

ANALYSIS OF USABILITY OF WEARABLE DEVICE METRICS AS  
PREDICTORS FOR BRAIN PHENOTYPES FROM CORRELATIONS

by

OLIVIER DEMERS

A thesis submitted to the  
Department of Computer Science  
in conformity with the requirements for  
the degree of Master of Science

Bishop's University  
Canada  
May 2024

Copyright © Olivier Demers, 2024  
released under a [CC BY-SA 4.0 License](https://creativecommons.org/licenses/by-sa/4.0/)

# Abstract

In the modern healthcare system, tracking a person's health can sometimes be expensive and time-consuming. Photoplethysmography (PPG) is a fairly easy non-invasive method to get some insights about a person's cardiovascular health. Some research has already been done with PPG in order to predict some properties of someone's brain from the signal. However, even if it could be possible to avoid complete brain scans to know more about our brain using PPG, it would still require a trip to the hospital. Furthermore, even if small household machines are capable of acquiring PPG data, they can still be quite expensive and non-practical for the users. If possible, using normal, consumer-grade, wearable electronic devices to detect anomalies or brain properties with the help of PPG could greatly benefit the healthcare system and its users by being less expensive, less time-consuming, and able to track the users' health throughout their day.

For this study, 52 subjects wore a consumer-grade smartwatch for about a month, recording the PPG data and accelerometer data. They also got a magnetic resonance imaging scan (MRI) of their brain. The smartwatch signals were then processed and the MRI images were segmented to compute the surface area, gray matter volume, and cortical thickness of some regions of the brain. The data from both sources were then compared to find correlations. Some correlations have been found in the data. The most relevant were between the heart rate and precentral gyrus, between the heart rate variability and parahippocampal gyrus, between the heart rate and the inferior parietal lobule, and between the heart rate variability and the lateral orbital cortex. Although some expected results were not present, or not as good as they could have been, some results were promising, which is encouraging for future research in this field. It would be interesting to perform this study using a smartwatch with a more precise sensor and to track the changes in the subjects over a longer period. It could also be interesting to test using machine learning.

# Acknowledgements

I would like to thank my family and my girlfriend, who have pushed me to finish writing this paper. They have given me the confidence and motivation that I needed to finish the project.

I also want to show my gratitude for receiving the Graduate Entrance Scholarship. It has allowed me to focus on my studies and research during this time.

Dr. Russell Butler also deserves my gratitude for the trust he had in me and the role he gave me in his research project. This has allowed me to grow as a student, a researcher, and a person.

Finally, I would like to thank my evaluation committee at Bishop's University, Dr. Yasir Malik, Dr. Layachi Bentabet and Dr. Rachid Hedjam, for their support and comments to make this paper better.

# Contents

<b>1</b>	<b>Introduction</b>	<b>1</b>
<b>2</b>	<b>Literature Review</b>	<b>2</b>
2.1	Background . . . . .	2
2.1.1	Gray Matter and Brain Regions . . . . .	2
2.1.2	About PPG Data . . . . .	2
2.1.3	Wearable sensors . . . . .	5
2.1.4	About Gray Matter . . . . .	6
2.2	Related Work . . . . .	7
2.2.1	Heart Rate Variability and Cortical Volume . . . . .	7
2.2.2	Behavior and Gray Matter . . . . .	7
<b>3</b>	<b>Materials and Methods</b>	<b>9</b>
3.1	Subjects . . . . .	9
3.2	Data Acquisition . . . . .	9
3.2.1	Smartwatch Data . . . . .	9
3.2.2	Brain Images . . . . .	11
3.3	Data Preparation . . . . .	12
3.3.1	Processing the Smartwatch Data . . . . .	12
3.3.2	Processing the Brain Data . . . . .	13
3.4	Correlation of the Data . . . . .	14
3.4.1	Note on the Distribution of the Data . . . . .	14
3.4.2	Computing of Correlations . . . . .	14
<b>4</b>	<b>Results</b>	<b>16</b>
4.1	Heart Rate and Heart Rate Variability . . . . .	16
4.2	Heart Rate Over the Day . . . . .	18
4.3	Brain Characteristics . . . . .	21
4.4	Heart Rate Correlation With Brain Data . . . . .	24
4.4.1	Brain Regions Area . . . . .	24
4.4.2	Brain Regions Gray Matter Volume . . . . .	27
4.4.3	Brain Regions Cortical Thickness . . . . .	30

4.5	Movement Correlation with Brain Data . . . . .	33
<b>5</b>	<b>Discussion</b>	<b>38</b>
5.1	Correlation Between HRV and BPM . . . . .	38
5.2	Detection of Activity . . . . .	38
5.3	Precentral Gyrus . . . . .	38
5.4	Parahippocampal Gyrus . . . . .	39
5.5	Inferior Parietal Lobule . . . . .	40
5.6	Lateral Orbitofrontal Cortex . . . . .	40
5.7	Precuneus . . . . .	41
5.8	Conclusion and Next Steps . . . . .	41
	<b>Bibliography</b>	<b>43</b>

# List of Tables

2.1 Lobes and their functions . . . . .	3
3.1 Galaxy Watch Active 2 Specifications . . . . .	10
4.1 Summary of results for correlations between PPG and brain data . .	33

# List of Figures

2.1	Example for measuring cortical thickness, gray matter volume and area . . . . .	3
2.2	Smartwatch-like device, SmartCare wrist-worn pulse Oximeter . . .	4
2.3	Examples of PPG acquisition points for sensors . . . . .	5
2.4	Demonstration of the Apple Watch PPG and ECG . . . . .	6
3.1	Slice of T1 weighted image . . . . .	11
3.2	HeartPy Heart Rate Signal Peak Detection . . . . .	13
3.3	Example of FreeSurfer volume and surface-based labeling . . . . .	13
3.4	Distribution of all the clean recordings. . . . .	14
4.1	Relation between BPM and HRV mean for every hour of all subjects .	16
4.2	Relation between BPM and HRV for all signal sections of randomly selected subject . . . . .	17
4.3	Relation between BPM and HRV mean for every hour of randomly selected subject . . . . .	18
4.4	Mean heart rate of all subjects for every hour . . . . .	19
4.5	Subject's mean heart rate for every hour . . . . .	19
4.6	Mean heart rate variability of all subjects for every hour . . . . .	20
4.7	Correlation matrix between the volume of gray matter in each recorded brain region . . . . .	21
4.8	Correlation matrix between the area of each recorded brain region . .	22
4.9	Correlation matrix between the cortical thickness of each recorded brain region . . . . .	23
4.10	Correlation matrix between the area of the brain regions and the heart rate of subjects at every hour . . . . .	24
4.11	Correlation matrix between the area of the brain regions and the heart rate of subjects relative to other hours at every hour . . . . .	25
4.12	Correlation matrix between the area of the brain regions and the heart rate variability of subjects at every hour . . . . .	25
4.13	Correlation matrix between the area of the brain regions and the heart rate variability of subjects relative to other hours at every hour	26

4.14	Correlation matrix between the volume of the brain regions and the heart rate of subjects at every hour . . . . .	27
4.15	Correlation matrix between the volume of the brain regions and the heart rate of subjects relative to other hours at every hour . . . . .	28
4.16	Correlation matrix between the volume of the brain regions and the heart rate variability of subjects at every hour . . . . .	28
4.17	Correlation matrix between the volume of the brain regions and the heart rate variability of subjects relative to other hours at every hour . . . . .	29
4.18	Correlation matrix between the cortical thickness of the brain regions and the heart rate of subjects at every hour . . . . .	30
4.19	Correlation matrix between the cortical thickness of the brain regions and the heart rate of subjects relative to other hours at every hour . . . . .	31
4.20	Correlation matrix between the cortical thickness of the brain regions and the heart rate variability of subjects at every hour . . . . .	31
4.21	Correlation matrix between the cortical thickness of the brain regions and the heart rate variability of subjects relative to other hours at every hour . . . . .	32
4.22	Mean movement for each hour of the day for all subjects. . . . .	34
4.23	Correlation matrix between the movement during sleep and the brain region properties . . . . .	35
4.24	Correlation matrix between the movement and the area of the brain regions for every hour . . . . .	36
4.25	Correlation matrix between the movement and the gray matter volume of the brain regions for every hour . . . . .	36
4.26	Correlation matrix between the movement and the cortical thickness of the brain regions for every hour . . . . .	37
5.1	Correlation between average subject BPM and area and volume of their precentral gyrus . . . . .	39
5.2	Correlation between average subject HRV and cortical thickness of their lateral orbitofrontal cortex . . . . .	41



# Chapter 1

## Introduction

Healthcare and medicine have improved a lot with the advancements in technology. With newer devices capable of detecting the smallest of anomalies in a person's body, it became easier for healthcare workers to detect diseases in their patients. The problem with these newer devices and procedures is that they can be quite expensive [4], require a lot of training to use and have long wait lists [5]. In order to improve the accessibility to healthcare, it would be interesting to have cheaper and smaller devices that people could own and use to predict or detect some things in their bodies.

Such devices already exist, but can be tedious to use, take up space or make noise. Recently, tech companies have started incorporating more and more health-related features into their smartwatches. However, most of them require the user to perform certain actions and stop moving for a bit. Although this is better than nothing, it would be better to be able to acquire information throughout the day. Most smartwatches already acquire their user's heart rate while they are wearing it, but the raw signal from the heart rate sensor, the photoplethysmogram (PPG), could be used for more [7].

The goal of this study is to indicate if smartwatches can be used as a preliminary diagnosis or follow-up device in healthcare. More precisely, we first need to find data with low noise that allows us to gather information about the subjects. Then, using the clean data, find if it is possible to find correlations with phenotypes from the subjects' brains. If such correlations are found, it would suggest that smartwatches are capable of acquiring data that could be used for characterizing the brain, which could be used in healthcare.

In this study, raw signals from smartwatches and subjects' magnetic resonance imaging (MRI) scans will be correlated. The correlations will then have to be explained using other research that used medical sensors. This should indicate if signals coming from smartwatches without human intervention could be reliable enough to be used in healthcare. However, this study will not cover implementation strategies for healthcare.

# Chapter 2

## Literature Review

### 2.1 Background

#### 2.1.1 Gray Matter and Brain Regions

When we think about the brain, we often think about white and gray matter. While both are essential, gray matter plays a more important part in the cognitive function of beings. The white matter serves as a bridge for the information "computed" by the outer layer of the brain, the gray matter [26]. The density of the cells present in the gray matter explains its color compared to the less dense white matter.

Other than the gray matter and white matter, there are other ways the segment a brain. We can also separate the brain by the function of different parts. The main separation of the brain is between the left and right hemispheres. These hemispheres are covered in some sort of wrinkles, which are called gyri, for the hills, and sulci, for the valleys. Separated by the sulci are different lobes of the brain. Each lobe has its function, but all lobes communicate together to make the brain as a whole work. Most lobes take their names from the skull bone they sit under [10]. Table 2.1.1 names all the lobes in the brain and their function [35]. Their location is not included in this table as it will not be relevant to this paper. Each lobe is also subdivided into smaller parts with more specific functions. However, due to the number of structures in the brain, they will not all be described here. Also, these regions are often measured by the area of the surface of the region, the volume of gray matter in the region, and the thickness between the white/gray surface and the pial surface, so the thickness of gray matter.

