Identifying requirements for mapping physiological measurements to distress

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Abstract. Advances in wearable devices that record physiological changes provide researchers with greater opportunities to detect stress and other psychological states in real-time. This paper describes research that explores the use of heart rate monitors to gather physiological data from participants over several days. From this research, we make observations from a user perspective, and discuss implications for the use of these devices in real-world contexts.

Keywords. Wearable devices, Physiological Measurement, distress, usability.

1. Introduction

Recent advances in the field of wearable technologies have resulted in an increase in the commercial availability and use of smartwatches and smartbands which can record physiological data. Such innovations provide opportunities for both practitioners and researchers to explore the nature of physiological changes in applied contexts and environments. Heart rate (HR) devices, for example, have historically been cumbersome or impractical for everyday use, making gathering longitudinal data a difficult task. With the emergence of these new wearable technologies, greater amounts of data can be gathered over extended periods of time. One potential area in which these technologies could be used is in tracking physiological changes over time, and using these changes to make inferences about an individual's psychological state during tasks. These inferences are made possible by using previously-established links between heart rate variability (HRV) and workload, electrodermal activity (EDA) and arousal (Boucsein, 2012; Thayer et al., 2009). Tracking physiological changes over time can be particularly useful in travel as passengers can get stressed during their journey for a number of contextual and personal reasons.

PASSME (passme.eu) is an EU-funded Horizon 2020 project which aims to reduce passengers' overall journey time in European airports by 60 minutes. This is achieved through: redesigning airport interiors; restructuring luggage journeys; providing real-time information to passengers via personalised device and app; and modelling passenger flows. The project also aims to enhance passenger experience and *reduce stress* during their journey. This is to be achieved through a technological mediation framework, consisting of a smartphone application that tracks passenger movements and physiological responses, as well as providing them with timely information throughout their journey. One potential way for utilising physiological responses, would be to detect passenger stress levels based on fluctuations in HR, and so contributing to new understandings of situation awareness e.g. personal bodily situation awareness versus contextual environmental situation awareness. In developing such a system, however, we need to explore device usability, general HR trends throughout routine days, and identify potential barriers to user uptake. This paper reports results from a pilot study that aims to establish a benchmark of individual passenger physiological responses to contrast against our forthcoming transport-based study metrics. It also provides insight into how to investigate these areas, as well as explore trends emerging from pilot data.

2. Methods

2.1 Participants

There were 5 participants (M = 28.2 years, SD = 4.97; 3 males, 2 females), a mix of students and employees from the University of Nottingham. They were recruited using opportunity sampling. All were in reasonable health, with none reporting any health issues that may have impacted on their HR. They were paid £20 in vouchers for taking part in the study.

2.2 Materials

The HR monitor used in the current study was the Sony Smartband 2 (Sony, 2015), a commercially available monitor primarily used to track HR during exercise activities. The Smartband 2 is made from soft rubber, and is worn like a regular watch. The sensors are located in a small, white attachment that can be removed easily from the wristband for recharging. The phones used in the study were Samsung Galaxy A3 phones running the Android 5.0.2 operating system. Four key applications were installed on the phones: Google Fit; Smartband 2; an application to retrieve and record HR information from the smartband; and an application to prompt participants to record information on their tasks.

2.3 Procedure

During an initial training session, participants were briefed on the purpose of the study and provided signed consent to take part. They then answered a number of basic demographic questions, including ones on their familiarity with wearable devices. Finally, they were introduced to the smartband and smartphone devices that they would be using in the study. They were also given troubleshooting tips on dealing with any potential issues arising during the week, along with a checklist to remind them of the study requirements throughout the five-day period. Training sessions typically lasted for 30 minutes.

The second phase of the study was a 5-day period (Healey et al, 2010) with a 3-day period as a minimum requirement, during which each participant's physiological data and mobile app entries were gathered. In this paper, we report a sample of the data from the 3 days (one weekend / leisure day and 2 working days). Participants engaged in their regular routine while wearing the HR monitors all day and at night while asleep. The monitor is designed to be worn during sport and physical activity but participants were able to remove it if felt uncomfortable or unsafe. During data collection, participants were required to provide input through the custom smartphone application (see Figure 1). The aim of the smartphone app was to provide a brief indication of what they had been doing since the last entry and their subjective stress levels. The application prompted them to complete an entry every 2 hours throughout the day but not during sleeping hours to avoid waking them. The day entries could be as brief or extensive as the participant wished but they were asked to provide as much detail as possible. For each entry, they were also asked to rate three 7-item Likert scale questions on their perceived distress, contentment, and task engagement during that period.

