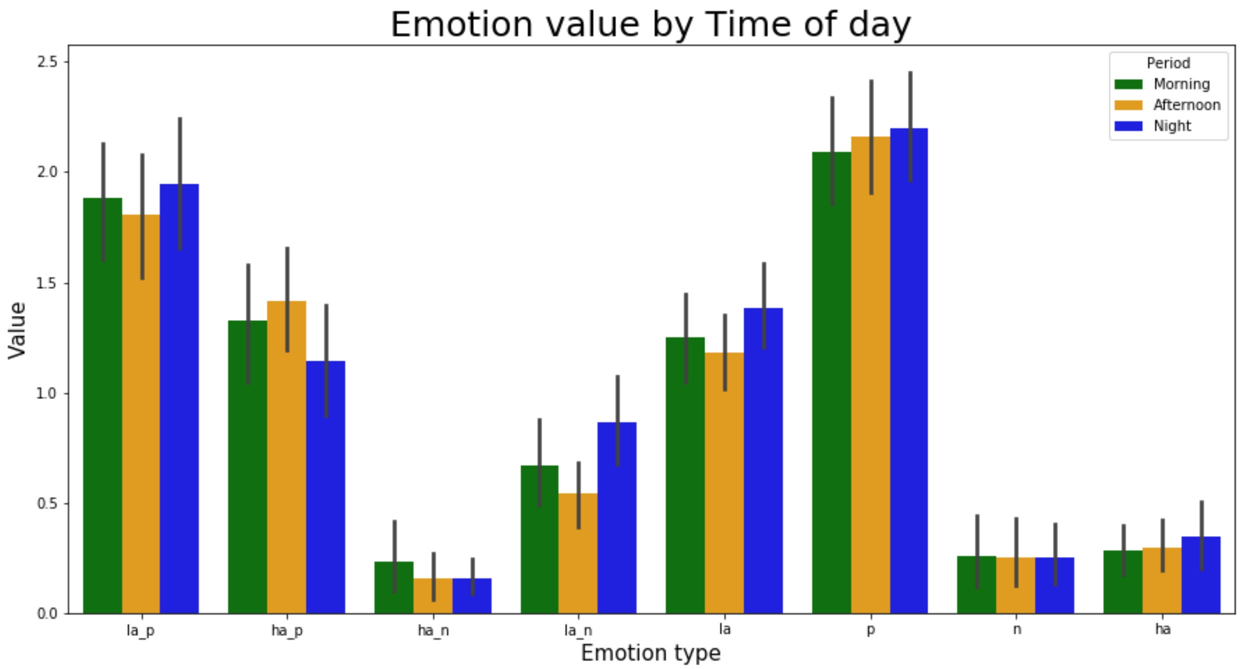

Figure 3. Average Emotional state value reported by the subjects of the R00 experiment. The graph shows the average for all the surveys of all subjects segmented by time of day . The error bars show a 95% CI.

Personality. The literature reports that Individuals with high neuroticism tend to have more vulnerability to daily stressors and report higher levels of daily stress (Duggan et al. 1995)[24]. Nevertheless when we performed a correlation analysis we observed that it's the personality trait that less correlate with the different emotional states. The results for Extraversion seems to be coherent with the literature having a positive correlation with HAP (emotions as 'Excited' or 'Enthusiastic' , and negative correlation with LAP (emotions like 'Calm' or 'Relaxed'). We would like to highlight that it also correlates positively with HAN. Conscientiousness showed a negative correlation with HAN.