#### 2.1.2 About PPG Data

##### Acquiring Data Reliably

The first important thing to know is if other researchers have found PPG data from smartwatches to be reliable enough for their use and the first step in using PPG

Table 2.1: Lobes and their functions

Lobe	Function
Frontal Lobe	Voluntary movement, attention, short-term memory, planning
Parietal lobe	Awareness of the body, language processing
Temporal lobe	Visual and auditory input decoding and interpretation for memory
Occipital lobe	Visual processing
Insular lobe	Taste, pain and balance
Limbic lobe	Emotions, involuntary movement, learning, memory

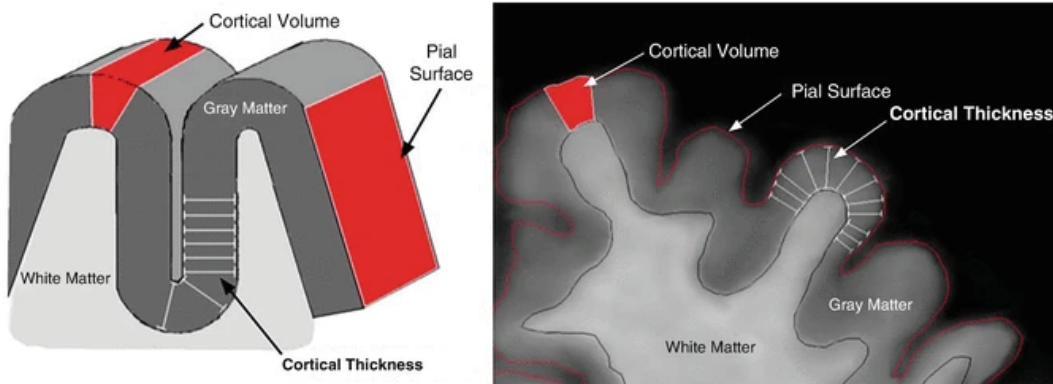


Figure 2.1: Example for measuring cortical thickness, gray matter volume and area [15, Figure 1]

data from a smartwatch is to acquire the data. We must first find out if users can wear their devices reliably. Charlton (2020) [8] has already conducted a study on this matter. They had one adult subject who had to wear a smartwatch-like device for four weeks, six days per week. They also had to record their daily activities. At the end of the four weeks, their subject had worn the watch 75.0% of the time, with signals being acquired 60.6% of the time. For 30.5% of the total possible wear time, their signal was of good quality. It should also be noted that their device, shown in figure 2.2 was also less fashionable and a lot bulkier than modern smartwatches. It would be safe to assume that subjects would be more inclined to wear new smartwatches as daily drivers.



Figure 2.2: Smartwatch-like device used by Charlton, SmartCare wrist-worn pulse Oximeter [8, Figure 1]

Charlton's paper also had some lessons from their study. One of them was to try to improve the battery life of the device as much as possible to increase the amount of time the user can wear it. Their device had to stream data to a phone using Bluetooth and had some connection problems, so they advised to store the data directly on the device or have a reliable connection to stream on. They also recommended acquiring data during the night, or when the user does not move much, as it tends to be of higher quality. They concluded by saying that they believe that it could be used to track cardiovascular characteristics changes, which is promising.

### PPG in Healthcare

PPG is already used in the medical field and has multiple applications [1], but most devices used in the area are difficult to use in the day-to-day. Studies have found

potential uses for PPG data coming from wearable devices in the medical field. Some say that processing PPG data from wearable devices could allow healthcare professionals to better track their patients' cardiovascular health [7]. It could help them detect some diseases that usually happen at an older age faster than during occasional visits to the hospital. More precisely, with the processing power already present in modern wearable devices, algorithms can be run on the devices directly, which allows for an even earlier detection. An example of such an algorithm is the deep-learning model BayesBeat [11]. It detects atrial fibrillation and has alleged high detection rates, even with noisy signals, while being efficient enough to run on low-power devices. However, even if these studies suggest that PPG data from wearable devices are good enough to use for detecting cardiovascular anomalies, they do not mention its usability for the prediction of brain characteristics.

### 2.1.3 Wearable sensors

In the past, it was a lot more difficult to have any metrics about what was happening in our bodies. We had to go to the hospital or own big and/or complicated machines. This takes a lot of time and could cost a lot. Now, with the advancements in technology, sensors have become quite small, small enough for them to be worn all day. The most common sensors for cardiovascular data in wearable devices are photoplethysmographic (PPG) and electrocardiograms (ECG) [9].

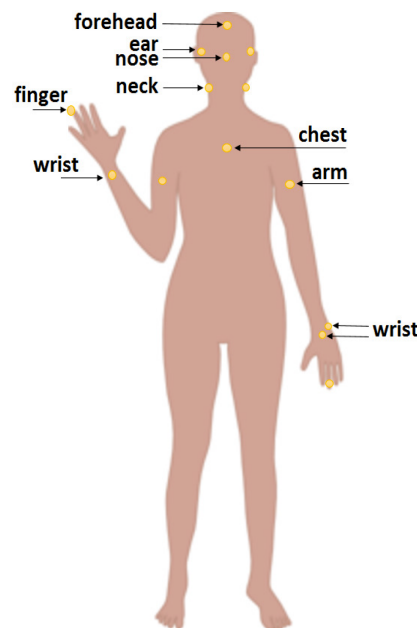


Figure 2.3: Examples of PPG acquisition points for sensors [19, Figure 1]

## Types of Devices

Multiple types of devices can be used to acquire cardiovascular data. One of these devices takes the shape of a little claw that goes at the tip of the patient's finger or earlobe, but this would not be considered wearable. Most of the early wearable devices branded themselves as exercise monitors. A lot of them are worn as chest straps or armbands. Nowadays, a lot of smartwatches are capable of getting PPG data from the users' wrists. Some other devices take the form of a ring, the data from these devices are more precise because, by their nature, their sensors are always in contact with the users' skin. For this study, smartwatches were chosen because they are the most accessible device and most likely to be worn by a great number of people.

## ECG and PPG signals

In wearable devices, PPG is often used to estimate the heart rate of a user [18]. Sensors detect changes in blood volume passing through the skin near the device, generating the PPG. This can be done without direct intervention from the user, which makes it ideal for monitoring heart rate and other metrics throughout the day and at night. The ECG is more complicated to generate and requires the user to do specific manipulations to start a scan and during the scan [3] [16] [32]. For this reason, only PPG will be looked at during this study.

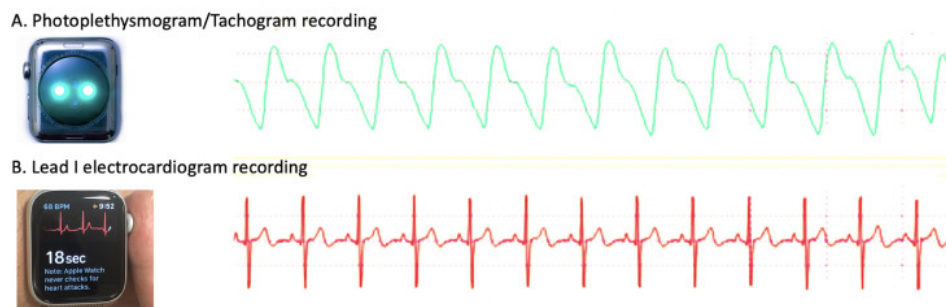


Figure 2.4: Demonstration of the Apple Watch PPG (A) and ECG (B) [18, Figure 1]

One of the problems with using wearable devices' PPG data, is that it is very prone to noise. One of the reasons for this noise is simply the movement of the user during the acquisition of the data, which affects the reading of the sensor. This will have to be considered during this study.

### 2.1.4 About Gray Matter

The three metrics that are looked at in this study are the surface area, the volume of gray matter, and the cortical thickness, which is the thickness of the gray matter,

for each region. It has been found that the area and thickness are independent, but both influence the volume, with the area's influence being more important [40]. Figure 2.1 shows a visual representation of these three metrics. Since the surface area and cortical thickness can explain most of the volume, only these two would have to be analyzed, but this study will still go over the three metrics to have a broader view.

## 2.2 Related Work

The amount of research regarding using smartwatch signals to predict phenotypes in the human brain is not big, but some have already been able to find correlations between signals coming from smartwatches and subjects' brain characteristics [12]. However, the goal of this thesis project is to find correlations using the smartwatch data and to explain these correlations using results from studies that used more precise equipment. There has been a lot of research that can be useful for that. For example, studies that correlate heart rate variability and the structure of the brain [39].

### 2.2.1 Heart Rate Variability and Cortical Volume

Studies have suggested that the medial prefrontal cortex and lateral orbitofrontal cortex are linked with heart rate variability. It is also suggested that biofeedback therapy, which can change a person's heart rate variability, can also change the parts of the brain that control it [41]. This could indicate that different heart rate variabilities are correlated with the shape of the prefrontal cortex and lateral orbitofrontal cortex. A decline in heart rate variability and cortical thickness has been found to happen at a higher age [28] [22]. They have also found that the orbitofrontal cortex's cortical thickness explains this change, even without accounting for aging [21]. This also suggests a correlation between the two.

Other studies have also found a correlation between heart rate variability and gray matter volume in the central autonomic network, which includes the amygdala, insula, parahippocampal gyrus, striatum, and superior temporal gyrus [25].

### 2.2.2 Behavior and Gray Matter

Other studies have found correlations between the brain's gray matter characteristics and other properties such as behavior. For example, Gaser (2003) suggests that professional musicians have more gray matter in regions that are critical to playing or understanding music compared to amateurs or non-musicians [17]. It has also been found that, in rats, learning motor skills and exercising had the potential to change the volume of gray matter in certain regions of the brain [2]. This also seems to be the case for humans, as Erickson (2014) suggests that exercise and

fitness are correlated with the volume of gray matter in the prefrontal cortex and the hippocampus [13]. Another study also found a link between the sleep schedule of adolescents and their brain's gray matter volume in some regions [23]. Some regions, like the inferior parietal lobe, are also involved in dreams [27], which might be detectable from the amount of movement a patient does in their sleep.



## Chapter 3

# Materials and Methods

### 3.1 Subjects

52 subjects were selected for this study from Bishop's University community or the population of Sherbrooke, Quebec. They were healthy 18-40 years old with a 50% sex ratio. The participants were given some guidelines regarding their use of the smartwatch to gather better results such as wearing the watch at night, wearing it comfortably tight, etc. Consent was given by all subjects before the beginning of the data collection and all were given a 150\$ monetary compensation. Any personal information about the subjects, such as their name, age, gender, or status, was removed from the data, so they were not used as discriminators later in the experiment.

### 3.2 Data Acquisition

#### 3.2.1 Smartwatch Data

##### Smartwatch Choice

For this study, the smartwatch that was used is the Samsung Galaxy Watch Active 2 [31]. It was a good example of a mainstream smartwatch.

For this watch, the HR Sensor is a PPG sensor and the watch can compute the heart rate from it. It is also possible to acquire the raw signal directly.

Table 3.1: Galaxy Watch Active 2 Specifications

Connectivity	Bluetooth, Wi-Fi, NFC
Dimensions (HxWxD)	44 x 44 x 10.9 mm
Weight	30g
Display	360x360, 34.5mm, Super AMOLED, Touch
OS	Tizen
Internal Storage	4GB, 1.4GB Available
RAM	0.75GB
Battery Capacity	340mAh
Sensors	Accelerometer, Barometer, Gyro Sensor, HR Sensor, Light Sensor, ECG Sensor

### Watch Application

In order to acquire the data from the smartwatch, we had to create an app. An existing app on Github [34] already had a lot of the functionalities that we needed:

- Service that runs in the background starts and stops 5 minutes recordings every 30 minutes.
- Data is saved to CSV files.
- After recording data, CSV files are sent to a web server.

However, we changed some of these features to better accommodate our needs.

- The time of the recordings was changed to 1 minute and the interval to 10 minutes, as we did not need long acquisitions, but wanted more frequent recordings.
- In order to have better battery life, we removed the part of the app that sent the data to a web server and instead downloaded all the data from the smartwatches after some months of acquiring data. The actual amount of time during which data was acquired varied between subjects.

Data was acquired from all sensors except for the light sensor used for the screen brightness and the ECG sensor because it requires the user to touch a button on the watch to work. The data was acquired at a frequency of 10Hz as it was the maximum frequency for the watch. The UNIX timestamp was also recorded for every data point to allow for time-based correlations.

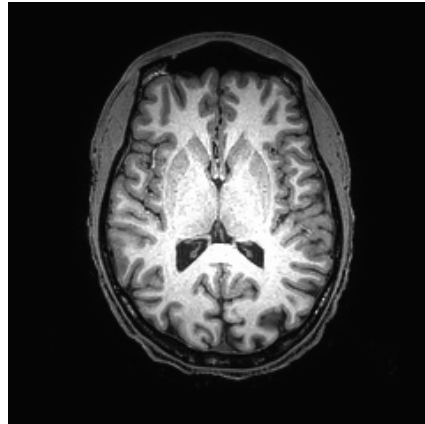


Figure 3.1: Slice of T1 weighted image

### 3.2.2 Brain Images

T1 weighted images of all the subjects' brains were acquired at CHUS Fleurimont using a Philips Ingenia 3.0T magnetic resonance imaging (MRI) machine. The goal of these images was to extract information about gray matter in the subjects' brains.

### 3.3 Data Preparation

#### 3.3.1 Processing the Smartwatch Data

After downloading the data from all the subjects' smartwatches, epochs with less noise were identified and selected as per the following steps. Along these epochs of around 13 seconds each, the hour of the day at which they were recorded was kept. The segments of data that had too much noise or were discarded.

