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Analysis of EEG signals to assess emotionality and well-being.

Degree in Biomedical Engineering

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Abstract

The purpose of this project is to look into the neural correlates of trait emotional intelligence. This study uses statistical analysis and machine learning to evaluate the relationship between EEG data and the psychological constructs emotionality and well-being, two components of the *Trait Emotional Intelligence Questionnaire*.
This project's data is derived from the paper "*A mind-brain-body dataset of MRI, EEG, cognition, emotion, and peripheral physiology in young and elderly individuals*" published in Scientific Data no6 (Article number: 180308) (Mikolajczak, Bodarwé, Laloyaux, Hansenn, & Nelis, 2010) .There is a hyperlink in this article to a publicly available database called "LEMON database". The LEMON dataset includes 224 subjects who were subjected to various tests and brain analysis methodologies.

The context, hypothesis, objectives, development, outcomes, and conclusions are the six phases of this research. In the developed program, the data was sorted into 12 brain regions. The activity of each brain region was segmented into 5s intervals, which were subsequently used to characterize the band power corresponding to 5 different brain waves (i.e. delta, theta, alpha, beta and gamma).

Theta is the band with the most relevant differential activation, with beta coming in second. Notably, stronger correlations are found in well-being than in emotionality, with significant p-values being less than 0.01.
In general, however, we cannot discriminate between high-scores and low-scores for such constructs (i.e. emotion/well-being) on the basis of the characterized EEG activity since no apparent separation between the groups emerges from the machine learning techniques.

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GLOSSARY

- EEG – Electroencephalography
- rs-EEG - Resting Estate Electroencephalography
- EO – Eyes Open
- EC – Eyes Closed
- Trait EI – Trait Emotional Intelligence
- TEIQue-SF - Trait Emotional Intelligence Questionnaire - Short Form
- BR – Brain Regions
- PSD - Power Spectral Density
- PCA – Principal Component Analysis

1. INTRODUCTION

This section provides the context to the problem that the final degree project tackles, indicates its motivation, and presents the structure that this document will follow.

In 2001, Petrides proposed the trait Emotional Intelligence (Trait EI) hypothesis, which defined the so-called emotional perceptions as (Petrides, 2009): "*what our emotional dispositions are and how good we believe we are in perceiving, understanding, managing, and utilizing our own and other people's emotions*" (Pérez, Saklofske, & Mavroveli, 2020). However, <u>can we find any patterns in the brain, which correlate with such perceptions</u>?

This study aimed to investigate the brain correlates of trait emotional intelligence, with special focus on **well-being** and **emotionality**, the two variables involved in the Trait EI test. On one hand, well-being is understood as a feeling across time, which is based around achievements, self-regard, and expectations. On the other hand, emotionality is regarded as the ability to perceive, express, and connect with emotions in self and others. Remarkably, few works (King, 2019) have been done in the well-being area. In this research, I aim to know more about this feature and elucidate whether this feature can tell us more about us. The few work that has been done point out different brain activations but the most concurrent one is the <u>posterior part of the brain</u> (King, 2019).
Similarly, emotionality is also a characteristic that has not received much attention. In contrast, the study of emotions and their neural correlates have been thoroughly investigated. In particular, it has been seen that emotions elicit most activity in the temporal lobe. Emotionality, in contrast, seems to be more related with activity in the <u>frontal part of the brain</u> (Palmiero & Piccardi, 2017).

The data I work on in this project is extracted from the article "*A mind-brain-body dataset of MRI, EEG, cognition, emotion, and peripheral physiology in young and old adults*" Anahit Babayan (principal author) in the journal Scientific Data nº6 (Article number: 180308 (2019)). In this article there is a link to a publicly available database named "*LEMON database*". The LEMON dataset consists of 224 participants that had submit to different test and brain analysis techniques: such us MRI, EEG, Cognitive test battery, Emotion and Personality Test Battery.

This research is divided in 6 steps: The context, hypothesis, objectives, development, results, and conclusions.

Through statistical analysis and machine learning, this project attempts to examine EEG data in order to measure and distinguish activity from emotionality and well-being.
The sequence of this study is as follows: state of the art, definition of the hypothesis and the goals to be achieved. Then, the overall methodology is presented. Finally, the results obtained, and the conclusions thereby derived are presented.

As shown in Figure 1, EEG raw data and a Trait Emotional Intelligence Questionnaire test were available from 225 participants. From the Trait Emotional Intelligence Questionnaire, no further process was need.

In the LEMON database, preprocessed resting state electroencephalography[1] (rs-EEG) data was available. So, all that remained was to organize the data to make it more suited, given that there are two files (EO and EC), each having 61 channels for each subject. The data was organized in 12 brain areas, and segmented into 5 s epochs. Such activity was subsequently characterized by the band power in distinct brain waves.

Once the data is acquired, the analysis and Machine Learning approach between each individual's Trait Emotional Intelligence Questionnaire and the Band Power indicated in the previous paragraph begin. As an outcome, the pattern of rs-EEG recordings in the frontal regions was highly related to emotional intelligence. In the **well-being** parameters, the temporal region displays significant rates in the p-value analysis. We may find stronger findings in well-being than in emotionality, with the p-value in the significant values consistently being less than 0.01. Globally, theta is the band with the most noteworthy activation, with beta coming in second. In general, we cannot tell whether a person has more or less emotion/well-being punctuation also since there is no apparent separation between the groups in the machine learning technique.

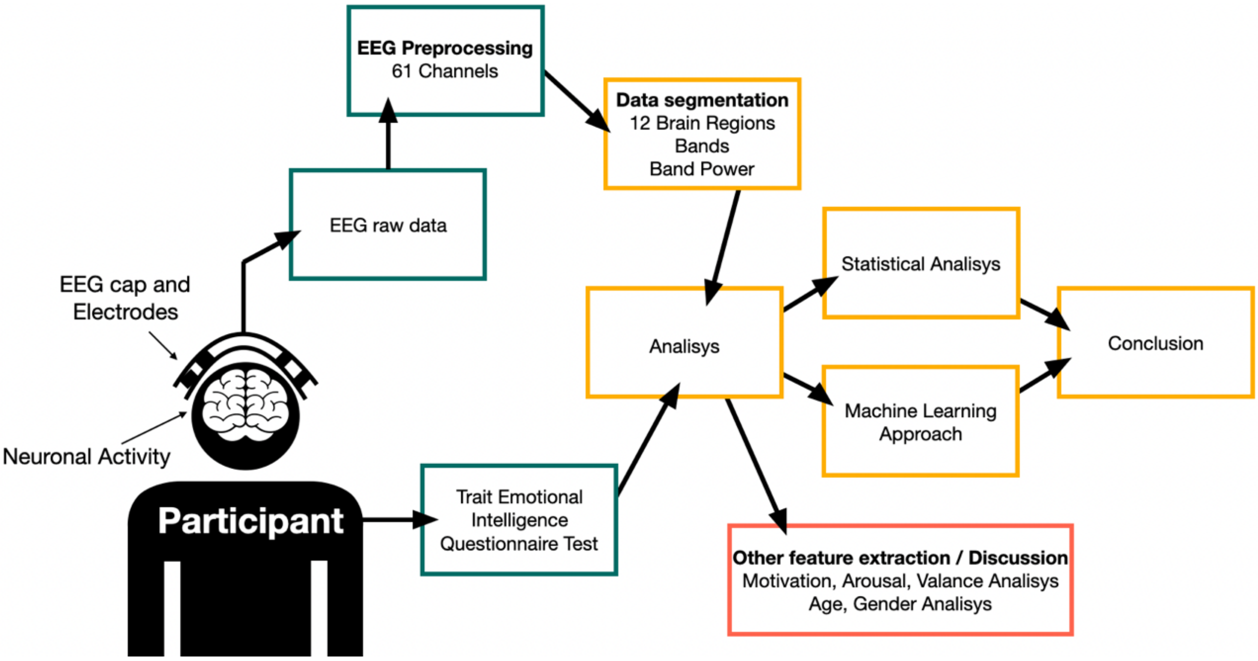

Figure 1: Project Structure: Divided in colors green, process done by the article; yellow, part developed in this project; orange, other feature analysis.

[1] Rs-EEG: The resting state EEG studies are used to assess intrinsic brain activity that isn't induced by a task.

2. CONTEXT

Next, we will see a summary of the state-of-the-art in the fields of **Trait Emotional Intelligence Questionnaire** (TEIQue-SF), as well as a brief review of the different **techniques to obtain functional brain data**.

2.1 Neuropsychological background

What exactly is a neuropsychological evaluation? It is an evaluation of how one's brain operates, which offers indirect information regarding the anatomical and functional integrity of your brain indirectly. A neuropsychological test is one of the components of this investigation. This exam is designed to learn more about how the brain works; it is standardized, which means that it is administered the same way every time.
Individual test scores are interpreted by comparing it to those of healthy individuals with comparable demographic backgrounds (i.e., same age, education, gender, and/or ethnic origin). Neuropsychological tests evaluate functioning in a number of areas including; intelligence, executive functions, attention, memory, language, perception, sensorimotor functions, motivation, mood state and emotion, quality of life, and personality styles (Department of Neurology, s.f.).