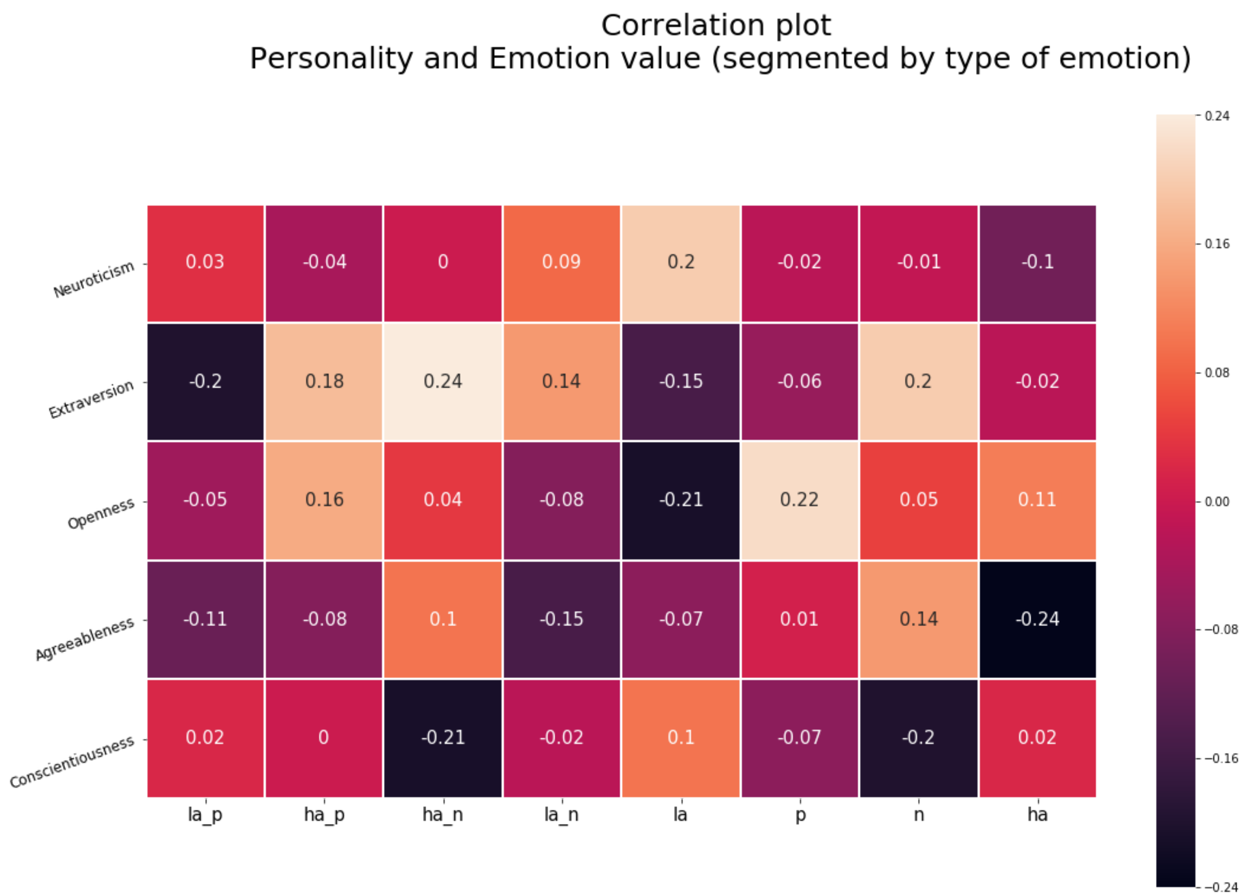

Figure 4. Correlation plot between personality traits and average emotional state's value.

In order to explore this we decided to check the average value emotional states reported by the subject with the highest neuroticism value (Figure 5). Despite that this is only an exploratory analysis the results do not support the classical theory.