1. Run a band-pass filter on every PPG recording to remove low and high frequencies that contain noise from the sensor or from the subjects' movement. The goal was to keep only frequencies that could correspond to a normal heart rate.
2. Resample signal to 30 Hz for a more precise peak detection.
3. Find peaks in the signal using SciPy [38].
4. Use peaks to epoch the recording into individual assumed heartbeats.
5. Cluster the assumed heartbeats with the k-means algorithm.
6. Visually inspect the clusters to find which ones correspond to real heartbeats and which are noise.
7. Find all 13-second sections in which the detected peaks are part of the good clusters.

For the case of this study, Scikit-learn's k-means implementation was used. Clustering was performed for 16 clusters and the results were sufficient for this study, so no other attempt at discerning between good and bad segments of the PPG data was done.

After selecting clean epochs, the average heart rate and heart rate variability were computed for each of them using the HeartPy Python library [36][37]. The HRV is calculated from the root mean square of successive differences (RMSSD), which has the following equation, where  $RR$  is the time between two peaks in the signal.

$$RMSSD = \sqrt{\frac{1}{n-2} \sum_{i=0}^{n-2} (RR_i - RR_{i+1})^2}$$

The heart rate and heart rate variability were then used for analysis with the data from the brain.

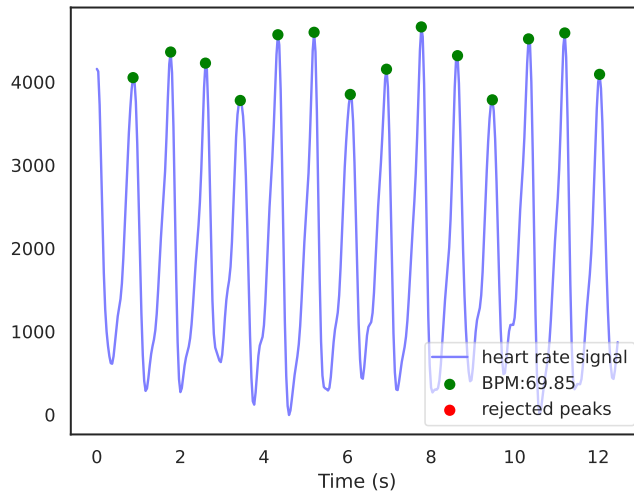


Figure 3.2: HeartPy Heart Rate Signal Peak Detection for Subject at 9 AM

### 3.3.2 Processing the Brain Data

The MRI T1 weighted images were processed using FreeSurfer [14][30] for cortical reconstruction and segmentation. This allowed us to easily have important information about the subjects' brains, such as the gray matter volume, surface area, and cortical thickness in all the regions of the brain supported by FreeSurfer. The processing of this data was done on computers managed by Calcul Québec ([calculquebec.ca](http://calculquebec.ca)) and the Digital Research Alliance of Canada ([alliancecan.ca](http://alliancecan.ca))

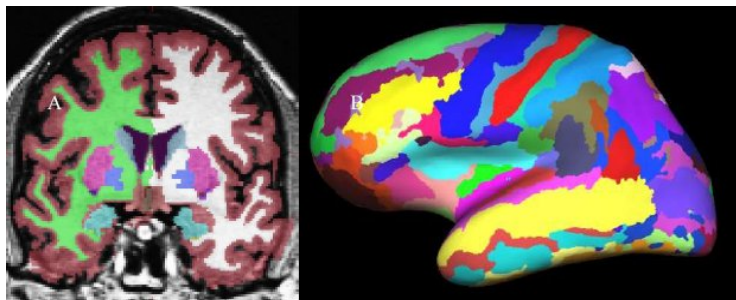


Figure 3.3: Example of FreeSurfer volume and surface-based labeling [33, Figure 4]

This data was then imported into Python from the files created by FreeSurfer for analysis.

## 3.4 Correlation of the Data

### 3.4.1 Note on the Distribution of the Data

Although data was recorded on the smartwatches throughout the day, there was not the same amount of clean recording for every hour. As figure 3.4 shows, most clean recordings were acquired during the night. This could mean that subjects mostly wore the watch during the night or that the data that was acquired during the day was too noisy to analyze.

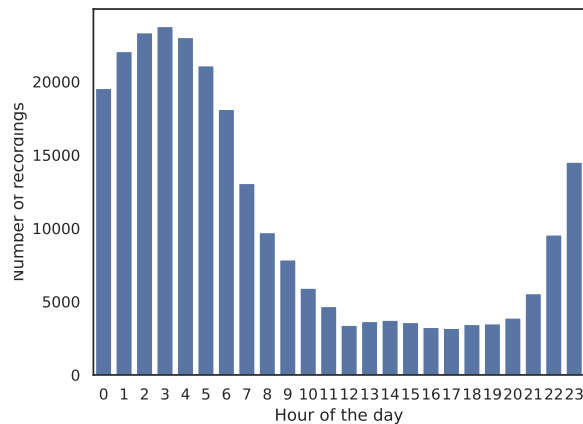


Figure 3.4: Distribution of all the clean recordings.

Either way, this would mean that the results related to the data that was acquired during the day could be less generalized as the sample size was smaller. Some subjects even have no data at all in some hours.

### 3.4.2 Computing of Correlations

Now that all the data is processed, it is time to compute the correlations. The correlations in this study are all calculated using SciPy's Pearson correlation coefficient and p-value calculation. The correlation coefficient is also represented with a lowercase  $r$  in the results and is between -1 and 1. Correlation coefficients farther from 0 are stronger and negative values indicate a negative correlation. The p-value is two-sided and indicates the probability that data with no real correlation would produce a correlation coefficient as strong or stronger.

For analysis of the results, most of the correlations are visualized using correlation matrices between the cardiac metrics and the brain metrics. The x-axis of the matrices is for each hour of the day, from midnight (0) to 11 PM (23). The y-axis is for all the brain sections. The values in the matrices are the correlation coefficients. The

vectors used for correlation coefficients are the average of a cardiac characteristic for every subject at a specific hour and their specific brain characteristic.

The heart rate is correlated in two different ways, which will be referred to as "average heart rate" and "relative heart rate". For both, outlier heart rates and heart rate variabilities are removed before averaging. The first is computed by averaging the heart rate recorded in different segments at the same hour for each subject. For the second, the average heart rate at every hour is then z-scored with the heart rate at the other hours. The goal of using these two ways is to compare the heart rate of every subject compared to each other but also compared to themselves throughout the day.

Movement and sleep disturbance are computed from the values of the accelerometer. Movement is the sum of the derivative of the accelerometer value, which is the acceleration of the device in every axis in meters per second squared. The sleep disturbance is computed by applying a threshold on accelerometer values during the night and counting the amount of values exceeding the threshold.

## Chapter 4

# Results

After performing an analysis of the data we extracted from the smartwatches and the brain MRIs, we have found some interesting results.

### 4.1 Heart Rate and Heart Rate Variability

Figure 4.1 shows the correlation between the average heart rate (BPM) and average heart rate variability (HRV) for every hour (0-23) for every subject. The computed Pearson correlation is moderate and negative:  $r(1181) = -.51, p = .000$ .

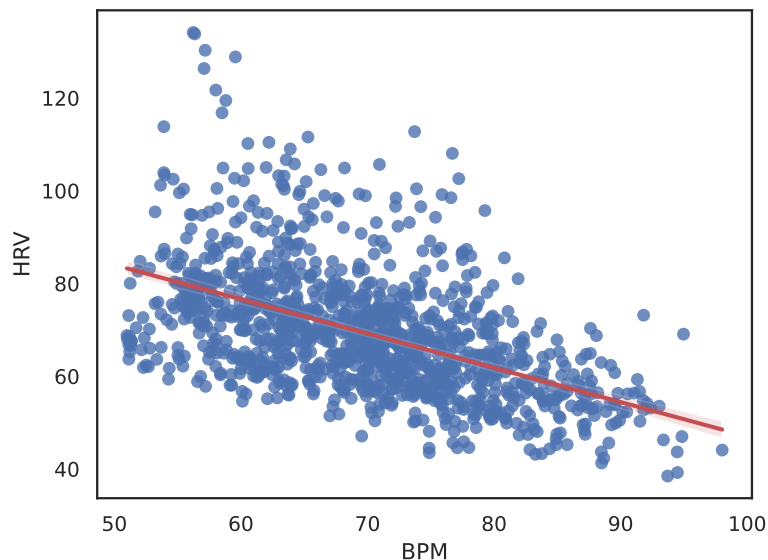


Figure 4.1: Relation between BPM and HRV mean for every hour of all subjects



Figure 4.2 shows the correlation between the heart rate (BPM) and heart rate variability (HRV) for every clean section selected for a randomly selected subject. The computed Pearson correlation is weak and negative:  $r(7576) = -.23, p = .000$ .

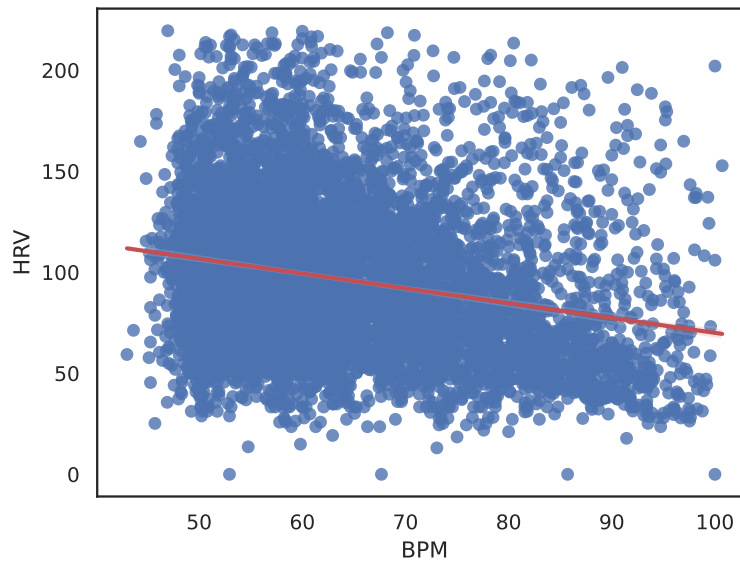


Figure 4.2: Relation between BPM and HRV for all signal sections of randomly selected subject

Figure 4.3 shows the correlation between the average heart rate (BPM) and average heart rate variability (HRV) for every hour (0-23) for the same subject as figure 4.2. The computed Pearson correlation is strong and negative:  $r(22) = -.87, p = .000$ .

In this section, we can see that the heart rate variability decreases when the heart rate increases.

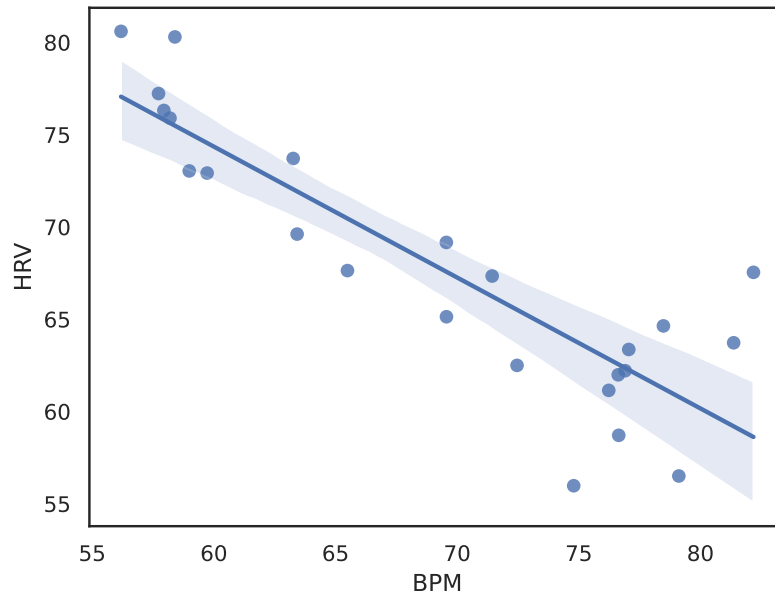


Figure 4.3: Relation between BPM and HRV mean for every hour of randomly selected subject

## 4.2 Heart Rate Over the Day

Figure 4.4 shows the mean heart rate for every hour of the day for all subjects.

Figure 4.5 shows the mean heart rate for every hour of the day for a randomly selected subject, which is the same as for figures 4.2 and 4.3.

Figures 4.4 and 4.5 show similar results. In general, the heart rate of the subjects was higher during the day and lower during the night.

Figure 4.6 shows the mean heart rate variability for every hour of the day for all subjects.