Trait Emotional Intelligence Questionnaire (TEIQUE) is a configuration of emotion-related traits, capturing the scope to which people experience, attend, identify, understand, regulate, and utilize their emotions and those of others (Petrides K. , 2019). In the article "*Construct and concurrent validity of the short- and long-form versions of the trait emotional intelligence questionnaire*" they review the validity[2] of the test. (Laborde, Allen, & Guillén, 2016).

Some reviews conclude that TEIQue (Trait Emotional Intelligence Questionnaire) is a questionnaire which is significantly more reliable for characterizing trait EI than other questionnaires (Gardner, Qualter, & Tremblay, 2010). In this research, the emotion-related data was measured by means of the so-called Trait Emotional Intelligence Questionnaire - Short Form (TEIQue-SF) (Petrides, 2009). In fact, TEIQue inherently includes our two dimensions of interest: **well-being** and **emotionality** (besides Sociability, self-control and the general punctuation of all the dimensions). We will next review what has research taught us so far regarding these two dimensions.

[2] The validity of a test reflects how accurately it measures the theoretical construct it is designed to assess and if it can be utilized for its intended purpose.

2.1.1 Well-Being

The definition of well-being (King, 2019) is quite challenging since this concept can be understood in the context of many life domains (e.g. health, economics, or social relations, among others) and can also be examined from different perspectives (e.g. individual vs societal).

Kahneman Daniel, Diener, Edward, & Schwarz, Norbert (in the book Well-Being: Foundations of Hedonic Psychology) describe well-Being as a related feeling across time-based around achievements, self-regard, and expectations. (Kahneman Daniel, 2003)

Given the complexity in its definition, it was not until the 1960s that an increase in well-being research occurred. This move toward investigating well-being may reflect the growing awareness that well-being is not simply the absence of mental illness (Vàzquez, Hervás, Rahona, & Gómez, 2009).

Nevertheless, few works consider specifically the relation between **brain activity** and **well-being**. In a review of 22 studies[3] examining such association (King, 2019), each study shared the foundational aim to elucidate the relationship between well-being and the brain data; all the methods, and techniques by which this relationship was investigated proved heterogeneous across the literature. Overall, it became clear that generally speaking the following brain areas: **frontal lobe, parietal lobe, and temporal lobe** are the ones that seem to have a more relevant role in the relation brain — well-being. But in terms of which brain wave is predominant in the brain — well-being relationship, there are no concluding results (King, 2019).

2.1.2 Emotionality

Emotionality has been defined as the ability to perceive, express, and connect with emotions in self and others, which can create successful interpersonal relationships (Petrides, 2009). High scores in emotionality equal a tendency to perceive and identify one's emotions as well as others (Mikolajczak, Bodarwé, Laloyaux, Hansenn, & Nelis, 2010).

Several studies have provided converging evidence that **frontal asymmetries** were determinants of emotion dispositions and behaviors (Mikolajczak, Bodarwé, Laloyaux, Hansenn, & Nelis, 2010). They hypothesized that the level of emotional intelligence might be associated with differential frontal activation. Notably, emotionality is not as studied as emotion itself.

Most of the research in the brain-emotionality relation analyzes the brain data in the frequencies between 8 – 12 Hz, i.e., **alpha waves**. Also, this frequency band is generally used in frontal asymmetry and emotion research (Palmiero & Piccardi, 2017).

[3] In these articles, it is worth noting that few participants were analyzed.

2.2 Technological background

Different sensors and imaging modality can be used to evaluate bio-signals in the Central nervous system (CNS). In the following table, we can see some non-invasive techniques together with their main features.

Table 1: Brain Techniques.

Technique	Advantages	Disadvantages
EEG	- Temporal resolution (1^5 ms) - Easily Available - Relatively Low-cost - Silent - Lower sensitiveness to movement	- Less Sensitive in subcortical structures
fMRI	- Good spatial resolution (3–4 mm) - Similar cortical and subcortical sensitivity - Whole-brain acquisition - Broad availability	- Low temporal resolution (5–6s) - Acoustically noisy - Indirect measure of neutral activity
PET	- Good spatial resolution (5-10 s) - Whole-brain analysis - Less sensitive motion artifacts	- Invasive - Low temporal resolution - Expensive
MEG	- High resolution of brain structure, temporal and spatial - Milliseconds temporal resolution	- Very expensive - Limited resolution for deem structures

In this project, EEG data was selected. In the following sections, we will see in more depth what the EEG technique consists of.

2.2.1 EEG, Brain-analyzing techniques

Electrical impulses allow brain cells to communicate with one another. Electroencephalogram (EEG) is a test that measures electrical activity in the brain by measuring the differences in electric potential at the scalp (the Excitatory systematic current seen in the figure 2). As a method for studying brain activity, EEG offers various advantages. EEGs can detect changes in milliseconds, which is impressive given that an action potential takes between 0.5 and 130 milliseconds to travel through a single neuron, depending on the kind of neuron.

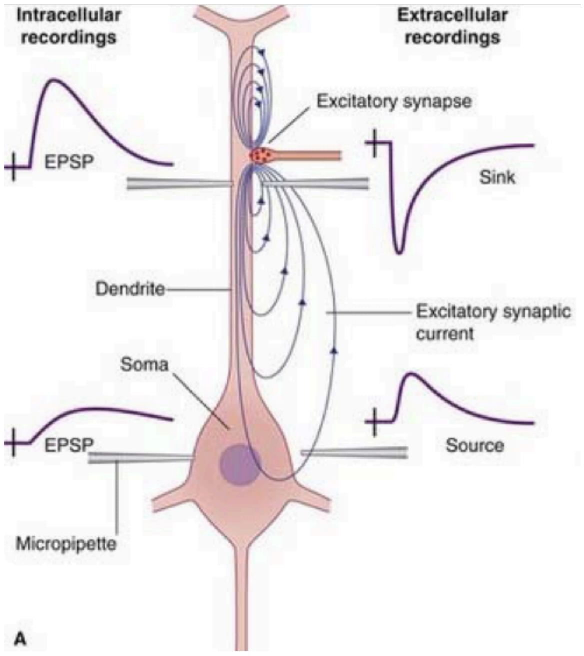

Figure 2: Excitatory Post-Synaptic Potential (EPSP): The depolarization of the postsynaptic cell is caused by the inflow of positive Na+ ions at the apical dendrites. (Source: (Holmes & Khazipov))

2.2.1.1 History Electroencephalography, EEG:

The history of clinical electroencephalography (EEG) has just passed the 70-year mark. However, Duboi-Reymoit (1848) was the first to report the presence of electricity in the human brain. In 1875, Caton utilized this discovery to measure the subtle electric changes in a rabbit's scalp. Then, in **1929**, **Hans Berger** created and recorded a clinical EEG. (JW, LC, JL, & et., 2016). From there EEG was widely used in physiocratic and neurological data.

2.2.1.2 Technical aspects of EEG data acquisition

For the EEG acquisition process, three components are required.

1. EEG cap
2. Amplifier
3. Data acquisition computer

The EEG cap is composed of a set of electrodes, small metal discs usually made of stainless steel, tin, gold, or silver covered with a silver chloride coating. These electrodes are positioned in a standardized location stipulated by the 10-20, 10-10, or 10-05 International System of Electrode Placement, a unified system (Jurcak, Tsuzuki, & Dan, 2017) [9]. This project uses the 10-20 system, one of the most commonly used. This arrangement uses distances in percentages from a couple of fixed points on the head, as shown in Figure 3.

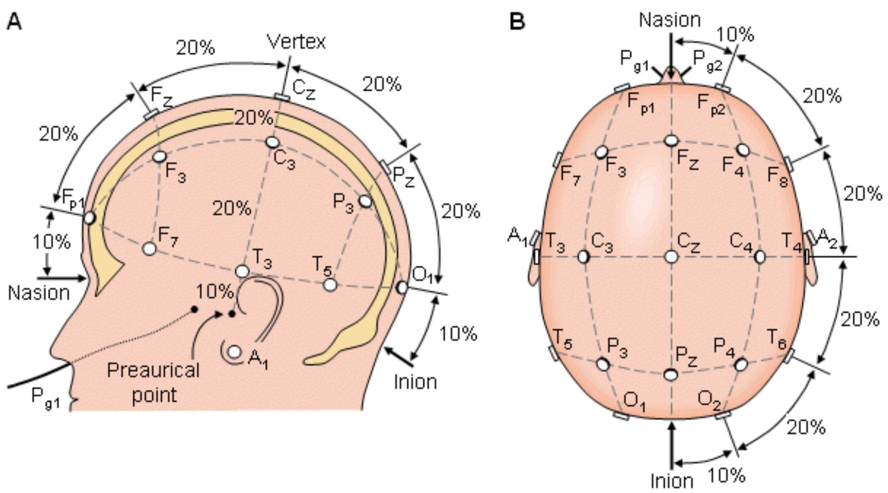

Figure 3: The 10-20 International System of Electrode Placement (Source: http://www.bem.fi/book/13/13.htm)

The EEG amplifier and the data acquisition computer are responsible for accommodating, amplifying, and converting the analog electrical signals from the EEG Cap into a digital signal that the computer can process. The signal is characterized by a series of parameters:

- The **sampling rate** describes the number of times the signal is measured (i.e. sampled) per unit of time. It is, thus, a frequency variable and is hence measured in Hertz (Hz) = 1 sample/second. The sampling rate should be at least twice the maximum frequency of the signal[4] being measured (Nyquist sampling theorem, Jones, 2014)

[4] EEG signals carry information within a bandwidth between 0.5 Hz and 80 Hz, and this bandwidth is referred to as the EEG bands in the power spectrum. In the part 2.2.1.4, we will see the waves.