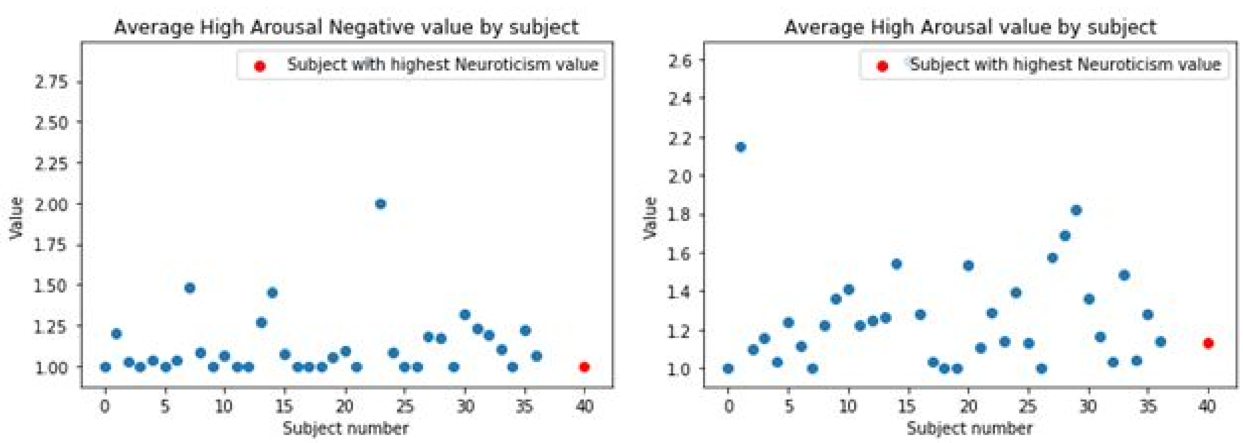

Figure 5. Scatter plot showing the average emotional state value for the subject with highest neuroticism in R00.

According to Schneider (2004)[25], High neuroticism confers stress vulnerability, but only when conditions are construed as threatening. The subjects were followed for a period of 10 days, in this short period the probabilities of facing threatening circumstances is low, so that maybe could explain why we did not see any effect.

Affect Valuation Index. The Affect Valuation Index (AVI) is used to measure the difference between the ideal emotional state and the current one. According to Larsen's (2000) model of mood regulation, the affective discrepancy of actual and desired affect is the central determinant of affect regulation [8]. For example, a larger discrepancy between actual and ideal LAP was associated with more physical health symptoms (Scheibe et al, 2013)[26]. We wanted to observe if there was any relation between the affective discrepancy reported before the experiment and the emotional states values reported during the same (Figure 6).