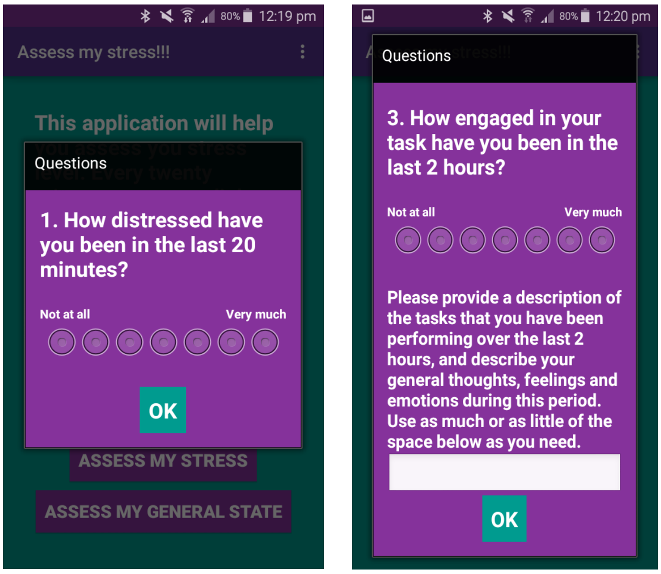

Figure 1. Screenshots of the self-report application.

Between these two-hour periods, participants were prompted every 20 minutes (via a phone notification) to rate one 7-item Likert scale question on their subjective distress in the previous 20 minutes. They were required to respond to this question within 20 minutes. If more than two prompts were missed, the prompts would stop appearing and the participant would need to reset the prompt cycle. This was a deliberate decision, as it was assumed that if participants missed more than two prompts then they were otherwise engaged.

The final phase of the study, after the data gathering, was an interview during which participants were asked for their general thoughts and feelings towards using the Sony Smartband 2 and smartphone application. These interviews are not explored here, due to limited space.

3. Results

3.1 Treatment of data

For each participant, a baseline HR score was established for each day by: taking the average HR (in beats per minute; BPM) over the final hour of sleep; the average HR in BPM over the first 20 minutes after waking; and averaging these two scores for the Daily Baseline Score. Waking state in our context refers to the moment participants got out of bed and was established from participants self-reports and post-study interviews. For each self-reported distress score, the previous 20 minutes of BPM was averaged. In some cases, the distress score had no preceding 20-minute period, or an inadequate number of HR data points, which could be attributed to loss of connectivity or similar technological issues. This information was not included in the subsequent analyses.

3.2 Individual Analysis

Participant 1 was a 28-year-old male who works as a researcher. He did not have any mobility issues or any history of health issues that might affect HR. Figure 2 (left) shows the percentage change from baseline for HR over the course of the working day. There are gaps and some variation between the time frames on the x-axis because the 20-minute time periods were obtained from the time when they were inputted by the participant. The HR change score over the day has a slight quadratic trend, with an initial decrease during the middle of the day before rising towards the end of the day. The subjective ratings for the same time periods are relatively stable, remaining at low levels throughout the day. Figure 2 (right) shows the percentage change from baseline for HR over the course of a day at home. The HR change score was fairly stable, with no large deviations up or down for the majority of the day, before experiencing a large increase towards the end of the watch period. The subjective ratings for the same time periods were relatively stable, remaining at low levels throughout the day, before increasing towards the end of the day. For both days of data, a Pearsons correlation was performed between the change scores and the subjective ratings. Bias corrected and accelerated bootstrap 95% confidence intervals are reported in square brackets. A moderate correlation between the two was found, r = .409, p = .013 [.146, .615]. This significant correlation should be viewed with some caution however, as it may be overly influenced by the large number of same subjective rating scores.