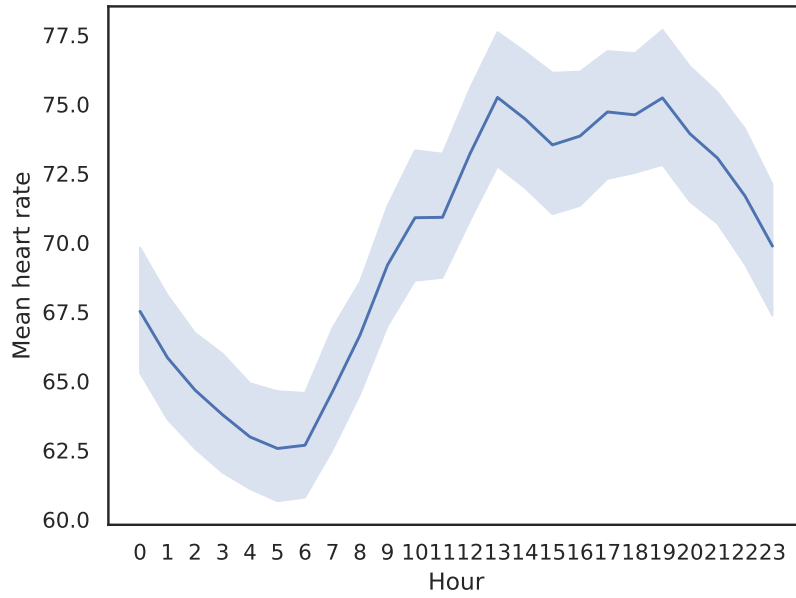


Figure 4.4: Mean heart rate of all subjects for every hour

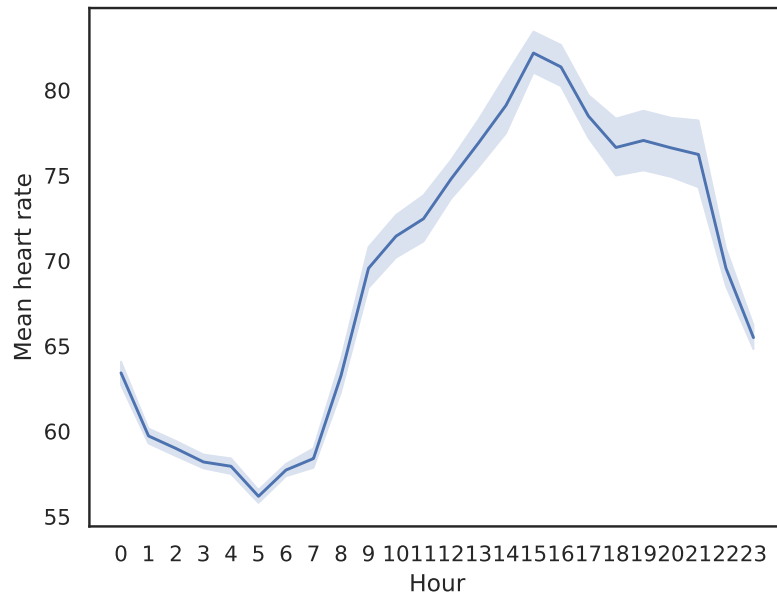


Figure 4.5: Subject's mean heart rate for every hour

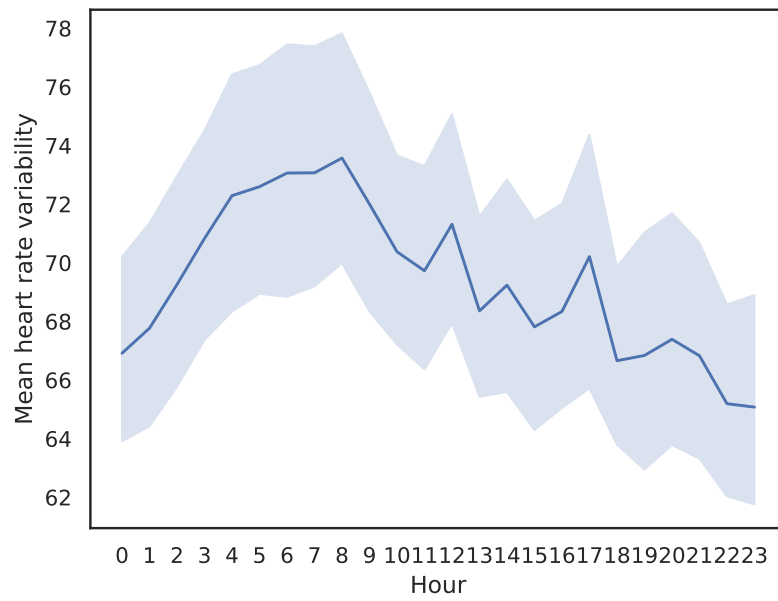


Figure 4.6: Mean heart rate variability of all subjects for every hour

### 4.3 Brain Characteristics

Figure 4.7 shows the correlation between the volume of gray matter in each of the regions of the brain that were segmented and identified by FreeSurfer [14]. Correlations can be identified between regions with similar functions.

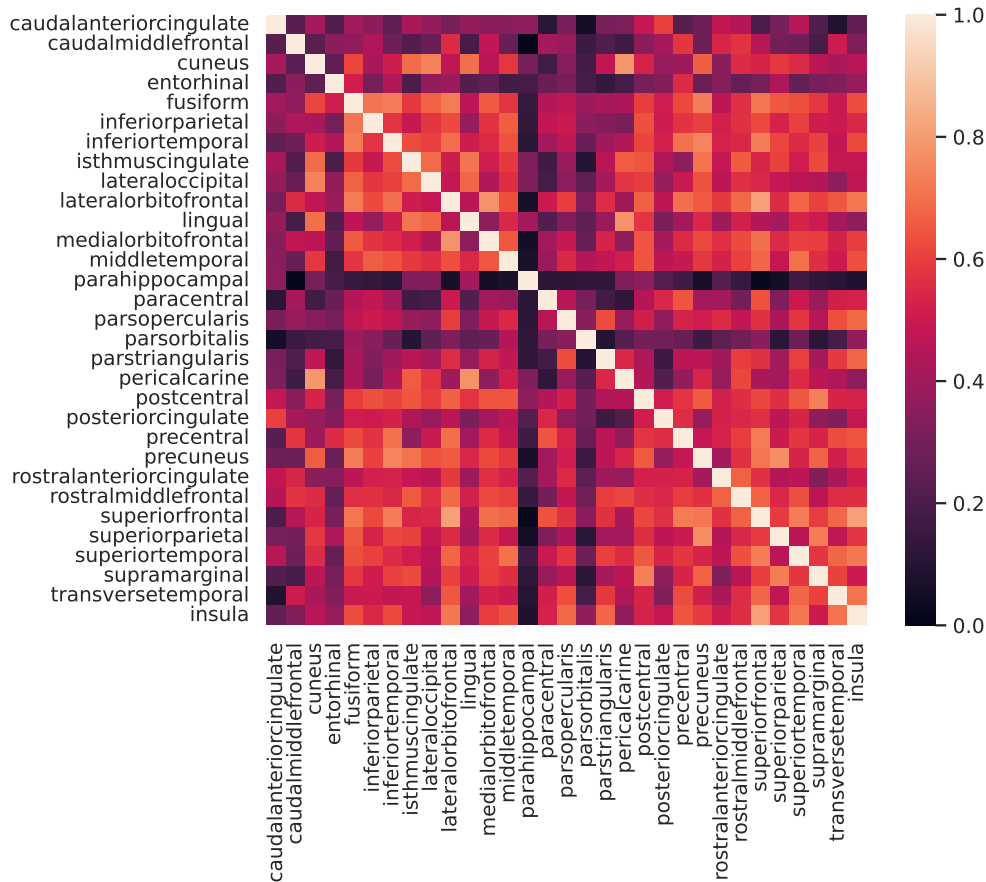


Figure 4.7: Correlation matrix between the volume of gray matter in each recorded brain region

Figure 4.8 shows the correlation between the area of each of the regions of the brain. Correlations can be identified between regions with similar functions.

Figure 4.9 shows the correlation between the cortical thickness of each of the regions of the brain. It has the lowest correlation out of the three characteristics.

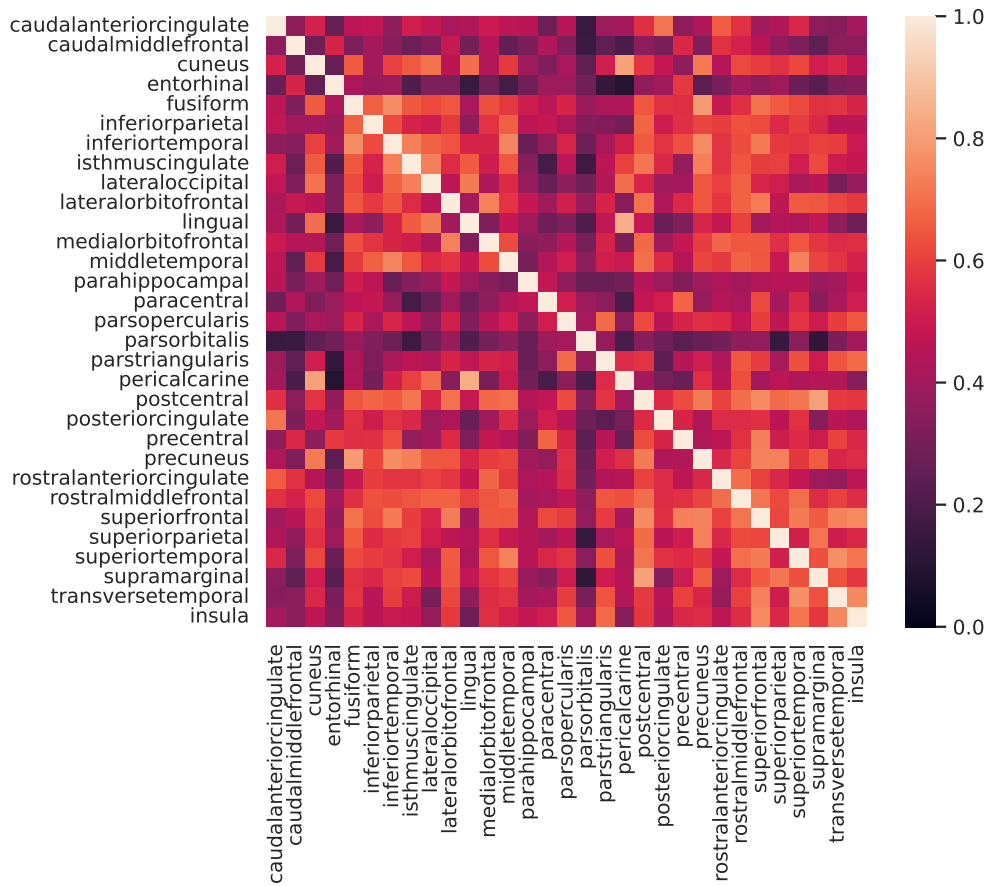


Figure 4.8: Correlation matrix between the area of each recorded brain region

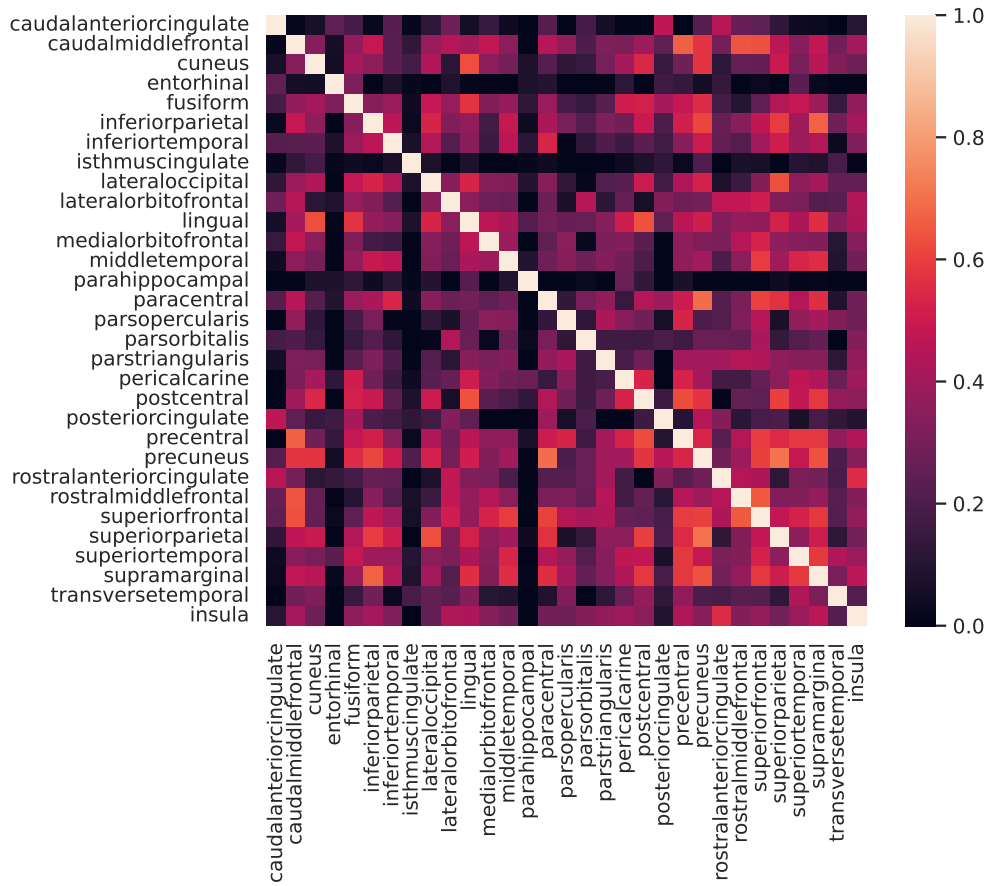


Figure 4.9: Correlation matrix between the cortical thickness of each recorded brain region

## 4.4 Heart Rate Correlation With Brain Data

### 4.4.1 Brain Regions Area

Figure 4.10 shows the correlation between the average heart rate of every subject at every hour and their area of brain regions. A negative correlation can be seen for the precentral gyrus for most of the day. A positive correlation can be seen for the parahippocampal gyrus during the night. Some other weaker negative correlations can be seen for the paracentral lobule and entorhinal cortex in the morning.