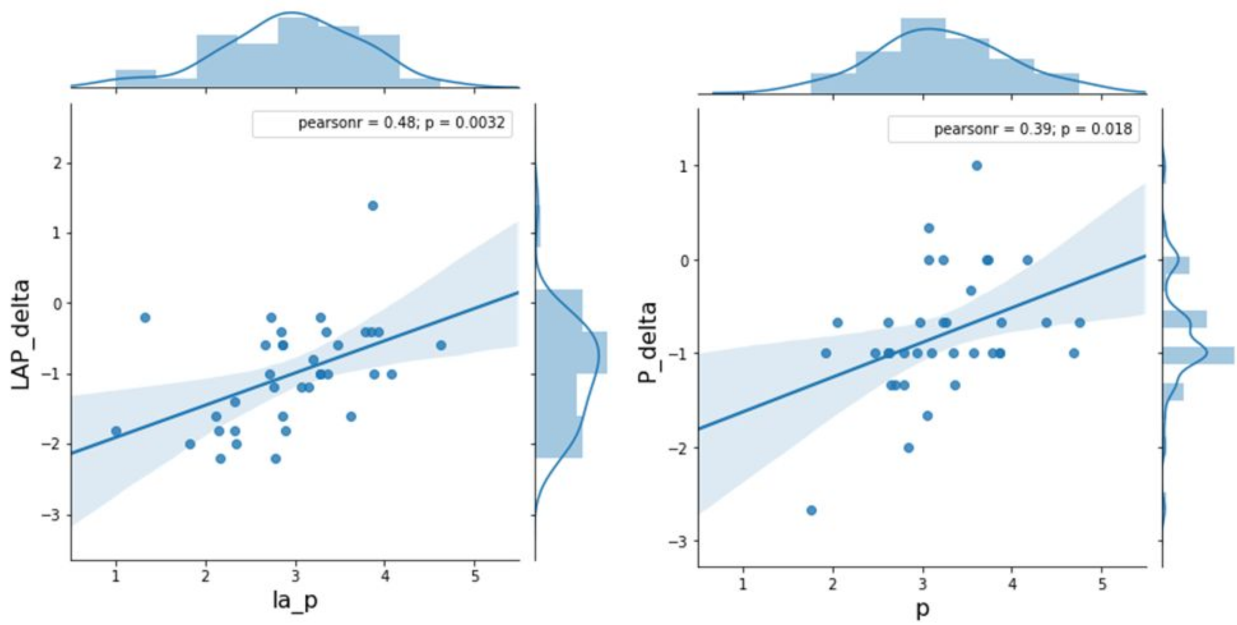

Figure 6. Join Plot between AVI discrepancies and average emotional states reported.

We observed that the discrepancy between an ideal state and the actual state before starting the experiment correlates with the average emotional state during the next 10 days for the emotional states P and LAP. In other words, if a subject report having a positive discrepancy (the actual emotional state is higher than the ideal emotional state) it would correlate with higher values of that emotion for LAP and P. There were no statistical correlation between discrepancies and the remaining states (HAP = .27, LA = .39, N = .58, HAP = .57, HAN = .76).

Sleep data. Among healthy individuals, sleep difficulties were associated with enhanced negative affect to unpleasant events and a dulled response to neutral events (O'Leary et al., 2017)[27]. Padmaja et al. (2018)[28] showed that the amount of hours in bed and the amount of sleep were significant features to predict stress, being the hours of sleep negatively correlated with the perceived stress. We decided to realize a single subject exploration of the data (Figure 7). We could observe that it seemed that a decrease in the amount of minutes asleep correlates with an increase of negative feelings like dullness and sleepiness. Given the low amount of HAN values different than 1 we cannot see any effect.

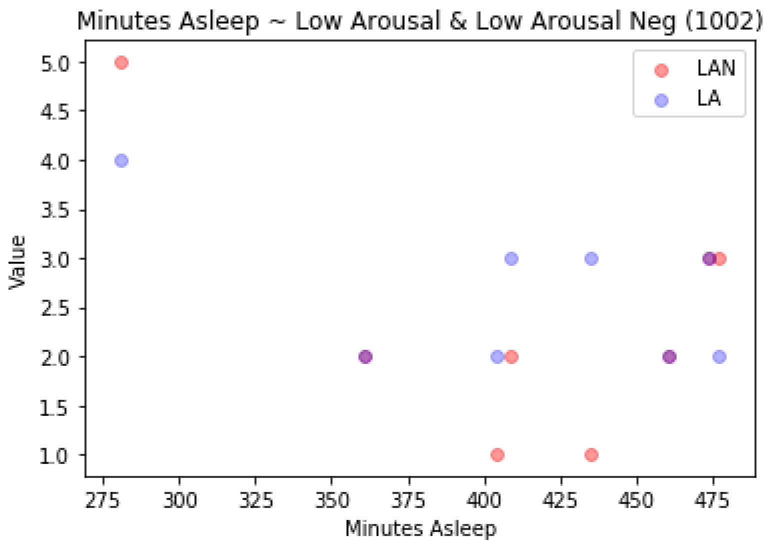

Figure 7. Scatter plot between the amount of minutes asleep and the emotional values reported for the subject 1002 from the experiment R00.

Finally, we decided to explore both Heart rate data and Steps by minute in order to see evidence of possible relationships. We could observe that the Heart rate data is correlated with the Numbers of steps given by minute (Figure 8)