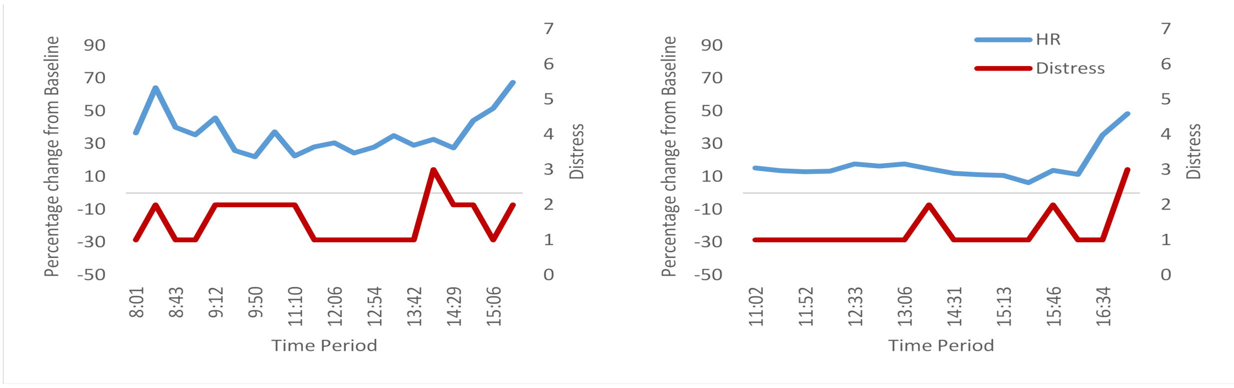

Figure 2. Participant 1 HR and subjective distress scores for Day 1 (left) and Day 2 (right).

Participant 2 was a 31-year-old female who works as a researcher. She did not have any mobility issues or any history of health issues that might affect HR. Figure 3 (top left) shows the percentage change from baseline for HR over the course of the working day. The HR change score over the day stayed at stable levels, with no significant change. The subjective ratings for the same time periods were also stable, remaining at low levels throughout the day. Figure 3 (top right) shows the percentage change from baseline for HR over the course of a day at home. The HR change score stayed relatively close to zero change for the first half of the day, before rising towards the end of the day. The subjective ratings for the same time periods show an initial increase from lower levels in the morning, and remain at a comparatively elevated level throughout the day. Figure 3 (bottom) shows the percentage change from baseline for HR over the course of a day at home. The HR change score started at a much higher than baseline level, and gradually drops throughout the day before returning to below baseline levels in the final period of watch. Compared to previous days, the participant reported elevated levels of subjective distress throughout the entire day. For all days of data, a Pearsons correlation was performed between the change scores and the subjective ratings. Bias corrected and accelerated bootstrap 95% confidence intervals are reported in square brackets. A small non-significant correlation between the two was found, r = .258, p = .129 [-.043, .527].