Figure 4.11 shows the correlation between the relative average heart rate of every subject at every hour compared to the rest of the time and their area of brain regions. A positive correlation can be seen for the parahippocampal gyrus and the paracentral lobule during the night.

Figure 4.12 shows the correlation between the average heart rate variability of every subject at every hour and their area of brain regions. A negative correlation can be seen for the parahippocampal gyrus for the evening and night.

Figure 4.13 shows the correlation between the relative average heart rate variability of every subject at every hour compared to the rest of the time and their area of brain regions. A positive correlation can be seen for some regions at 8 AM.

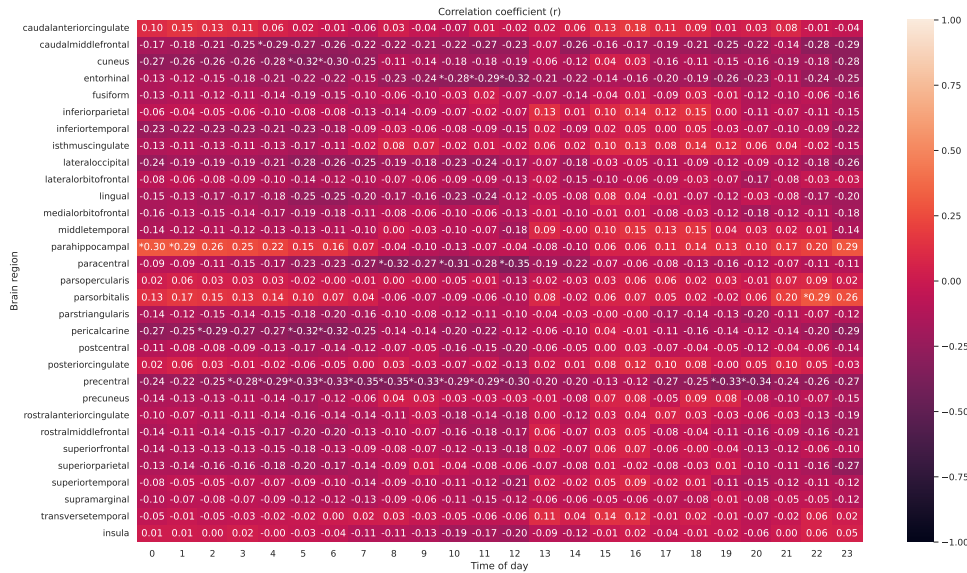


Figure 4.10: Correlation matrix between the area of the brain regions and the heart rate of subjects at every hour. Asterisks represent values with a p-value under 0.05.





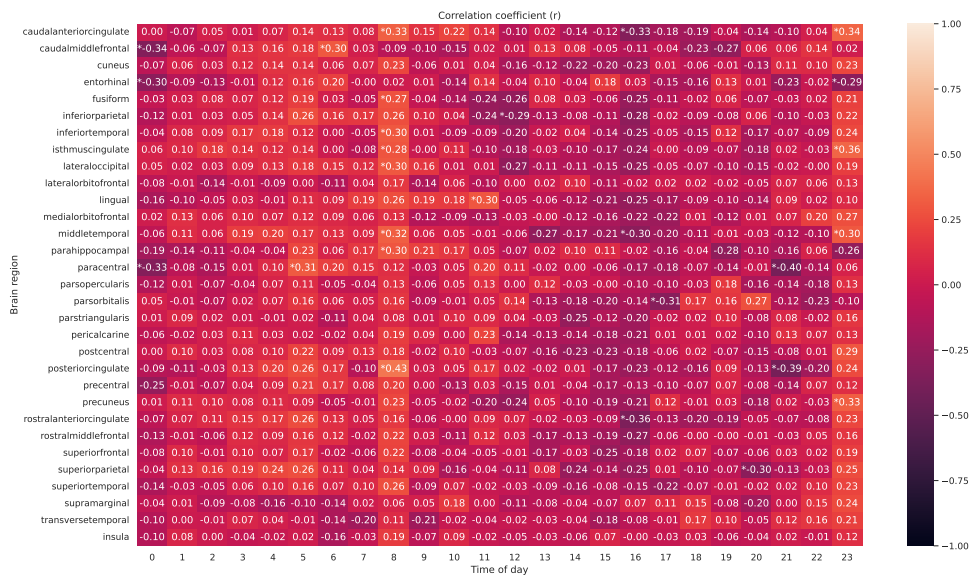


Figure 4.13: Correlation matrix between the area of the brain regions and the heart rate variability of subjects relative to other hours at every hour. Asterisks represent values with a p-value under 0.05.

### 4.4.2 Brain Regions Gray Matter Volume

Figure 4.14 shows the correlation between the average heart rate of every subject at every hour and the volume of brain regions. A negative correlation can be seen for the precentral gyrus for most of the day. A negative correlation can be seen for the pericalcarine region during the night. Some other weaker negative correlations can be seen for the paracentral lobule in the morning.

Figure 4.15 shows the correlation between the relative average heart rate of every subject at every hour compared to the rest of the time and the volume of brain regions. A negative correlation can be seen for the parahippocampal gyrus between 10 and 12 AM.

Figure 4.16 shows the correlation between the average heart rate variability of every subject at every hour and the volume of brain regions. A positive correlation can be seen for the paracentral lobule around noon.

Figure 4.17 shows the correlation between the relative average heart rate variability of every subject at every hour compared to the rest of the time and the volume of brain regions. A positive correlation can be seen for some regions at 8 AM.

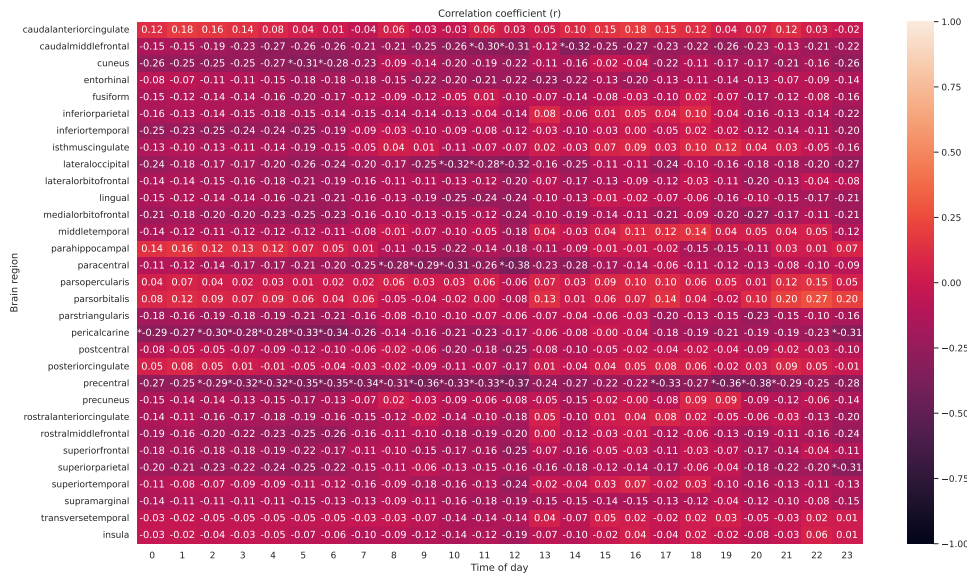


Figure 4.14: Correlation matrix between the volume of the brain regions and the heart rate of subjects at every hour. Asterisks represent values with a p-value under 0.05.



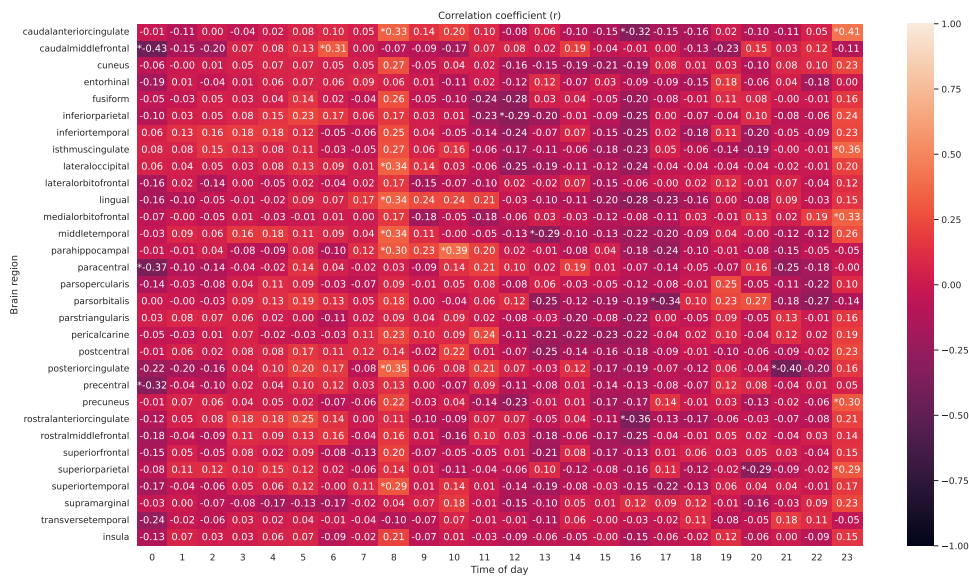


Figure 4.17: Correlation matrix between the volume of the brain regions and the heart rate variability of subjects relative to other hours at every hour. Asterisks represent values with a p-value under 0.05.

### 4.4.3 Brain Regions Cortical Thickness

Figure 4.18 shows the correlation between the average heart rate of every subject at every hour and the cortical thickness of brain regions. A negative correlation can be seen for the inferior parietal lobule at night and the superior parietal during the day.

Figure 4.19 shows the correlation between the relative average heart rate of every subject at every hour compared to the rest of the time and the cortical thickness of brain regions. A negative correlation can be seen for some regions in the evening. A positive correlation can be seen for some regions in the day.

Figure 4.20 shows the correlation between the average heart rate variability of every subject at every hour and the cortical thickness of brain regions. A positive correlation can be seen for the lateral orbitofrontal cortex all the time. Other positive correlations can be seen with other regions at some points during the day.

Figure 4.21 shows the correlation between the relative average heart rate variability of every subject at every hour compared to the rest of the time and the cortical thickness of brain regions. A negative correlation can be seen for the caudal anterior cingulate gyrus between 4 and 6 AM.