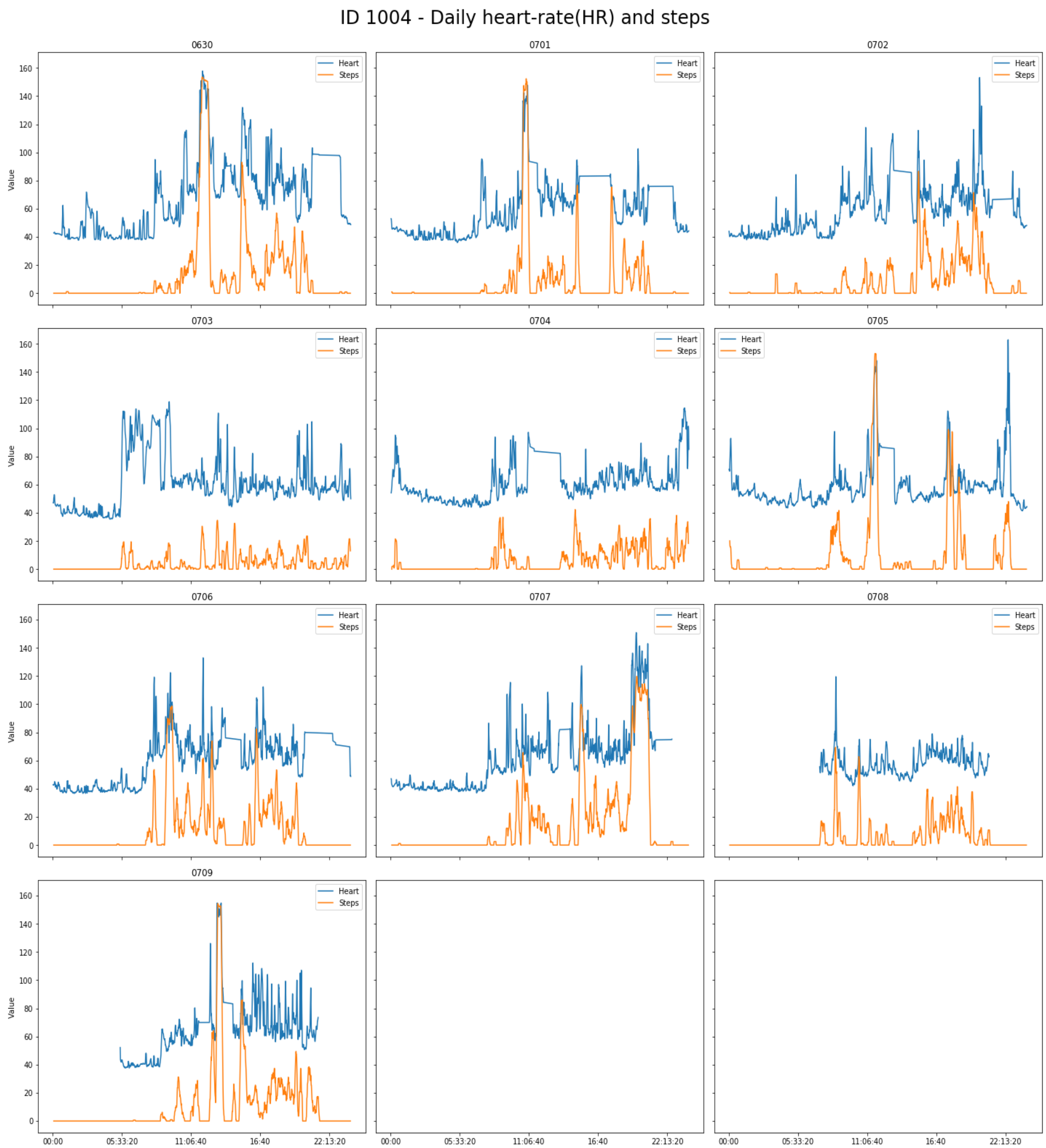

Figure 8. Line plot of the amount of steps by minute (orange) and heart rate (blue) for the subject 1004 of the experiment R00.