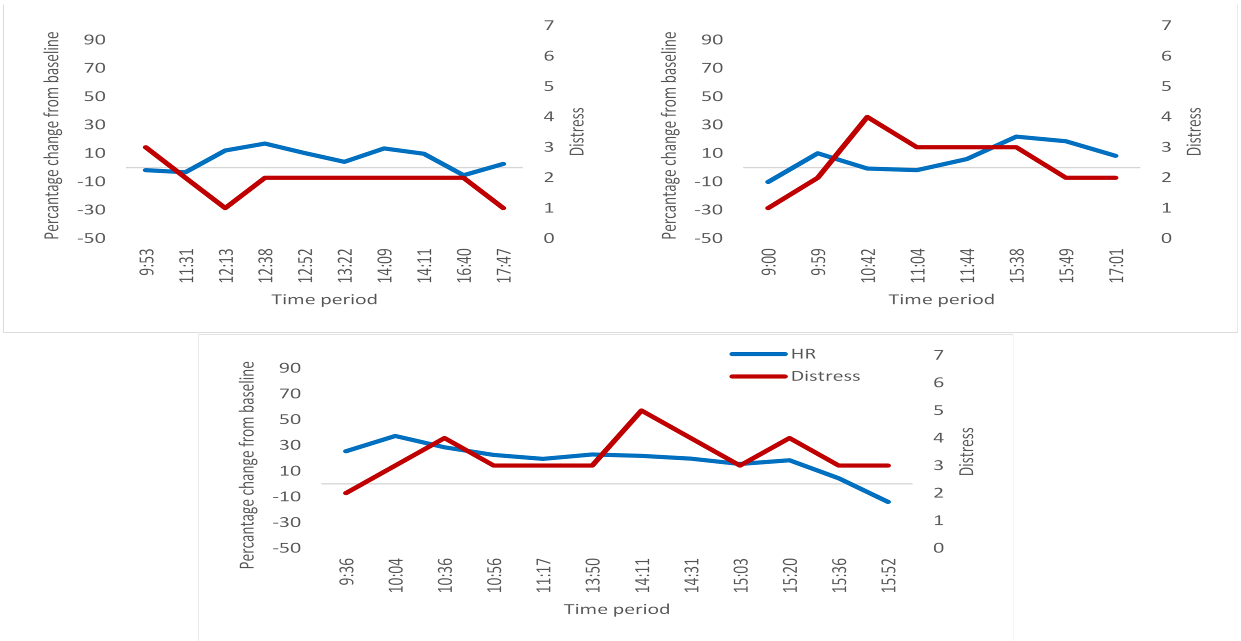

Figure 3. Participant 2 HR and distress scores for Day 1 (top left), Day 2 (top right), and Day 3 (bottom).

Participant 3 was a 29-year-old male who is a PhD student. He did not have any mobility issues or any history of health issues that might affect HR. Both days presented for this participant were working days and for both there was little fluctuation in HR change from baseline over the course of the day. In terms of subjective distress, the first day showed little fluctuation in ratings, with the self-report scores between 2 and 3 for the majority of the day. For the second day there was greater fluctuation in distress scores (between 2 and 4), however this was not matched by fluctuations in HR. Daily trends for this participant are shown in Figure 4. For all days of data, a Pearsons correlation was performed between the change scores and the subjective ratings. Bias corrected and accelerated bootstrap 95% confidence intervals are reported in square brackets. A small non-significant correlation the two was found, $r = .254$, $p = .253$ [-.333, .735].

Participant 4 was a 20-year-old male student. He did not have any mobility issues or any history of health issues that might affect HR. The data gathered from this participant spanned two days (one working, one weekend). The participant showed no substantial variation in either his HR or subjective distress ratings over the two days. The higher HR reading found at the start of the first day is considered to be an outlier based on the other readings observed throughout the two days. Daily trends for this participant are shown in Figure 6. For all days of data, a Pearsons correlation was performed between the change scores and the subjective ratings. Bias corrected and accelerated bootstrap 95% confidence intervals are reported in square brackets. Similarly to participant 3, a small non-significant correlation between the two was found, $r = -.095$, $p = .638$ [-.216, .032].

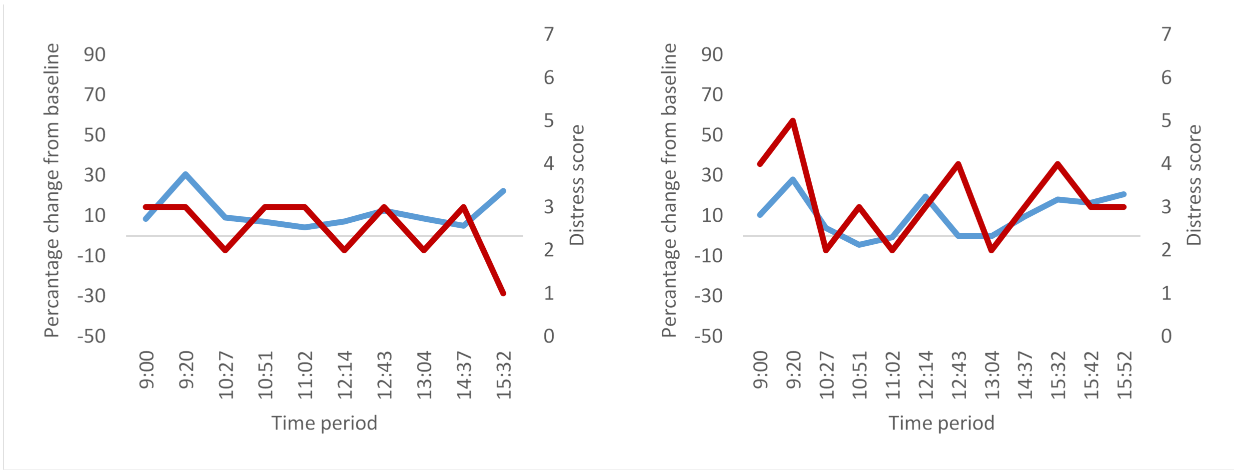

Figure 4. HR and distress scores for Day 1 (left) and Day 2 (right) for Participant 3.