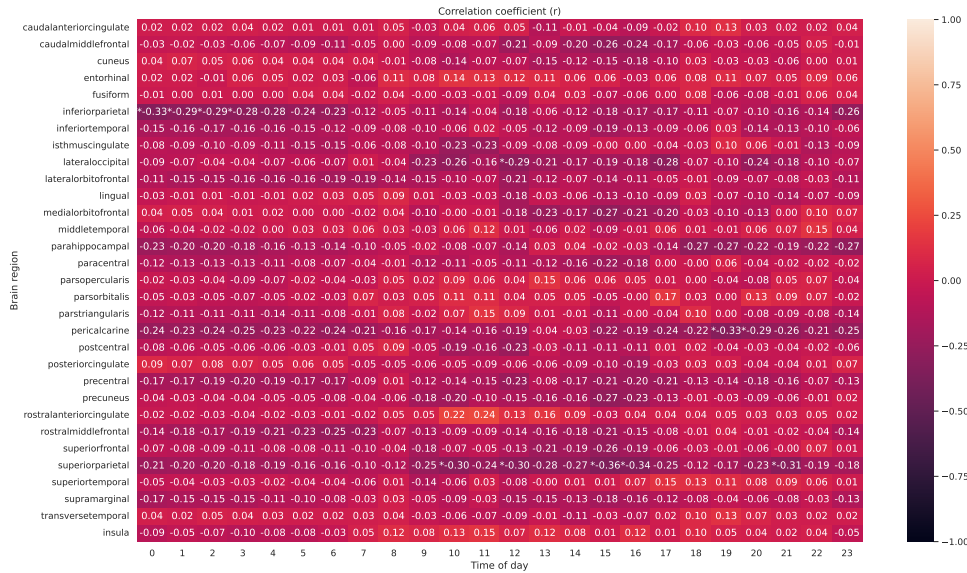


Figure 4.18: Correlation matrix between the cortical thickness of the brain regions and the heart rate of subjects at every hour. Asterisks represent values with a p-value under 0.05.



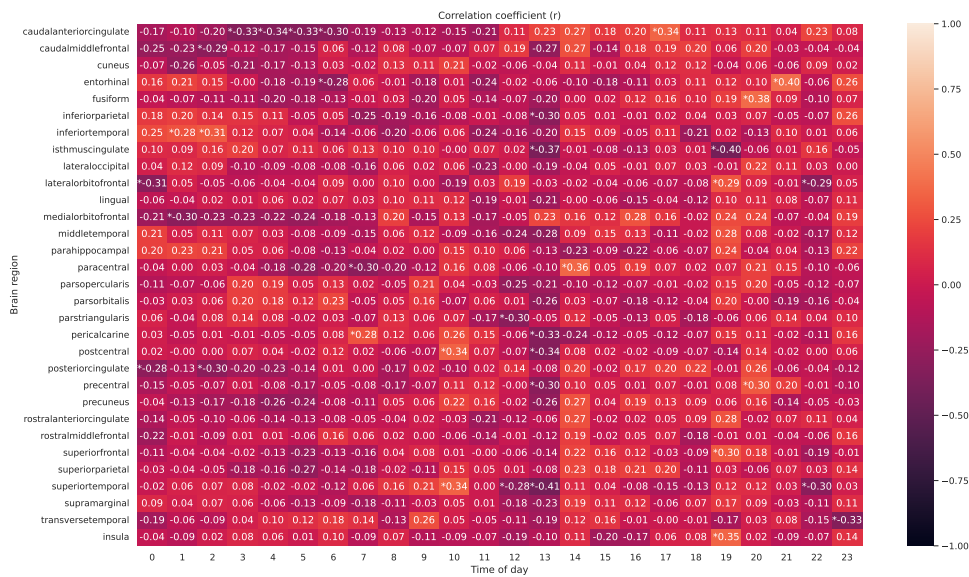


Figure 4.21: Correlation matrix between the cortical thickness of the brain regions and the heart rate variability of subjects relative to other hours at every hour. Asterisks represent values with a p-value under 0.05.



Table 4.1 served as a summary for most of the results, as they can be hard to read quickly.

Table 4.1: Summary of results for correlations between PPG and brain data

Brain Region	Properties	Corr	Time
Precentral Gyrus	Average BPM	-	Most of the time
	Average BPM	-	Most of the time
Paracentral Lobule	Average BPM	-	Morning
	Relative BPM	+	Night
	Average BPM	-	Morning
	Average HRV	+	Noon
Parahippocampal Gyrus	Average BPM	+	Night
	Relative BPM	+	Night
	Average HRV	-	Evening and night
	Relative BPM	-	10-12 AM
Pericalcarine	Average BPM	-	Night
Entorhinal Cortex	Average BPM	-	Morning
Inferior Parietal Lobule	Average BPM	-	Night
Superior Parietal Lobule	Average BPM	-	Day
Lateral Orbitofrontal Cortex	Average HRV	+	All the time
Caudal Anterior Cingulate Gyrus	Relative HRV	-	4-6 AM

## 4.5 Movement Correlation with Brain Data

Figure 4.22 shows the average movement for all subjects at every hour of the day. The movement is lower during the night and higher during the day.

Figure 4.23 shows the correlation between the quantity of movement during the subjects' sleep and their brain properties. Negative correlations can be seen for the gray matter volume and area in the cuneus, fusiform gyrus, inferior parietal lobe, medial orbitofrontal cortex, middle temporal gyrus, pericalcarine region, precuneus, rostral middle frontal gyrus, superior frontal gyrus, superior parietal lobule, and superior temporal gyrus.

Figure 4.24 shows the correlation between the quantity of movement of every subject at every hour and their area of brain regions. A negative correlation can be seen for the pars orbitalis during most of the day. A negative correlation can be seen for some regions in the evening, the strongest being for the precuneus, the

rostral anterior cingulate cortex, and the superior frontal gyrus.

Figure 4.25 shows the correlation between the quantity of movement of every subject at every hour and the volume of gray matter in their brain regions. A negative correlation can be seen for some regions in the evening, the strongest being for the precuneus, the rostral anterior cingulate cortex, and the superior frontal gyrus. A positive correlation can be seen for the inferior temporal gyrus between 4 and 6 AM.

Figure 4.26 shows the correlation between the quantity of movement of every subject at every hour and the cortical thickness of their brain regions. Positive correlations can be seen for the middle temporal gyrus during the night and for the caudal anterior cingulate gyrus in the afternoon.

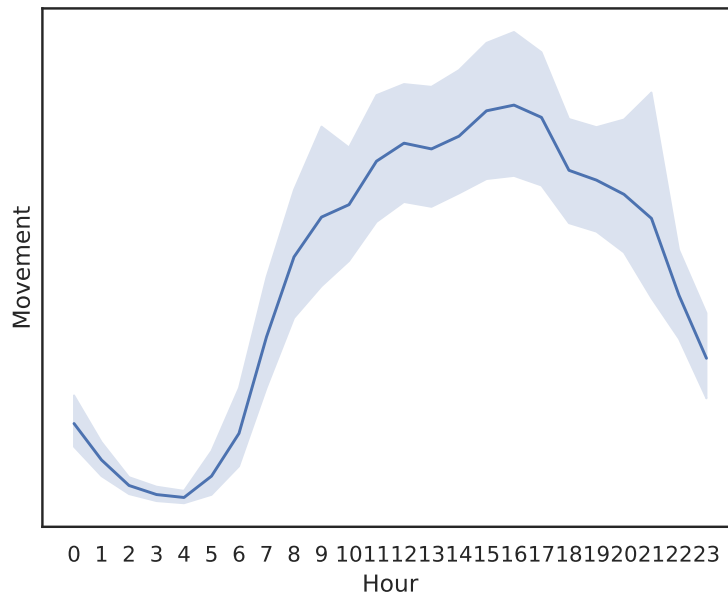


Figure 4.22: Mean movement for each hour of the day for all subjects.

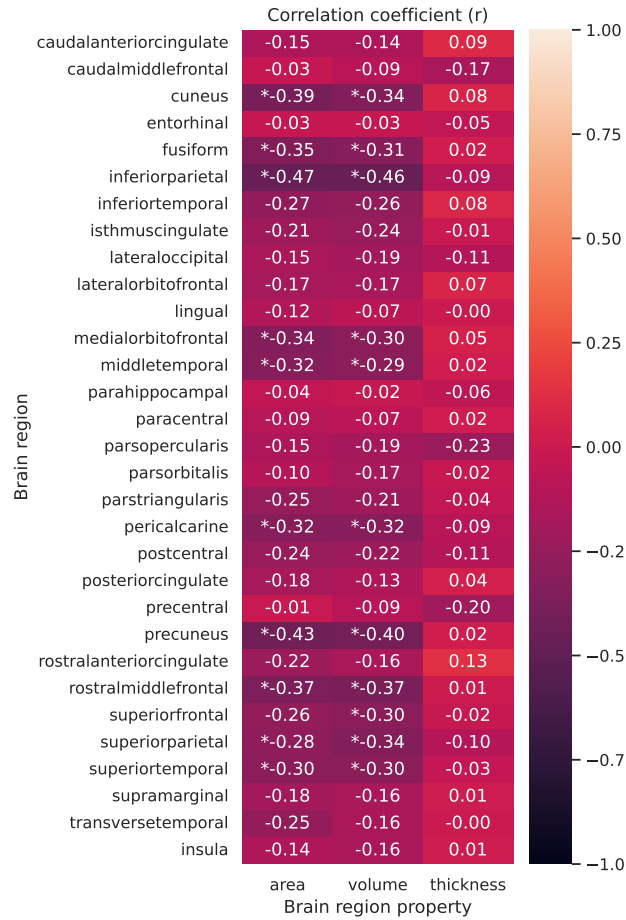


Figure 4.23: Correlation matrix between the movement during sleep and the brain region properties. Asterisks represent values with a p-value under 0.05.

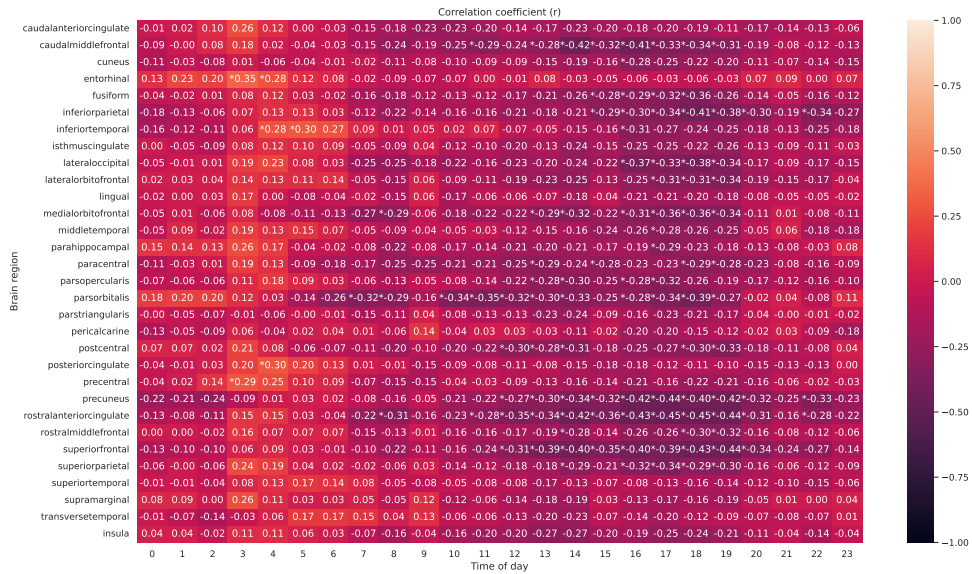


Figure 4.24: Correlation matrix between the movement and the area of the brain regions for every hour. Asterisks represent values with a p-value under 0.05.

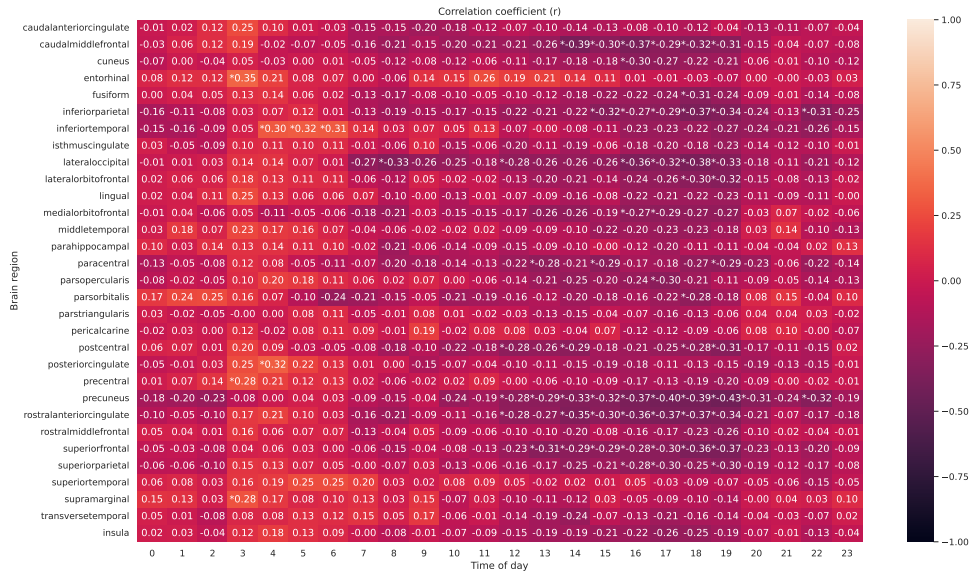


Figure 4.25: Correlation matrix between the movement and the gray matter volume of the brain regions for every hour. Asterisks represent values with a p-value under 0.05.