- **Bandwidth**, effective frequency band that the EEG system can measure according to the sample rate and the internal filters of the amplifier.

- **Internal filters**: These typically include a low pass filter to agree with the Nyquist[5] theorem; and a high pass filter whose mission is to eliminate EEG offsets and DC components in order to avoid the saturation of internal electronics. Those amplifiers without high pass filters are called DC coupled.

2.2.1.4 Brain Waves

Our brains, as we all understand, are continually active. Even when we are sleeping, our brain's neurons are busy transmitting impulses. This electrical impulses are hence continuous and vary depending on our mental state. The frequency, amplitude, and shape of these waveforms, as well as the locations on the scalp where they are recorded, are often used to classify them:

Delta

Delta brain waves have low frequency and strong penetrating power, located between 2Hz[6] to 4Hz frequency. They are produced in deep sleep.

Theta

Theta brain waves are most common during sleep, but they also dominate during meditation (this would be also the frequency caused by tiredness or the early phases of sleep.) They can be found in the frequency between 4Hz and 8Hz.

Alpha

Alpha brain waves dominate the awake quite state or the static state of the brain. The frequency of alpha is comprised between 8-12 Hz.

Beta

Beta is a "quick" activity that occurs when we are alert, attentive, or involved in problem-solving, judgment, decision-making, or concentration activities. Frequencies are found between 12Hz – 30Hz.

[5] Nyquist's theorem states that a periodic signal must be sampled at more than twice the signal's highest frequency component.
[6] In different sources, the frequency can be stipulated a little bit differently; this divisions are from the book analyzing neural times series data, theory and practice, Mike X Cohen, 2014, page 33.

Lower gamma & Upper gamma

Gamma brain waves are the fastest brain waves (high frequency) and are identified with data from various brain regions districts simultaneously. Gamma mind waves can send data rapidly (As we can see in the Figure 4 compared to the other waves).

Gamma frequencies can be divided into gamma lower 30Hz-45Hz and upper gamma +45Hz.

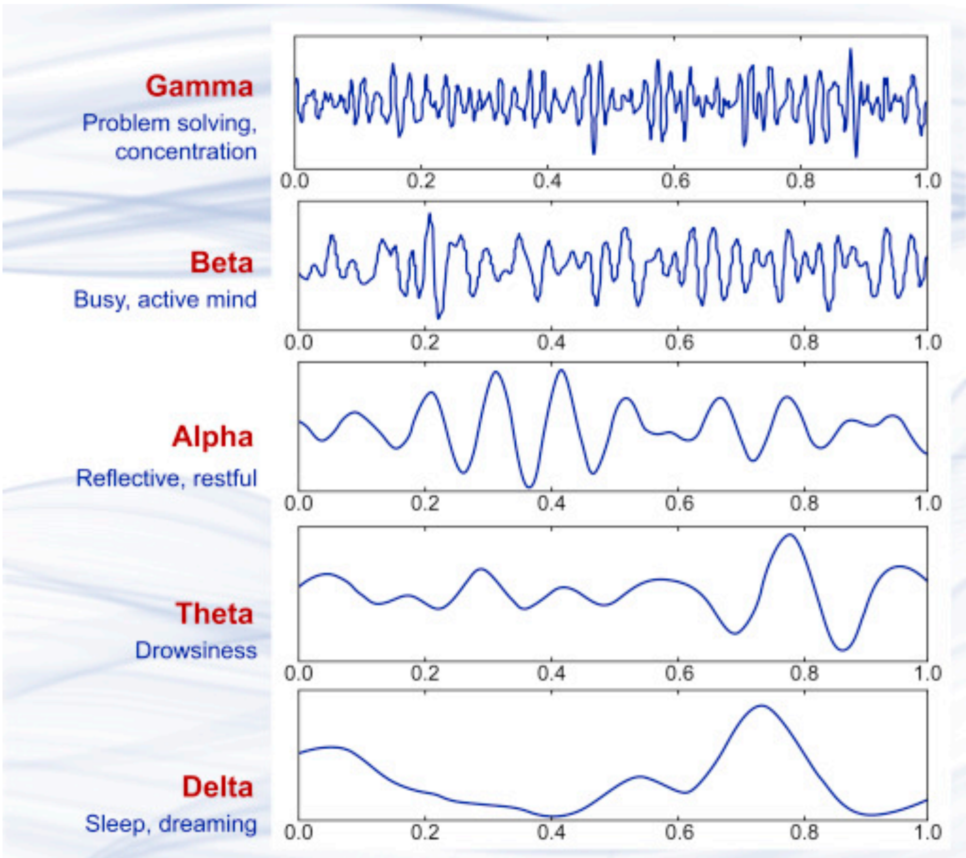

Figure 4: Brain wave samples with dominant frequencies belonging to beta, alpha, theta, and delta bands and gamma waves. (Source: (Abhang, Gawali, & Mehrotra, 2016)

3. Hypothesis

The purpose of the study is to investigate the relationship between brain activity (derived from rs-EEG data) and trait EI (assessed by the Trait Emotional Intelligence Questionnaire; TEIQue-SF).

3.1 Hypothesis 1 (Well-Being)

Our first hypothesis, grounded in previous research, aims at finding relevant answers to the following questions: Can we know where in the brain well-being is *located*? Does it occur mostly in a particular wave? Only looking at the EEG data, can we predict the well-being score of a specific participant (from 1 to 7 as the TEIQue-SF test)?

Based on state of the art, we can expect a correlation between well-being and brain activity in the **frontal lobe, parietal lobe, and temporal lobe zones.** Since the patients are in a relaxed/resting state, maybe we can expect in the **wave's theta** (Vàzquez, Hervás, Rahona, & Gómez, 2009). To the best of our knowledge, there are no studies on the predicting well-being on the basis of EEG activity. In the prediction of the well-being score we may contemplate for a correlation between the high well-being values and the low ones in the frontal lobe, parietal lobe, and temporal lobe zones.

3.2 Hypothesis 2 (Emotionality)

Our second hypothesis, grounded again in previous research, aims at finding relevant answers to the following questions: Could we determine which areas of the brain contain emotionality? Is this part of a certain wave? Could we tell the emotionality of a certain person (from 1 to 7 as measured by the TEIQue-SF test) just by looking at the EEG data?

Based on the state of the art, we can expect a correlation between emotionality and the brain in **frontal asymmetries**. As we have reviewed in the state of the art, we can expect to find such correlated in the **alpha waves**. There seems to be no study on the relationship between a person's emotionality score and brain data. In addition to determining the emotionality score, we can look for a correlation between high and low values in some frontal asymmetries.

4. Objectives

We can divide the objectives of this project into the research objectives and the academic goals.

Research Objectives of this project are:

- Exploring the neural traits of well-being, as assessed by rs-EEG data.
- Exploring the neural traits of emotionality, as assessed by rs-EEG data.
- Developing an algorithm for emotionality and well-being classification based on the analysis of the spectral components of the rs-EEG signals.

The **Academic goals** are:

- Understanding how to process and acquire EEG data.
- Developing a code to process the LEMON data set.
- Applying statistical analyses and machine learning approaches in the neuroscience domain.
- Perform an iterative process of dimensionality reduction, feature definition and classification until the classification performance is satisfying.
- Acknowledge how to analyze and interpret the results.

5. Methodology

In this section, we first present a brief description of the **dataset** considered in the study, and then the **tools** selected to process[7] and analyze the data.

5.1 THE LEMON DATABASE

This study uses a publicly available database named "LEMON database," published on 12th February 2019. All the data can be found in the following link: https://ftp.gwdg.de/pub/misc/MPI-Leipzig_Mind-Brain-Body-LEMON/. All the methods applied to obtain this data are explained in the article "*A mind-brain-body dataset of MRI, EEG, cognition, emotion, and peripheral physiology in young and old adults*" Anahit Babayan (principal author) in the journal Scientific Data nº6 (Babayan, Erbey, Kumral, & al., 2019).

In summary, the LEMON dataset is particularly suited to comprehensively relate cognitive and emotional traits or states to physiological characteristics of brain and body. While focusing on fundamental mind-body-emotion interactions in healthy younger and older adults.

As previously stated, several psychological evaluations (testing methods) were utilized to correlate data states to physiological features of the brain and body. The many tests that were used, some are listed below.

- **Cognitive test battery**: California Verbal Learning Task (CVLT), Test of Attentional Performance (TAP), Trail Making Test (TMT), California Verbal Learning Task, Wortschatztest (WST), Subtest 3 of the "Leistungsprüfsystem 2" (LPS-2), Regensburger Wortflüssigkeitstest (RWT).