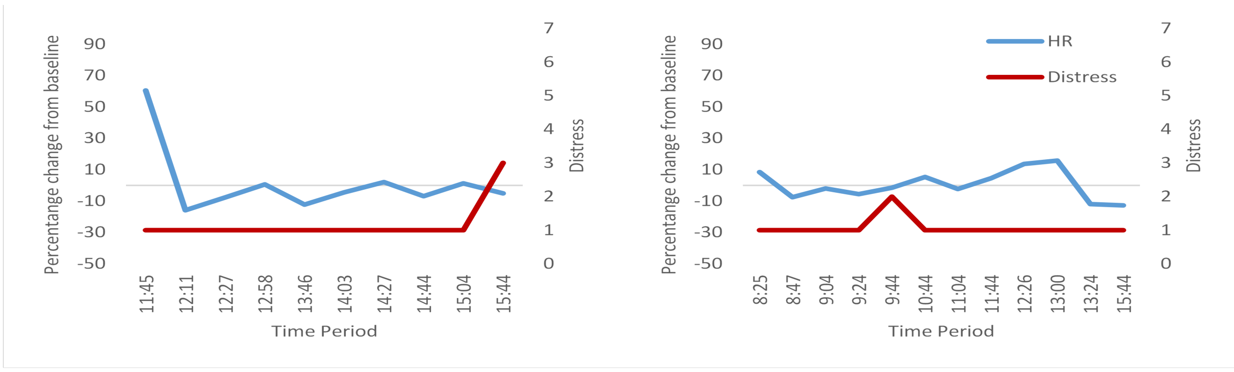

Figure 5. HR and distress scores for Day 1 (left) and Day 2 (right) for Participant 4.

Participant 5 was a 33-year-old female PhD student. She did not have any mobility issues or any history of health issues that might affect HR. The data gathered spans three days (two working, one weekend). For the first day, there is very little deviation in HR from baseline, with the trend staying around the zero change mark. There was a large increase in subjective distress towards the end of the day, however this did not have any associated increase in HR. For the second day, there was more variance in HR in the initial periods, which was due to the participant walking in to work. In terms of subjective distress, there was much greater variance compared to the previous day. Again, however, there was no corresponding HR change for changes in subjective distress. The third day again showed little deviation in HR over time, perhaps due to the participant relaxing during the weekend. Distress ratings also showed little variation over the day compared to the previous weekday, working environment readings. Daily trends for this participant are shown in Figure 5. For both days of data, a Pearsons correlation was performed between the change scores and the subjective ratings. Bias corrected and accelerated bootstrap 95% confidence intervals are reported in square brackets. A moderate correlation between the two was found, r = .344, p = .014 [.008, .703].