Limitations

- The Experience sampling data was collected using a questionnaire that it does not seem really sensitive to measure emotional states or stress.Other works had used the Perceived Stress Scale (**PSS**) to predict stress using wearable devices (Lawanont et al., 2018[15] & Padmaja et al., 2018[28]).
- The HR data that we have has a **low sampling rate** (1 value per five second). We cannot do a Heart-Rate-Variability (HRV) analysis with this data. HRV See Tahyer et al. (2009)[29] for a review of how this measure is useful to measure stress.
- Other works had used weather[14} (Bogomolov et al.,2014) and geolocation (Sano et al., 2018[30]]) to predict emotions. We do not have access to this data.
- **Temporal sample size**. We count with approximately 109 subjects that have been followed for 10 days. Similar works that tried to predict emotions counted with bigger temporal samples. Padmaja et al. (2018)[28] employed 10 subjects with 300 sample points each, Bogomolov et al. (2014)[14] used 117 subjects followed for 6 months, Sano et al.(2018)[30] employed one month data from 201 college students.

REFERENCES

[1] Russell, J. A. (1980). A circumplex model of affect. Journal of personality and social psychology, 39(6), 1161.

[2] Posner, J., Russell, J. A., & Peterson, B. S. (2005). The circumplex model of affect: An integrative approach to affective neuroscience, cognitive development, and psychopathology. Development and Psychopathology, 17(03). https://doi.org/10.1017/S0954579405050340

[3] Baum, A., Davidson, L. M., Rectanus, E., & McArdle, S. (1987). Chronic stress as a factor in physiologic reactivity to challenge. Health Psychology, 6(3), 221

[4]Watson, D., & Clark, L. A. (1984). Negative affectivity: the disposition to experience aversive emotional states. Psychological bulletin, 96(3), 465.

[5]Suls, J. (2001). Affect, stress, and personality.

[6] Rusting, C. L., & Larsen, R. J. (1997). Extraversion, neuroticism, and susceptibility to positive and negative affect: A test of two theoretical models. Personality and individual differences, 22(5), 607-612.

[7] Carver, C. S., & White, T. L. (1994). Behavioral inhibition, behavioral activation, and affective responses to impending reward and punishment: the BIS/BAS scales. Journal of personality and social psychology, 67(2), 319.

[8] Larsen, R. J. (2000). Toward a science of mood regulation. Psychological Inquiry, 11(3), 129-141.

[9] Kim, M. J., Loucks, R. A., Palmer, A. L., Brown, A. C., Solomon, K. M., Marchante, A. N., & Whalen, P. J. (2011). The structural and functional connectivity of the amygdala: From normal emotion to pathological anxiety. Behavioural Brain Research, 223(2), 403–410. https://doi.org/10.1016/j.bbr.2011.04.025

[10] Golkar, A., Johansson, E., Kasahara, M., Osika, W., Perski, A., & Savic, I. (2014). The Influence of Work-Related Chronic Stress on the Regulation of Emotion and on Functional Connectivity in the Brain. PLOS ONE, 9(9), e104550. https://doi.org/10.1371/journal.pone.0104550

[11] Picard, R. W., Vyzas, E., & Healey, J. (2001). Toward Machine Emotional Intelligence: Analysis of Affective Physiological State. IEEE Trans. Pattern Anal. Mach. Intell., 23, 1175–1191. https://doi.org/10.1109/34.954607

[12] Choi, J., & Gutierrez-Osuna, R. (2009). Using Heart Rate Monitors to Detect Mental Stress. 2009 Sixth International Workshop on Wearable and Implantable Body Sensor Networks, 219–223. https://doi.org/10.1109/BSN.2009.13

[13] de Santos Sierra, A., Sanchez Avila, C., Guerra Casanova, J., & Bailador del Pozo, G. (2011). A Stress-Detection System Based on Physiological Signals and Fuzzy Logic. IEEE Transactions on Industrial Electronics, 58(10), 4857–4865. https://doi.org/10.1109/TIE.2010.2103538

[14] Bogomolov, A., Lepri, B., Ferron, M., Pianesi, F., Alex, & Pentland. (2014). Daily Stress Recognition from Mobile Phone Data, Weather Conditions and Individual Traits. Proceedings of the ACM International Conference on Multimedia - MM '14, 477–486. https://doi.org/10.1145/2647868.2654933