- **Emotion and Personality Test Battery (18):** Big-Five of Personality (NEO-FFI), Impulsive Behavior Scale (UPPS), Behavioral Inhibition and Approach System (BIS/BAS), Emotion Regulation Questionnaire (ERQ), Cognitive Emotion Regulation Questionnaire (CERQ), Multidimensional Scale of Perceived Social Support (MSPSS), Optimism Pessimism Questionnaire-Revised (LOT-R), Perceived Stress Questionnaire (PSQ), Emotional Intelligence Questionnaire (TEIQue-SF), *More in the article* (Babayan, Erbey, Kumral, & al., 2019)

[7] All the processes will be explained; although some of them were already implemented by the authors Babayan et al. These parts will be labeled as LEMON data or indicated.

- **Physiological data**: Resting-state fMRI (70min) and Resting-state EEG (16min)

- **Others**: Seated Resting Blood Pressure, Peripheral Blood Sample Collection and Analysis, anthropometry and hair sample.

In the next subsections 5.1.1 and 5.1.2, we shall describe the experimental subjects recruited in the study and then the psychophysiological data used in this study, which includes: the Emotional Intelligence Questionnaire (TEIQue-SF) and the rs-EEG data.

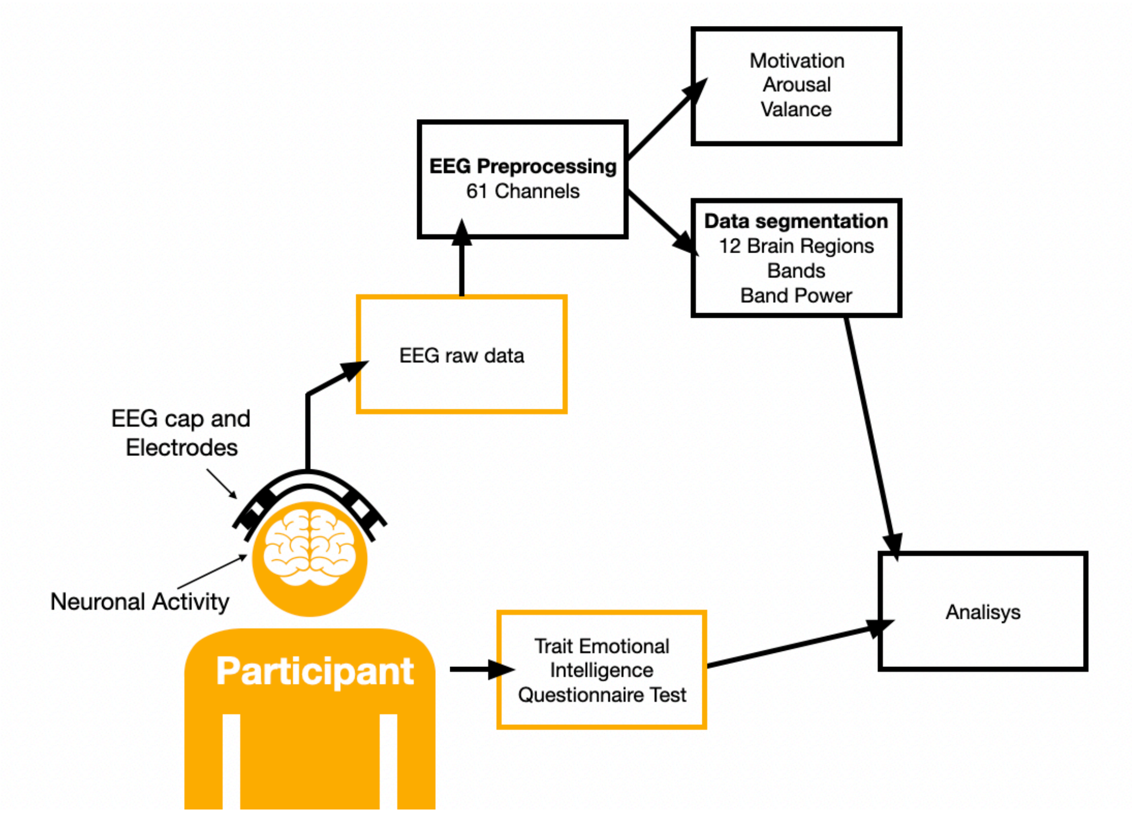

Figure 5: Methodology process scheme. In yellow the parts provided by the Lemon Dataset.

5.1.1 PARTICIPANTS

The LEMON data set contains registers from 227 participants. All subjects were assessed at the University Clinic Leipzig's Day Clinic for Cognitive Neurology and the Max Planck Institute for Human, Cognitive, and Brain Sciences (MPI CBS) in Leipzig, Germany for three days. In Figure 6 we can see the procedure done.

Due to missing event information, different sampling rates, mismatching header files, or corrupted files, 40 participants were excluded from the study. Out of the remaining 187 participants, 123 were males, and 64 were females. In this dataset, the subjects who completed the TeiQue-SF questionnaire were also divided into 9 age categories; '20-25': 79, '25-30': 60, '60-65': 19, '30-35': 13, '70-75': 22, '65-70': 25, '75-80': 4, '55-60': 4, '35-40': 1. Gender and age were not taken into account in this study. I present a gender and age-based analysis that was undertaken independently in the discussion section.

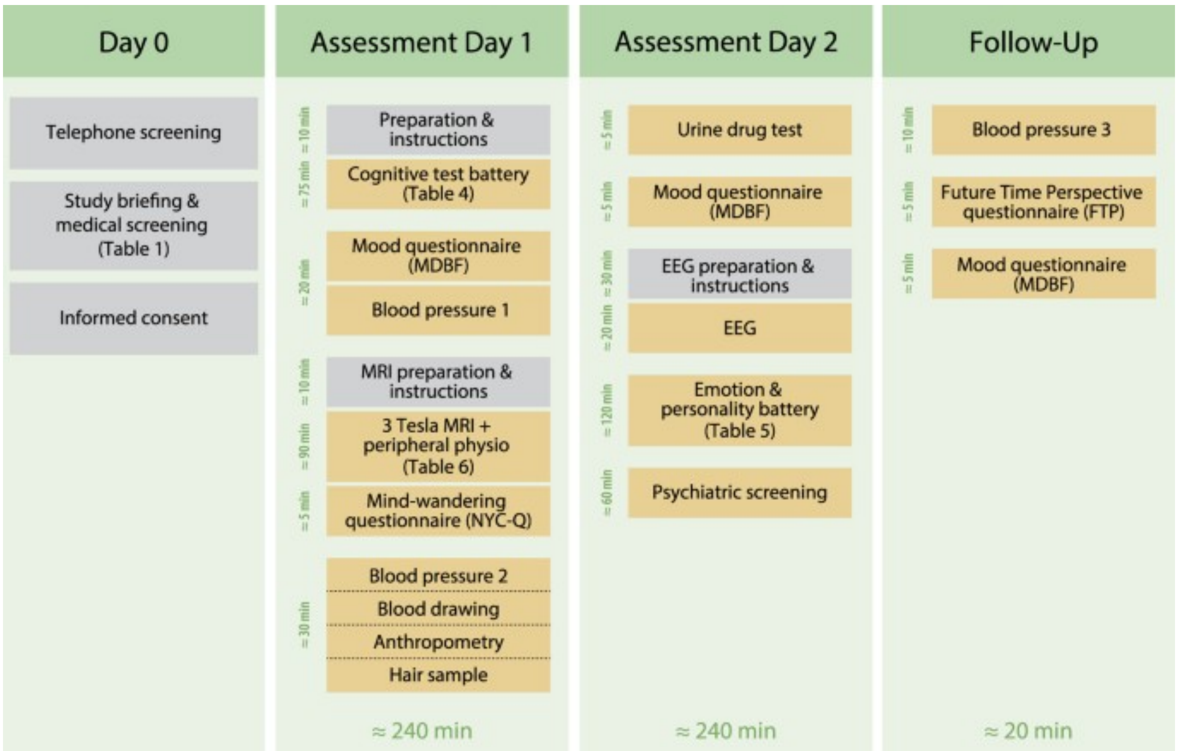

Figure 6: A summary of data gathering. On each assessment day, measures are listed in the order in which they were acquired and for how long. Extracted from (Babayan, Erbey, Kumral, & al., 2019).

5.1.2 Trait EI Questionnaire and rs-EEG data

From all the participants described in the previous section, both the scores from the Trait Emotional Intelligence Questionnaire and the rs-EEG data were extracted, and subsequently analyzed.

a) *TEIQue-SF ACQUISITION in the LEMON data set*

The short version of the 30-item Trait Emotional Intelligence Questionnaire (TEIQue-SF) is used to measure emotion-related dispositions and self-perception abilities (see the test in Figure 7). The scale contains four subscales of Well-being, Self-control, Emotionality, and Sociability, which can be averaged as a " Global Trait Emotional Intelligence " score. The answer is scored in a 7-point format, ranging from 1 (completely disagree) to 7 (completely agree).

In this project, only the well-being and emotionality features were selected from the TEIQue-SF to perform the analysis.