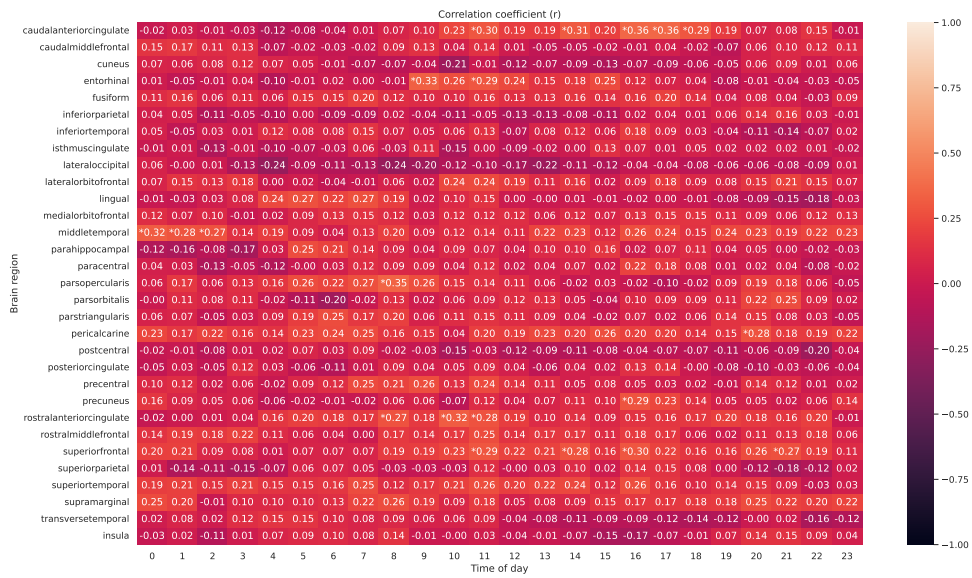


Figure 4.26: Correlation matrix between the movement and the cortical thickness of the brain regions for every hour. Asterisks represent values with a p-value under 0.05.

## Chapter 5

# Discussion

### 5.1 Correlation Between HRV and BPM

As can be seen in figures 4.1, 4.2, and 4.3, there is a correlation between the heart rate and heart rate variability in the data. This correlation was also found in other studies [20]. This suggests that the PPG data coming from the smartwatches, with some processing, was reliable enough to reproduce the correlation between these two cardiovascular metrics.

### 5.2 Detection of Activity

Looking at figures 4.5 and 4.4, it is clear that the heart rate of a person is higher during the day. Looking at 4.22, it is also clear that the subjects moved a lot less during the night than during the day. In both cases, the variance was a lot higher during the day, which could indicate that there is some variability in the amount and intensity of activity performed by the subjects and that people's nights are a lot more similar. The heart rate variability however had a lot more variance throughout the day, which could indicate that it is a better indicator or that it is harder to compute precisely. The average heart rate variability was also higher during the night, which fits with the correlation stated previously.

### 5.3 Precentral Gyrus

A correlation was found between both the surface area and gray matter volume of the precentral gyrus and the average heart rate of the subjects. This correlation appeared mostly in the morning and evening. A negative correlation between the average heart rate would mean that the people with a higher average heart rate tend to have a smaller precentral gyrus. This could also indicate that the resting heart rate of the subjects is related to the size of their precentral gyrus.

The correlation is easier to visualize in figure 5.1, where we can see the correlation for both the surface area ( $r(50) = -.34, p = .012$ ) and the gray matter volume ( $r(50) = -.36, p = .008$ ).

This correlation could be explained by the fact that the precentral gyrus is responsible for voluntary movements and that exercise can reduce a person's resting heart rate [29]. It could be that a person who exercises more has a lower resting heart rate and uses their body more, which would be linked to the size of their precentral gyrus.

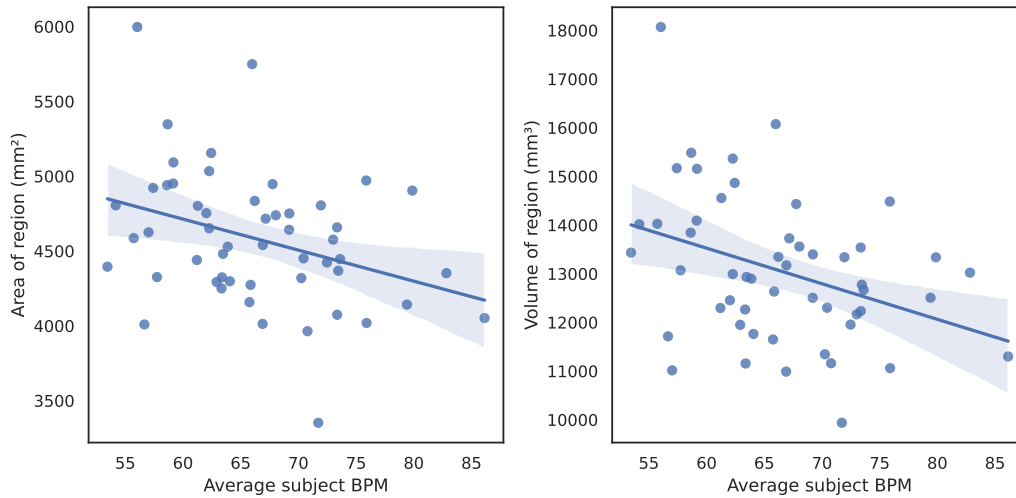


Figure 5.1: Correlation between average subject BPM and area and volume of their precentral gyrus

## 5.4 Parahippocampal Gyrus

The negative correlation between the area of the surface of the parahippocampal gyrus of the subjects and their heart rate variability could be partly explained by the correlation with its gray matter volume found in other studies [25] and the fact that the surface area and gray matter volume are correlated [40].

There would be further investigation needed to find why the results of this study did not suggest a correlation between the gray matter volume of the parahippocampal gyrus and the heart rate variability of the subjects.

## 5.5 Inferior Parietal Lobule

The results of this study suggested a negative correlation between the cortical thickness of the inferior parietal lobule and the average heart rate of the subjects at night. In general, the subjects with the lower heart rate at night had a thicker cortical region in the inferior parietal lobule.

It has been suggested in other studies that the inferior parietal lobule is important for dreams to happen [27]. It is also suggested that a person's heart rate can vary when entering and during rapid eye movement (REM) sleep, which is when dreams occur [6]. The combination of these findings could suggest that there is indeed a correlation between the thickness of a person's inferior parietal lobule and their heart rate during the night.

Also, the correlations found in figure 4.23 would suggest that subjects who had more sleep disturbance had inferior parietal lobules with more volume and surface area. This would make sense if increased dreams caused increased movement during the night and the inferior parietal lobule is the cause of these dreams.

## 5.6 Lateral Orbitofrontal Cortex

Another strong correlation that was found in the results of this study is the positive correlation between the heart rate variability of the subjects and the cortical thickness of their lateral orbitofrontal cortex. This correlation was present for almost every hour of the day, and even when the average HRV of the subject for all hours was computed as shown in figure 5.2 ( $r(50) = -.39, p = .004$ ). This correlation matches what was found in other studies [28] [21] [22]. Being able to find this correlation with the results from the smartwatch data could suggest that it would be possible to track this using wearable devices.



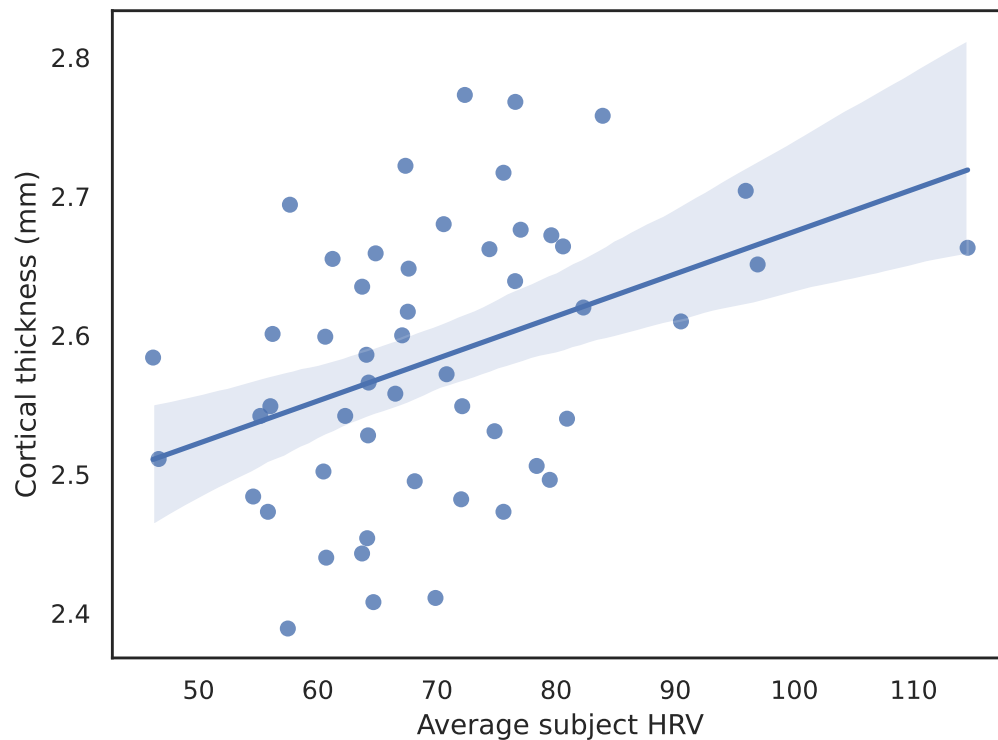


Figure 5.2: Correlation between average subject HRV and cortical thickness of their lateral orbitofrontal cortex

## 5.7 Precuneus

Studies have found that the precuneus could be related to sleep quality for people suffering from major depression [24]. This could be represented in figure 4.23 as subjects who had more sleep disturbance, or lesser quality sleep, also had less surface area and gray matter volume in the precuneus. Although no data related to the mental state of the patients was recorded for this study, this result could still be relevant.

## 5.8 Conclusion and Next Steps

Some correlations could be found using the smartwatch data and some of them match the correlations from the literature. However, a lot of other correlations found in other studies [39] were not present in the results from this study. Also, some correlations were found in the results of this study that could not be corroborated in other research.

That said, some correlations found in this study show that the data coming from smartwatches could be used to predict some of the phenotypes of some brain regions. Some of these correlations have even been found with heart rate variability, which requires a lot of precision. It would be interesting to see if other correlations could be found on devices with sensors with faster sampling rates.

Further research should be done regarding the use of smartwatches to detect anomalies or track the changes in some of the phenotypes over time.

# Bibliography

- [1] M. A. ALMARSHAD, M. S. ISLAM, S. AL-AHMADI, AND A. S. BAHAMMAM, *Diagnostic features and potential applications of ppg signal in healthcare: A systematic review*, *Healthcare*, 10 (2022).
- [2] B. J. ANDERSON, P. B. ECKBURG, AND K. I. RELUCIO, *Alterations in the thickness of motor cortical subregions after motor-skill learning and exercise*, *Learn Mem*, 9 (2002), pp. 1–9.
- [3] APPLE, *Take an ECG with the ECG app on Apple Watch — support.apple.com*. <https://support.apple.com/en-ca/HT208955>, 2023. [Accessed 09-03-2024].
- [4] CADTH, *Use of mri and ct in private imaging facilities in canada (2021-2023)*, *Canadian Journal of Health Technologies*, 3 (2023).
- [5] ———, *Wait list strategies for ct and mri scans*, *Canadian Journal of Health Technologies*, 3 (2023).
- [6] C. CAJOCHEN, J. PISCHKE, D. AESCHBACH, AND A. A. BORBÉLY, *Heart rate dynamics during human sleep*, *Physiology & Behavior*, 55 (1994), p. 769–774.
- [7] D. CASTANEDA, A. ESPARZA, M. GHAMARI, C. SOLTANPUR, AND H. NAZERAN, *A review on wearable photoplethysmography sensors and their potential future applications in health care*, *Int. J. Biosens. Bioelectron.*, 4 (2018), pp. 195–202.
- [8] P. H. CHARLTON, P. KYRIACOU, J. MANT, AND J. ALASTRUEY, *Acquiring wearable photoplethysmography data in daily life: The ppg diary pilot study*, *Engineering Proceedings*, 2 (2020).
- [9] P. H. CHARLTON AND V. MAROZAS, *12 - wearable photoplethysmography devices*, in *Photoplethysmography*, J. Allen and P. Kyriacou, eds., Academic Press, 2022, pp. 401–439.
- [10] L. CRUMBIE, *Topography of the cerebral hemispheres — kenhub.com*. <https://www.kenhub.com/en/library/anatomy/topography-of-the-cerebral-hemispheres>. [Accessed 08-03-2024].