[15] Lawanont, W., Mongkolnam, P., Nukoolkit, C., & Inoue, M. (2018, June). Daily stress recognition system using activity tracker and smartphone based on physical activity and heart

rate data. In International Conference on Intelligent Decision Technologies (pp. 11-21). Springer, Cham.
[16] EMOTION DETECTION AND RECOGNITION (EDR) MARKET - GROWTH, TRENDS, AND FORECAST (2019 - 2024)
[17] Emotion Detection and Recognition Market by Software Tool (Facial Expression & Emotion Recognition, Gesture & Posture Recognition, and Voice Recognition), Application (Law Enforcement, Surveillance, & Monitoring; Entertainment & Consumer Electronics; Marketing & Advertising; and Others), Technology (Pattern Recognition Network, Machine Learning, Natural Language Processing, and Others), and End User (Commercial, Industrial, Defense, and Others) - Global Opportunity Analysis and Industry Forecast, 2017-2023
[18] Kobau, R., Sniezek, J., Zack, M. M., Lucas, R. E., & Burns, A. (2010). Well-being assessment: An evaluation of well-being scales for public health and population estimates of well-being among US adults. Applied Psychology: Health and Well-being, 2(3), 272-297. doi:http://dx.doi.org/10.1111/j.1758-0854.2010.01035.x
[19]Costa Jr, P.T., & McCrae, R.R. (1985).The NEO personality inventory manual. Odessa, FL: Psychological Assessment Recourses
[20] Lessing, E. E. (1968). Demographic, developmental and personality correlates of length of future time perspective (FTP). J. Personal. 36: 183-201.
[21] Tsai, J.L. Knutson, B., & Fung, H. H. (2006). Cultural variation in affect valuation. Journal of Personality and Social Psychology, 90, 288-307.
[22] Reise, S. P., Moore, T. M., Sabb, F. W., Brown, A. K., & London, E. D. (2013). The Barratt Impulsiveness Scale-11: reassessment of its structure in a community sample. Psychological assessment, 25(2), 631–642. doi:10.1037/a0032161
[23] Carver, C. S., & White, T. L. (1994). Behavioral inhibition, behavioral activation, and affective responses to impending reward and punishment: The BIS/BAS scales. Journal of Personality and Social Psychology, 67, 319-333.
[24] Duggan, C., Sham, P., Lee, A., Minne, C., & Murray, R. (1995). Neuroticism: a vulnerability marker for depression evidence from a family study. Journal of Affective Disorders, 35(3), 139-143.
[25] Schneider, T. R. (2004). The role of neuroticism on psychological and physiological stress responses. Journal of Experimental Social Psychology, 40(6), 795-804.
[26] Scheibe, S., English, T., Tsai, J. L., & Carstensen, L. L. (2013). Striving to feel good: Ideal affect, actual affect, and their correspondence across adulthood. Psychology and aging, 28(1), 160.
[27] O'Leary, K., Small, B. J., Panaite, V., Bylsma, L. M., & Rottenberg, J. (2017). Sleep quality in healthy and mood-disordered persons predicts daily life emotional reactivity. Cognition and Emotion, 31(3), 435-443.
[28] Padmaja, B., Prasad, V. R., & Sunitha, K. V. (2018). A Machine Learning Approach for stress Detection using a Wireless Physical Activity Tracker. Int. J. Mach. Learn. Comput, 8, 33-38.
[29] Thayer, J. F., Hansen, A. L., Saus-Rose, E., & Johnsen, B. H. (2009). Heart rate variability, prefrontal neural function, and cognitive performance: the neurovisceral integration

perspective on self-regulation, adaptation, and health. Annals of Behavioral Medicine, 37(2), 141-153.

[30] Sano, A., Taylor, S., McHill, A. W., Phillips, A. J., Barger, L. K., Klerman, E., & Picard, R. (2018). Identifying objective physiological markers and modifiable behaviors for self-reported stress and mental health status using wearable sensors and mobile phones: Observational study. *Journal of medical Internet research*, *20*(6), e210.