1 . . . . 2 . . . . 3 . . . . 4 . . . . 5 . . . . 6 7

Completely Disagree — **Completely Agree**

1. Expressing my emotions with words is not a problem for me.	1	2	3	4	5	6	7
2. I often find it difficult to see things from another person's viewpoint.	1	2	3	4	5	6	7
3. On the whole, I'm a highly motivated person.	1	2	3	4	5	6	7
4. I usually find it difficult to regulate my emotions.	1	2	3	4	5	6	7
5. I generally don't find life enjoyable.	1	2	3	4	5	6	7
6. I can deal effectively with people.	1	2	3	4	5	6	7
7. I tend to change my mind frequently.	1	2	3	4	5	6	7
8. Many times, I can't figure out what emotion I'm feeling.	1	2	3	4	5	6	7
9. I feel that I have a number of good qualities.	1	2	3	4	5	6	7
10. I often find it difficult to stand up for my rights.	1	2	3	4	5	6	7
11. I'm usually able to influence the way other people feel.	1	2	3	4	5	6	7
12. On the whole, I have a gloomy perspective on most things.	1	2	3	4	5	6	7
13. Those close to me often complain that I don't treat them right.	1	2	3	4	5	6	7
14. I often find it difficult to adjust my life according to the circumstances.	1	2	3	4	5	6	7
15. On the whole, I'm able to deal with stress.	1	2	3	4	5	6	7
16. I often find it difficult to show my affection to those close to me.	1	2	3	4	5	6	7
17. I'm normally able to "get into someone's shoes" and experience their emotions.	1	2	3	4	5	6	7
18. I normally find it difficult to keep myself motivated.	1	2	3	4	5	6	7
19. I'm usually able to find ways to control my emotions when I want to.	1	2	3	4	5	6	7
20. On the whole, I'm pleased with my life.	1	2	3	4	5	6	7
21. I would describe myself as a good negotiator.	1	2	3	4	5	6	7
22. I tend to get involved in things I later wish I could get out of.	1	2	3	4	5	6	7
23. I often pause and think about my feelings.	1	2	3	4	5	6	7
24. I believe I'm full of personal strengths.	1	2	3	4	5	6	7
25. I tend to "back down" even if I know I'm right.	1	2	3	4	5	6	7
26. I don't seem to have any power at all over other people's feelings.	1	2	3	4	5	6	7
27. I generally believe that things will work out fine in my life.	1	2	3	4	5	6	7
28. I find it difficult to bond well even with those close to me.	1	2	3	4	5	6	7
29. Generally, I'm able to adapt to new environments.	1	2	3	4	5	6	7
30. Others admire me for being relaxed.	1	2	3	4	5	6	7

Figure 7: The TeiQueSF Questions (Source: https://www.psychometriclab.com/adminsdata/files/The%20TEIQue-SF%20v.%201.50.pdf).

b) rs-EEG in the LEMON data set

The rs-EEG signals were recorded in an experiment that lasted 16-minutes. These registrations consist of 16 blocks, each 60 s long. Out of these blocks, 8 were acquired with eyes closed (EC), and 8 with eyes open (EO - the participants stayed awake while fixating eyes on a black cross presented on a white background). The two types of blocks were interspersed.

From each participant, the recordings included 62-channels (in Figure 8 the channels are represented), 61 scalp electrodes plus one electrode recording the VEOG below the right eye. The data was recorded using BrainAmp MR[8], and active ActiCAP electrodes. The ground was located at the sternum and the skin-electrode impedance was kept below 5 KΩ. The amplitude resolution was set to 0.1 µV. EEG was recorded with a bandpass filter between 0.015 Hz and 1 kHz and digitized with a sampling rate of 2500 Hz.

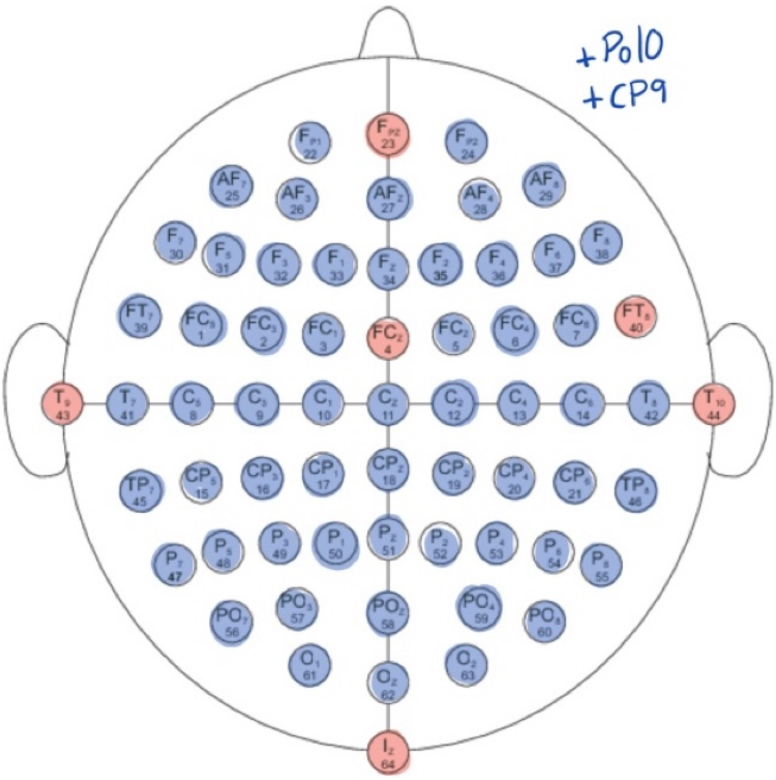

Figure 8: 61 Channels selected in the EEG recording in blue (the red ones are not included).

[8] Brain Amp is a shielded amplifier which can be taken directly inside the MRI chamber and placed in the bore right behind the subject's head (https://www.brainproducts.com/products_by_type.php?tid=1).

5.2 DATA PROCESSING

In a brief summary of the development, once we have the participants Trait Emotional Intelligence Questionnaire and EEG data. We select from the Trait Emotional Intelligence Questionnaire the elements of well-being and emotionality and collected EEG data. And, with this data, perform the following steps:

- Pre-processing of the EEG data (Already implemented in the LEMON database).
- Rearrange the data and extract the following features:
    - Spatial segmentation into 12 Brain Regions.
    - Spectral characterization.
    - Remove outliers.
- Statistical analysis of the data:
    - Correlation and p-value between band power and test scores.
    - Sorting the data into two groups (high-score *vs* low-score) and computing the rank-sum statistic and the p-value to assess data separability on the basis of band power.

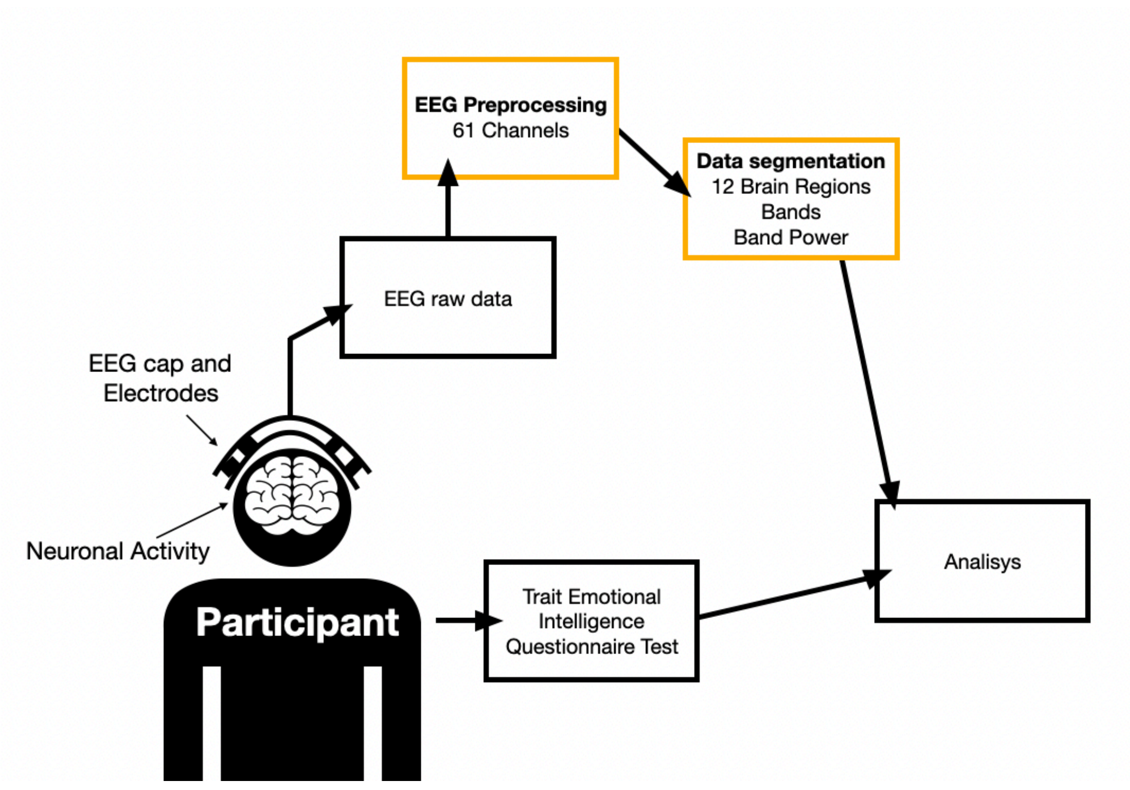

Figure 9: Schema development, in yellow the parts developed in this section.