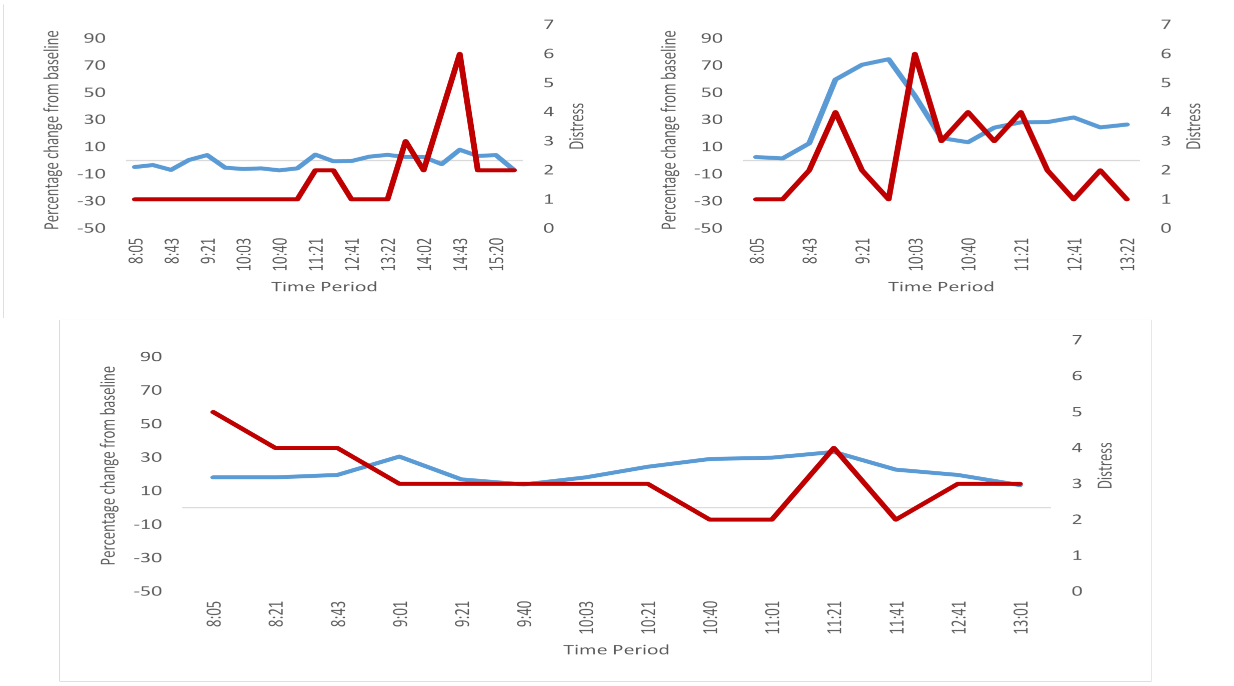

Figure 6. Participant 5 HR and distress scores for Day 1 (top left), Day 2 (top right), and Day 3 (bottom).

4. Discussion and Conclusion

Despite a history of research linking HRV and EDA to stress and despite suggesting links between HR and workload, we did not find a clear correlation between HR and distress in the current study. Research investigating such relationships are typically confined to laboratory environments, which allows for greater control over the stimuli that participants are exposed to. This could not be done in the current study and so may be a contributing factor to the lack of a clear relationship being found. Two participants did show a moderate correlation between BPM and distress, however this result may be skewed by the relatively little variance between distress scores over the observation period. Also, the devices used in the current study cannot record HRV or EDA, which means that these relationships cannot be explored in this instance. Future research is planned to utilise these measures on stress using a similar paradigm.

Another issue that emerges from this study is that of individual differences, both in terms of HR and subjective distress. This is a common issue in research in these areas (Appelhans & Luecken, 2006; Lyubormisky & Tucker, 1998). In terms of physiological differences this was to be expected, and was why percentage change was used rather than absolute BPM, a common method used to assess physiological measures. Any personalised system utilising HR (or any other physiological measure) will need to allow for an appropriate baseline gathering period for each individual to accurately assess fluctuations. In terms of distress, subjectivity will always be an issue with self-report questions. While one person may deem a particular event to be extremely stressful, another may find it relatively less stressful. This provides an interesting practical issue in developing a system to detect changes in psychological state, as physiological changes would need to be calibrated to each users' subjective level of distress. This highlights the importance of user-input into such a system and also has implications for privacy, security and user performance if such a framework was to be used for improving overall user experience.

4.1 Future Directions

This paper describes the methodology that is being adopted for the PASSME project to evaluate the usefulness of using physiological measures in a system designed to detect stress, as well as identifying ways in which uptake of such a system can be facilitated. At its core, the PASSME project emphasises the importance of personalisation, which is also a reoccurring theme in this study's finding such as individual differences in physiological changes to stress, subjective responses to particular situations, and preferences in the ways in which technologies are used. The PASSME project will look at ways in which these individual differences can be used to inform the application design, and how the technological innovations produced can adapt to each person's individual needs. Future PASSME research will also look to expand on the methodology used here, introducing potentially more complex physiological measures e.g. HRV and EDA, to make more refined inferences on psychological state.

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References

Appelhans, B. M., & Luecken, L. J. (2006). Heart rate variability as an index of regulated emotional responding. Review of general psychology, 10(3), 229.

Boucsein, W. (2012). Electrodermal activity. Springer Science & Business Media.

Healey, J., Nachman, L., Subramanian, S., Shahabdeen, J., & Morris, M. (2010, May). Out of the lab and into the fray: towards modeling emotion in everyday life. In International Conference on Pervasive Computing (pp. 156-173). Springer Berlin Heidelberg.

Lyubomirsky, S., & Tucker, K. L. (1998). Implications of individual differences in subjective happiness for perceiving, interpreting, and thinking about life events. Motivation and emotion, 22(2), 155-186.

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Sony, 2015 - SmartBand 2 Heart Rate Monitor
http://www.sonymobile.com/global-en/products/smart-products/smartband-2/

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.