- [11] S. S. S. DAS, S. K. SHANTO, M. RAHMAN, M. S. ISLAM, A. H. RAHMAN, M. M. MASUD, AND M. E. ALI, *Bayesbeat: Reliable atrial fibrillation detection from noisy photoplethysmography data*, Proc. ACM Interact. Mob. Wearable Ubiquitous Technol., 6 (2022).
- [12] C. DOMINGOS, M. PICÓ-PÉREZ, R. MAGALHÃES, M. MOREIRA, N. SOUSA, J. M. PÊGO, AND N. C. SANTOS, *Free-living physical activity measured with a wearable device is associated with larger hippocampus volume and greater functional connectivity in healthy older adults: An observational, cross-sectional study in northern Portugal*, Frontiers in Aging Neuroscience, 13 (2021).
- [13] K. I. ERICKSON, R. L. LECKIE, AND A. M. WEINSTEIN, *Physical activity, fitness, and gray matter volume*, Neurobiology of Aging, 35 (2014), pp. S20–S28. International Conference on Nutrition and the Brain.
- [14] B. FISCHL, *Freesurfer*, NeuroImage, 62 (2012), pp. 774–781. 20 YEARS OF fMRI.
- [15] S. D. GALE AND T. HUFF, *Cortical Thickness*, Springer International Publishing, Cham, 2017, pp. 1–2.
- [16] GARMIN, *How to Use the ECG App | ECG App | Health Science | Garmin Technology | Garmin — garmin.com*. <https://www.garmin.com/en-US/garmin-technology/health-science/ecg/use/>. [Accessed 09-03-2024].
- [17] C. GASER AND G. SCHLAUG, *Gray matter differences between musicians and non-musicians*, Annals of the New York Academy of Sciences, 999 (2003), pp. 514–517.
- [18] N. ISAKADZE AND S. S. MARTIN, *How useful is the smartwatch ECG?*, Trends Cardiovasc. Med., 30 (2020), pp. 442–448.
- [19] D. JARCHI, D. SALVI, L. TARASSENKO, AND D. A. CLIFTON, *Validation of instantaneous respiratory rate using reflectance PPG from different body positions*, Sensors (Basel), 18 (2018), p. 3705.
- [20] S. Z. H. KAZMI, H. ZHANG, W. AZIZ, O. MONFREDI, S. A. ABBAS, S. A. SHAH, S. S. H. KAZMI, AND W. H. BUTT, *Inverse correlation between heart rate variability and heart rate demonstrated by linear and nonlinear analysis*, PLoS One, 11 (2016), p. e0157557.
- [21] J. KOENIG, B. ABLER, I. AGARTZ, T. ÅKERSTEDT, O. A. ANDREASSEN, M. ANTHONY, K.-J. BÄR, K. BERTSCH, R. C. BROWN, R. BRUNNER, L. CARNEVALI, H. D. CRITCHLEY, K. R. CULLEN, E. J. C. DE GEUS, F. DE LA CRUZ, I. DZIOBEK, M. D. FERGER, H. FISCHER, H. FLOR, M. GAEBLER, P. J. GIANAROS, M. J. GIUMMARRA, S. G. GREENING, S. GUENDELMAN, J. A. J. HEATHERS, S. C. HERPERTZ, M. X. HU, S. JENTSCHKE, M. KAESS, T. KAUFMANN, B. KLIMES-DOUGAN, S. KOELSCH, M. KRAUCH, D. KUMRAL,

- F. LAMERS, T.-H. LEE, M. LEKANDER, F. LIN, M. LOTZE, E. MAKOVAC, M. MANCINI, F. MANCKE, K. N. T. MÅNSSON, S. B. MANUCK, M. MATHER, F. MEETEN, J. MIN, B. MUELLER, V. MUENCH, F. NEES, L. NGA, G. NILSONNE, D. ORDONEZ ACUNA, B. OSNES, C. OTTAVIANI, B. W. J. H. PENNINX, A. PONZIO, G. R. POUDEL, J. REINELT, P. REN, M. SAKAKI, A. SCHUMANN, L. SØRENSEN, K. SPECHT, J. STRAUB, S. TAMM, M. THAI, J. F. THAYER, B. UBANI, D. J. VAN DER MEE, L. S. VAN VELZEN, C. VENTURA-BORT, A. VILLRINGER, D. R. WATSON, L. WEI, J. WENDT, M. W. SCHREINER, L. T. WESTLYE, M. WEYMAR, T. WINKELMANN, G.-R. WU, H. J. YOO, AND D. S. QUINTANA, *Cortical thickness and resting-state cardiac function across the lifespan: A cross-sectional pooled mega-analysis*, *Psychophysiology*, 58 (2021), p. e13688.
- [22] J. KOENIG, P. PARZER, C. REICHL, A. ANDO, J. F. THAYER, R. BRUNNER, AND M. KAESS, *Cortical thickness, resting state heart rate, and heart rate variability in female adolescents*, *Psychophysiology*, 55 (2018), p. e13043.
- [23] W. LAPIDAIRE, A. S. URRILA, E. ARTIGES, R. MIRANDA, H. VULSER, P. BÉZIVIN-FRERE, H. LEMAÎTRE, J. PENTTILÄ, T. BANASCHEWSKI, A. L. W. BOKDE, U. BROMBERG, C. BÜCHEL, P. J. CONROD, S. DESRIVIÈRES, V. FROUIN, J. GALLINAT, H. GARAVAN, P. GOWLAND, A. HEINZ, B. ITTERMANN, D. PAPADOPOULOS-ORFANOS, T. PAUS, M. N. SMOLKA, G. SCHUMANN, M.-L. P. MARTINOT, J.-L. MARTINOT, AND IMAGEN CONSORTIUM, *Irregular sleep habits, regional grey matter volumes, and psychological functioning in adolescents*, *PLoS One*, 16 (2021), p. e0243720.
- [24] L. MA AND C. ZHANG, *The function and structure of precuneus is associated with subjective sleep quality in major depression*, *Frontiers in Psychiatry*, 12 (2022).
- [25] P. S. MATUSIK, C. ZHONG, P. T. MATUSIK, O. ALOMAR, AND P. K. STEIN, *Neuroimaging studies of the neural correlates of heart rate variability: A systematic review*, *J. Clin. Med.*, 12 (2023), p. 1016.
- [26] A. A. MERCADANTE AND P. TADI, *Neuroanatomy, gray matter*, in *StatPearls*, StatPearls Publishing, 2023.
- [27] E. F. PACE-SCHOTT, *Chapter 44 - the neurobiology of dreaming*, in *Principles and Practice of Sleep Medicine (Fourth Edition)*, M. H. Kryger, T. Roth, and W. C. Dement, eds., W.B. Saunders, Philadelphia, fourth edition ed., 2005, pp. 551–564.
- [28] S. RAMANOËL, E. HOYAU, L. KAUFFMANN, F. RENARD, C. PICHAT, N. BOUDIAF, A. KRAINIK, A. JAILLARD, AND M. BACIU, *Gray matter volume and cognitive performance during normal aging. a voxel-based morphometry study*, *Front. Aging Neurosci.*, 10 (2018).
- [29] A. K. REIMERS, G. KNAPP, AND C.-D. REIMERS, *Effects of exercise on the resting heart rate: A systematic review and meta-analysis of interventional studies*, *J. Clin. Med.*, 7 (2018), p. 503.

- [30] M. REUTER, N. J. SCHMANSKY, H. D. ROSAS, AND B. FISCHL, *Within-subject template estimation for unbiased longitudinal image analysis*, *NeuroImage*, 61 (2012), pp. 1402–1418.
- [31] SAMSUNG, *Galaxy Watch Active2 (44mm), Aqua Black (Bluetooth) Wearables - SM-R820NZKAXAR | Samsung US — samsung.com*. <https://www.samsung.com/us/mobile/wearables/smartwatches/galaxy-watch-active2-44mm-aqua-black-bluetooth-sm-r820nzkaxar/>. [Accessed 15-03-2024].
- [32] —, *How do I measure the ECG on Galaxy Watch device? — samsung.com*. [https://www.samsung.com/africa\\_en/support/mobile-devices/how-do-i-measure-the-ecg-on-galaxy-watch-device/](https://www.samsung.com/africa_en/support/mobile-devices/how-do-i-measure-the-ecg-on-galaxy-watch-device/). [Accessed 09-03-2024].
- [33] N. SCHMANSKY, *FreeSurferAnalysisPipelineOverview - Free Surfer Wiki — surfer.nmr.mgh.harvard.edu*. <https://surfer.nmr.mgh.harvard.edu/fswiki/FreeSurferAnalysisPipelineOverview>. [Accessed 23-03-2024].
- [34] S. K. SHANTO, *Raw data collection from sensors of tizen device*. <https://github.com/Subangkar/Tizen-Sensor-Raw-Data-Saving-Service>. [Accessed 09-03-2024].
- [35] S. STEWART, *Lobes of the brain — kenhub.com*. <https://www.kenhub.com/en/library/anatomy/lobes-of-the-brain>, 2023. [Accessed 07-03-2024].
- [36] P. VAN GENT, H. FARAH, N. NES, AND B. AREM, *Analysing noisy driver physiology real-time using off-the-shelf sensors: Heart rate analysis software from the taking the fast lane project*. unpublished, 11 2018.
- [37] P. VAN GENT, H. FARAH, N. VAN NES, AND B. VAN AREM, *Heartpy: A novel heart rate algorithm for the analysis of noisy signals*, *Transportation Research Part F: Traffic Psychology and Behaviour*, 66 (2019), pp. 368–378.
- [38] P. VIRTANEN, R. GOMMERS, T. E. OLIPHANT, M. HABERLAND, T. REDDY, D. COURNAPEAU, E. BUROVSKI, P. PETERSON, W. WECKESSER, J. BRIGHT, S. J. VAN DER WALT, M. BRETT, J. WILSON, K. J. MILLMAN, N. MAYOROV, A. R. J. NELSON, E. JONES, R. KERN, E. LARSON, C. J. CAREY, İ. POLAT, Y. FENG, E. W. MOORE, J. VANDERPLAS, D. LAXALDE, J. PERKTOLD, R. CIMRMAN, I. HENRIKSEN, E. A. QUINTERO, C. R. HARRIS, A. M. ARCHIBALD, A. H. RIBEIRO, F. PEDREGOSA, P. VAN MULBREGT, AND SCIPY 1.0 CONTRIBUTORS, *SciPy 1.0: Fundamental Algorithms for Scientific Computing in Python*, *Nature Methods*, 17 (2020), pp. 261–272.
- [39] T. WINKELMANN, J. F. THAYER, S. POHLACK, F. NEES, O. GRIMM, AND H. FLOR, *Structural brain correlates of heart rate variability in a healthy young adult population*, *Brain Structure and Function*, 222 (2016), p. 1061–1068.

- [40] A. M. WINKLER, P. KOCHUNOV, J. BLANGERO, L. ALMASY, K. ZILLES, P. T. FOX, R. DUGGIRALA, AND D. C. GLAHN, *Cortical thickness or grey matter volume? the importance of selecting the phenotype for imaging genetics studies*, *NeuroImage*, 53 (2010), pp. 1135–1146. Imaging Genetics.
- [41] H. J. YOO, K. NASHIRO, J. MIN, C. CHO, S. L. BACHMAN, P. NASSERI, S. PORAT, S. DUTT, V. GRIGORYAN, P. CHOI, J. F. THAYER, P. M. LEHRER, C. CHANG, AND M. MATHER, *Heart rate variability (HRV) changes and cortical volume changes in a randomized trial of five weeks of daily HRV biofeedback in younger and older adults*, *Int. J. Psychophysiol.*, 181 (2022), pp. 50–63.