5.2.1 rs-EEG data processing

In the LEMON dataset, the EEG data was already preprocessed. The complete preprocessing pipeline applied to the data can be found in: https://github.com/NeuroanatomyAndConnectivity/pipelines/tree/v2.0/src/lsd_lemon/.

In summary, the raw EEG data from 187 participants were down sampled from 2500 Hz to 250 Hz, bandpass filtered within the range 1-45 Hz (8th order, Butterworth filter), and split into EO and EC conditions. Also, data intervals containing extreme peak-to-peak deflections or large bursts of high-frequency activity were identified by visual inspection and removed. The data preprocessing was done in EEGLAB105 for MATLAB (by Delorme and Makeig, 2004). The dimensionality of the data was reduced using principal component analysis (PCA) by keeping PCs (NZ30) that explain 95% of the total data variance. Next, independent component analysis106 (ICA) was performed using the Infomax (runica) algorithm. Components reflecting eye movement, eye blink, or heartbeat-related artifacts were removed.

5.2.2 Software selection

The first challenge that we faced was the need to select a tool to process such large amount of data. Although, as previously discussed, the original data was processed with the EEGLAB MATLAB[9] library, one of the most used libraries for EEG data processing, in

this project, Python was selected as the software tool for further processing, with the Jupiter Notebook editor.

Python is a high-level, general-purpose programming language widely used. It was created by Guido van Rossum in 1991. Its design philosophy seeks readability in code. The selection of this tool was because I had previous experience with it, and it is easy to work with. Furthermore, it has a good editor and great libraries to work with this kind of data, such as the Python EEG library - also known as MNEPython (https://mne.tools/stable/index.html) - and another one is PyEEG (Bao, Liu, & Zhang, 2011).

[9] MATLAB is a numerical computing environment and a programming language. Made by the company MathWorks, it allows to effectively draw functions and data, implement algorithms, and communicate with other programs in other languages.

5.2.3 Pattern analysis

Before begging, a pattern analysis was done using the library **MNEPython**; since this library needs many specifications (that was not given) and is challenging to iterate, this library was only used to download the data and change the format from EEGLAB to a Python list and to visually inspect the data (see Figure 10).

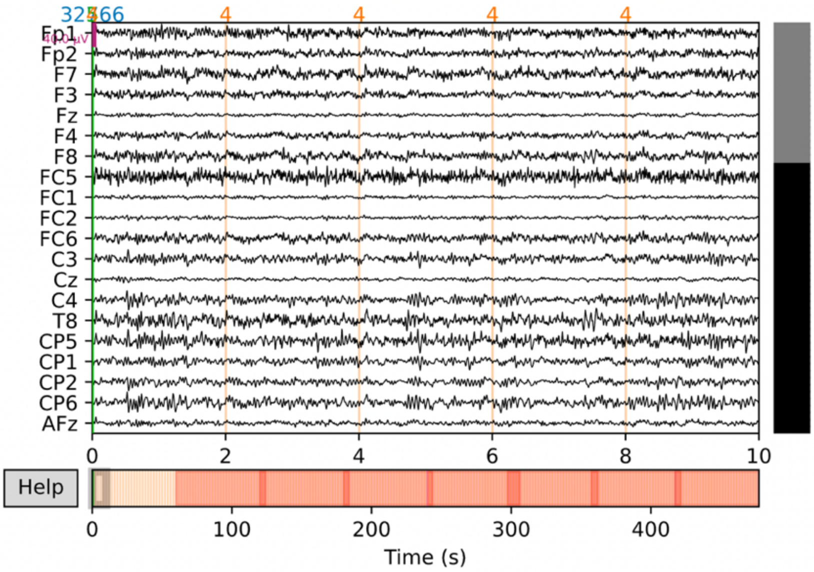

Figure 10: Participant 002, EO, function mne.preprocessing.ICA, to see the spectrum of the channels data.

5.2.4. rs-EEG segmentation

We subsequently processed the EEG data. All the data was structured as a stack of 2 matrices, corresponding to the EC/EO state. For each matrix, the first dimension indicates the participant Id and the second corresponds to all the band power channels (Figure 11).

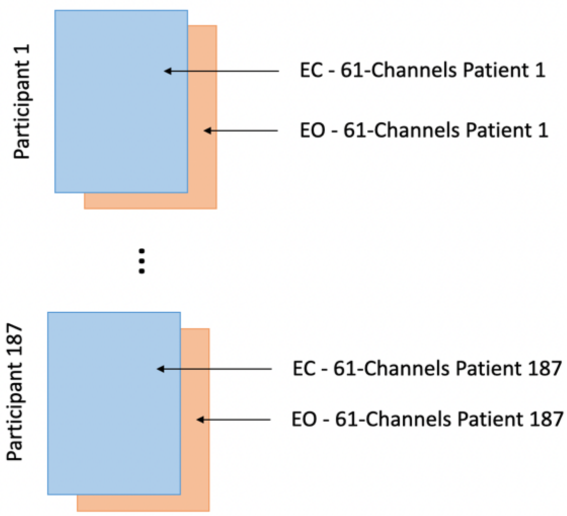

Figure 11: First data arrangement

The 61 channels (from each participant) were then separated into 12 regions of the brain (see Figure 12). These spatial arrangements was proposed by the StarLab Team. The arrangement of the channels and brain areas is shown below, as well as a visual depiction of the areas with the 61 channels in Figure 13. The data from the different electrodes was pooled by calculating the median of the distribution's median.

1. Anterior midline = "FPZ", "AFZ", "FZ", "FCZ", "CZ" (Light blue)
2. Left frontal = "F7", "F5", "F3", "F1", "AF7", "AF3", "FP1" (blue)
3. Right frontal = "FP2", "AF4", "AF8", "F2", "F4", "F6", "F8" (turquoise)
4. Left temporal = "FT7", "T7", "TP7" (oily)
5. Left central = "FC5", "FC3", "FC1", "C5", "C3", "C1" (Green)
6. Left parietal = "CP5", "CP3", "CP1", "P7", "P5", "P3", "P1" (Red)
7. Left Occipital = "PO7", "PO3", "O1", "PO9" (Purple)
8. Right Occipital = "PO4", "PO8", "O2", "PO10" (Pink)
9. Right parietal = "P2", "P4", "P6", "P8", "CP2", "CP4", "CP6" (Orange)
10. Right temporal = "FT8", "T8", "TP8" (yellow)
11. Posterior midline = "CPZ", "PZ", "POZ", "OZ", "IZ" (light pink)
12. Right central = "FC2", "FC4", "FC6", "C2", "C4", "C6" (light green)

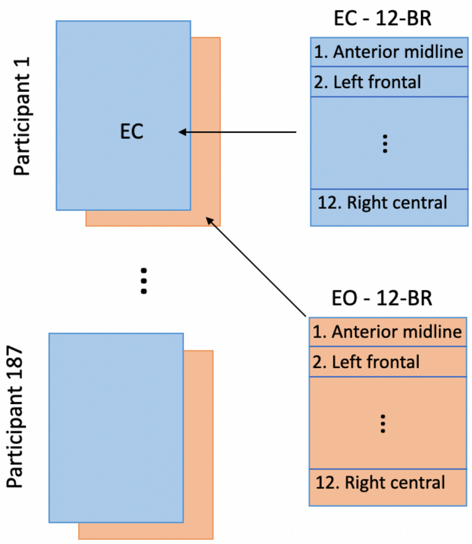

Figure 12: First data arrangement

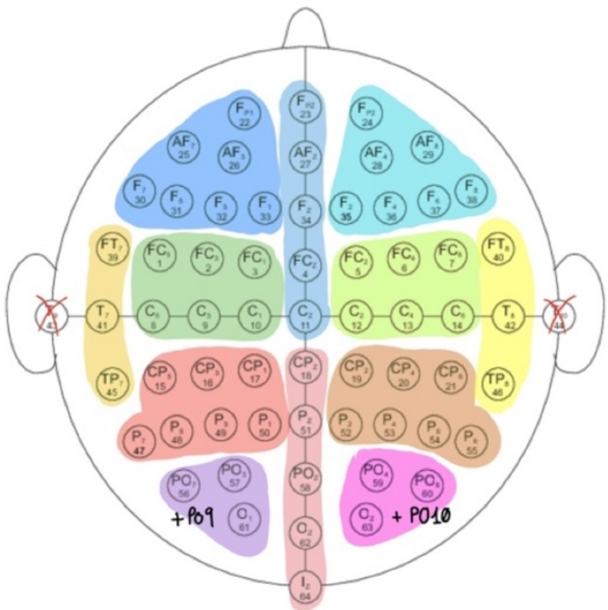

Figure 13: Brain Regions electrodes arrangement

Once we had these 12 brain areas, we split the data for each brain region (BR) into 5s periods (the data was passed from frequency (Hz) to time (seconds) domain). The first 5 s and the last 5 s were eliminated in order to remove the initial seconds of focus and have clearer data (this 5s are not overlapped). In the following image we have a visual representation of the process, Figure 13.

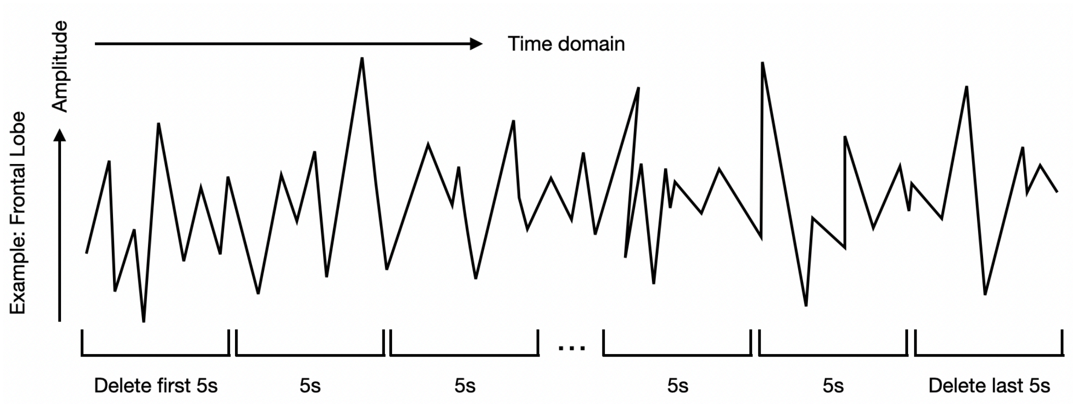

Figure 14: Sketch of the epoch definition and processing.

Once we had these 5s intervals, the relative band power[10] (BP) of **gamma lower**, **beta**, **alfa**, **theta**, and **delta** of each segment was extracted.

To compute the relative band power, I utilized the following function (Figure 15), that can be used to quickly determine relative power in a certain frequency band. This algorithm uses Welch's periodogram (it is similar to the MATLAB band power function, except that it uses a classical periodogram).

Welch's method is an approach for spectral density estimation. The spectral density (SD) of the signal describes the power present in the signal as a function of frequency, per unit frequency.

[10] Ratio of absolute band power to total power of all bands, expressed in percentage.

```python
def bandpower(data, sf, band, window_sec=None, relative=False):
    """ Parameters
    ----------
    data : 1d-array
        Input signal in the time-domain.
    sf : float
        Sampling frequency of the data. (250)
    band : list
        Lower and upper frequencies of the band of interest.
    window_sec : float
        Length of each window in seconds.
        If None, window_sec = (1 / min(band)) * 2
    relative : boolean
        If True, return the relative power (= divided by the total power).
        If False (default), return the absolute power.
    Return
    ------
    bp : float
        Absolute or relative band power.
    """

    band = np.asarray(band)
    low, high = band

    # Define window length
    if window_sec is not None:
        nperseg = window_sec * sf
    else:
        nperseg = (2 / low) * sf

    # Compute the modified periodogram (Welch)
    freqs, psd = welch(data, sf, nperseg=nperseg)

    freq_res = freqs[1] - freqs[0]  # Frequency resolution

    # Find closest indices of band in frequency vector
    idx_band = np.logical_and(freqs >= low, freqs <= high)

    # Integral approximation of the spectrum using Simpson's rule.
    bp = simps(psd[idx_band], dx=freq_res)

    if relative:
        bp /= simps(psd, dx=freq_res)
    return bp
```

Figure 15: Band Power extraction function.

Finally, a median was applied to distribution of band power values obtained for each **band** (alpha, beta, gamma, delta, and theta), which contained all of the 5s segments (epochs) with their relative band power. In other words, the alpha in an array contains all of the relative band power values of each 5s segment -we are talking about participant by participant, and brain region by brain region-, and a median is obtained from all of these band power values. In the following Figure 16 we can see visually the arrange of the storage data.

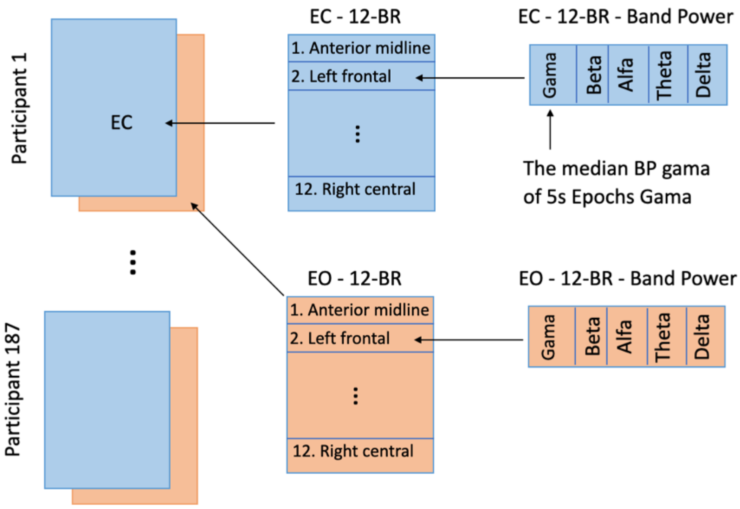

Figure 16: Third data arrangement

The data was subsequently standardized (see Eq. 1).

$$z = \frac{x - \mu}{\sigma} \qquad \text{Eq. 1}$$

μ = Mean of the intersection points between well-being score and band power

σ = Standard Deviation

The outliers between the subjects' well-being score and band power (point intersection) were deleted (this was done for each BR and band). To that objective, the Z-score[11] was obtained and all the scores outside the range Z e [-2.5, 2.5] were removed.

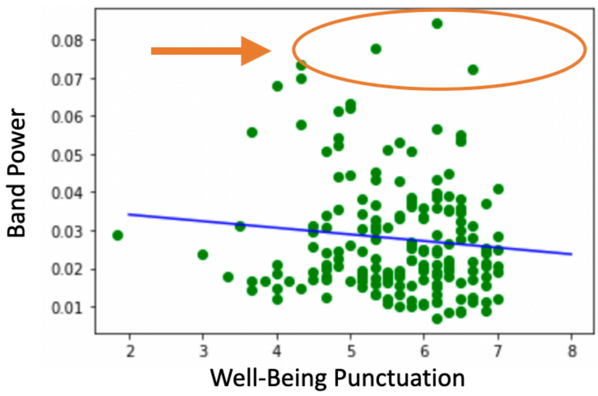

Figure 17: Example Correlation Well-Being punctuation vs. Band Power Alpha Band, EO, Left Temporal. In orange an example of what it could be an outlier visually.

[11] The z-score gives you an idea of how far from the mean (the most common value in a set of numbers) a data point is. So that allows the standardization of a distribution.

5.3. Towards establishing the neural correlates of emotionality and well-being

The first approach pursued to establish such neural correlates was based on a statistical analysis, in particular, the **correlation and the p-value** between the scores obtained from emotionality and well-being assessments, and the band power (for each band and brain region).

To obtain the correlation and the p-value, the library SciPy called **stats.pearsonr() was used.** Then, the data was plotted for visual inspection. One example of this plot can be found in Figure 18.

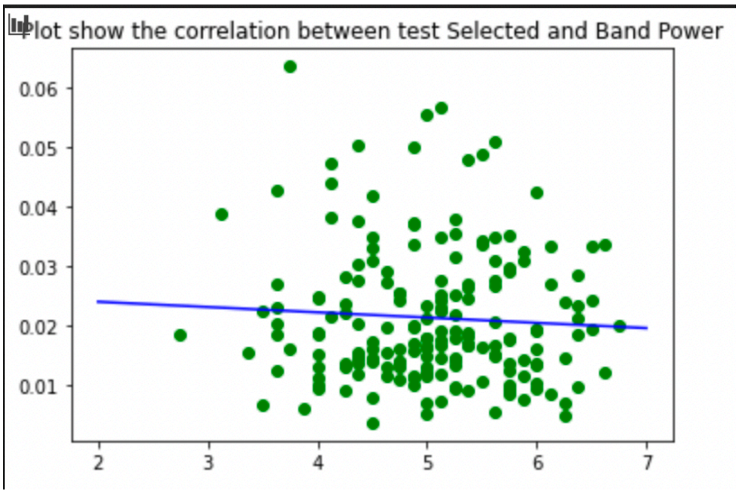

Figure 18: Example emotionality, EO, Posterior middle, Alpha.

We further analyzed the data to establish whether the band-power data could be used to discriminate the level of well-being and emotionality. In particular, the subjects were distributed in two groups, according to their scores in the neuropsychological tests. Different divisions were considered by changing the thresholds. This was due to the fact that when the central value (4) in the well-being/emotionality punctuation scale (the scale is from 1 to 7) was considered to define the low-score and high-score groups, such groups were unbalanced.

- A **5.5 threshold** value was implemented; which corresponds to the mean population score in the well-being scale.
- Another **5.0 threshold** value was implemented; this corresponds to the mean population score in the emotionality scale.
- A general one at **4.0**, as this is the central score.

For each of these three divisions, a bar plot was calculated comparing the mean band power (in each band), between the lower and high groups, as we can see in the following Figure 19.

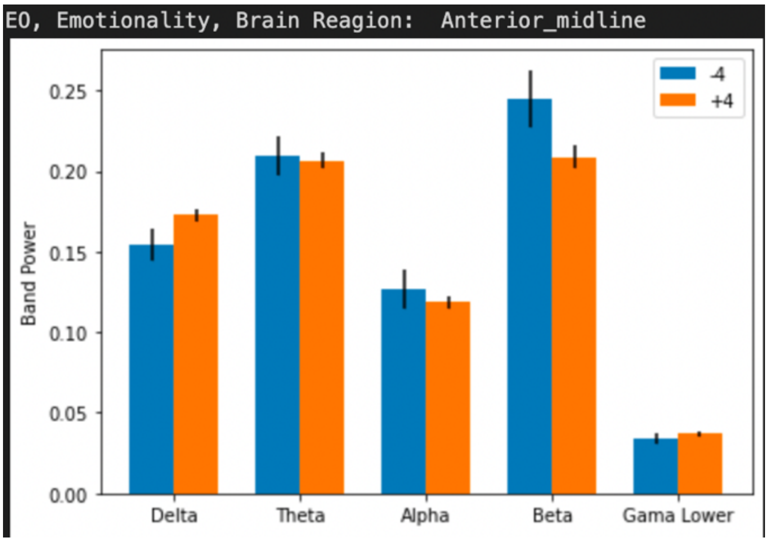

Figure 19: Example EO, Emotionality, Anterior Midline.

To assess whether there were significant differences between the two groups (i.e. low and high scores) a rank sum statistic was considered. This test assumes that the data is normally distributed; and evaluates a two-sided p-value (i.e. scipy.stats.ranksums in Python).

5.4 MACHINE LEARNING

As seen in the previous section, it seems that no clear univariate correlations emerge from the data. This suggests that the problem may not be well posed for a regression approach (see Figure 17). We then decided to further simplify the problem and consider a classification approach instead (high-score *vs* low-score) while considering Machine Learning approaches which could exploit the multivariate nature of the data.

Provided the high-dimensionality of the feature domain[12] (i.e. 12 spatial regions x 5 band powers = 60 features), we first performed a Principal Component Analysis (PCA) to visually inspect the type of data arrangement (see Figure 18), and for dimensionality reduction.

5.4.1 Principal Component Analysis (PCA) dimension reduction.

The first question to tackle is how many dimensions shall we keep? In the publications "*Stopping Rules in Principal Components Analysis: A Comparison of Heuristical and Statistical Approaches*" (Jackson, 1993) and "*How many principal components? stopping rules for determining the number of non-trivial axes revisited*" (Peres-Neto, Jackson, & Somers, 2005) summarized that we cannot infer a fixed technique or calculation to determine how many primary components are required. So different divisions are analyzed, comparing the original data with the PCA.

A common approach to guide this decision is to assess the percentage of variance explained by the different PCs. In our case, **27 PCAs**[13] account for a 98,8% of the total variance (Figure 20). PCA was applied to standardized data.

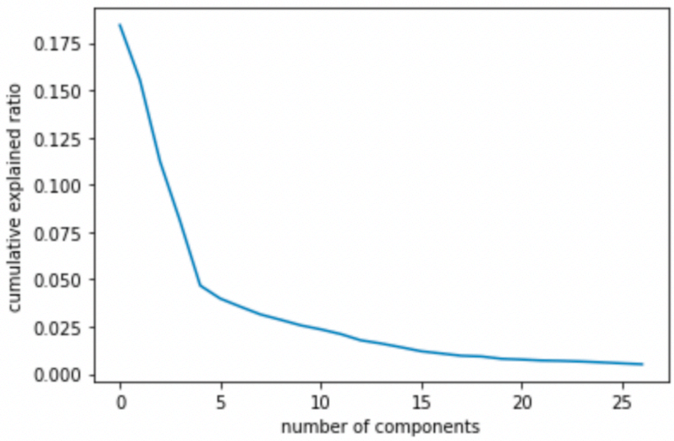

Figure 20: PCA variance ratio.

[12] Firstly, giving the values of the statistical analysis, 4 BR that do not give any significant result were excluded. But after analyzing it we thought that maybe the Machine Learning could find some hidden relation between brain regions.

[13] Dimensions selected 187x27.

Figure 21 shows the percentage of variance explained by each PC (derived from pca.explained variance ratio_). The red line represents the cumulative sum (calculated using pca.explained variance ratio .cumsum()). From the Scree plot we can read off the percentage of the variance in the data explained as we add more components. As a result, we observe that the 1st principal component explains 11% of the variance of the data set, the 1st and 2nd principal components explain 22%, the 1st, 2nd and 3rd jointly explain 28%, etc.

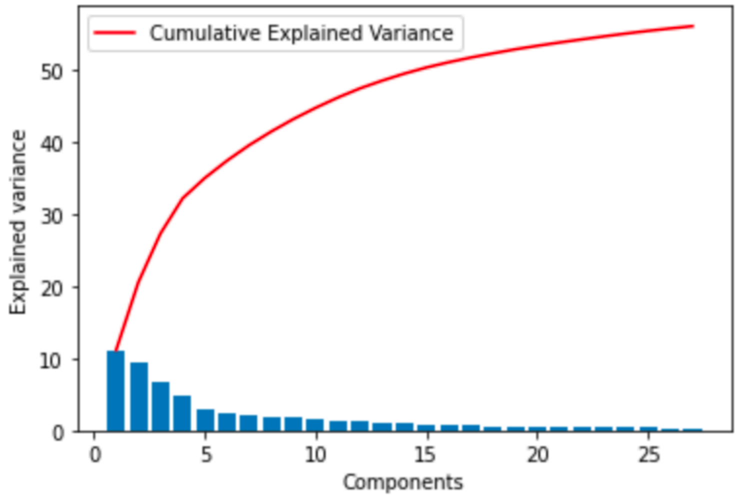

Figure 21: Graphic display PCA

Indeed, considering only the first few components does clearly indicate that no separation between the classes is possible with so few dimensions (see Figures 22 and 23). The question then is: would a better separation between the 2 groups emerge if we kept more variables?

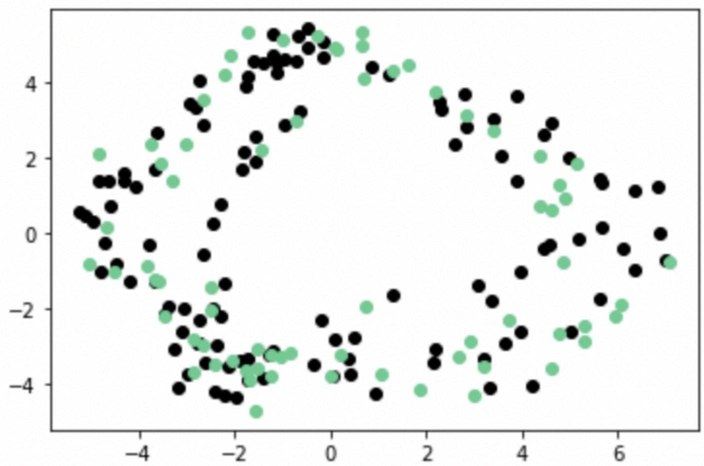

Figure 22: PCA well-being EO, PCA 1 & PCA 2, green results less than 5.5 and black more than 5.5 in the well-being test.

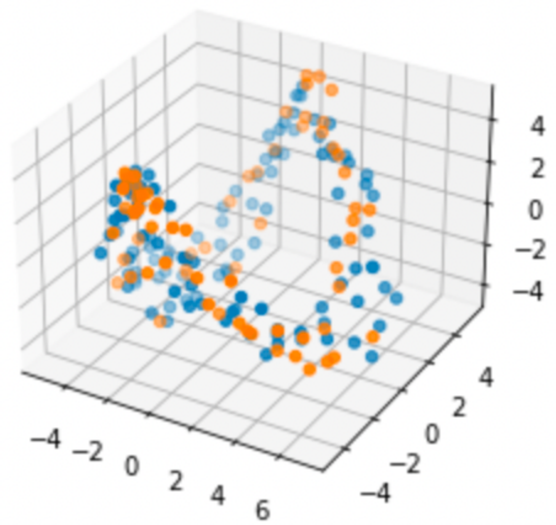

Figure 23: PCA well-being EO, PCA 1, PCA 2 & PCA 3, blue results less than 5.5 and orange more than 5.5 in the well-being test

Since It's difficult to gees the exact punctuation in range from 1 to 5, I categorized the data in the two groups generated by the thresholds, so our target models now only need to be classified. So, in this scenario, we want to see if we can distinguish between the test's low and high scores.

5.4.1 Trained models

Nearest neighbor classification is a machine learning method that aims at labeling previously unseen query objects while distinguishing two or more destination classes. Parameters.

Random forest classifier builds multiple decision trees and merges them together to get a more accurate and stable prediction.

Gaussian Naive Bayes algorithm is specifically used when the features have continuous values. It's also assumed that all the features are following a gaussian distribution.

XGB Classification is a decision-tree-based ensemble Machine Learning algorithm that uses a gradient boosting framework.

5.4.2 Training and validation process

To train the selected models, a loop was created to accommodate four different groupings, i.e. test and training data split at different levels (10%, 20%, 30% and 40% in the test).

Inside this loop, 100 iterations shuffle the data every time, so the test and train data are splatted differently each time (check if in the split the amount of data of the two targets are indicative). Then there's the standardization, process of putting diverse variables on the same scale, in this case the train data (the test is standardized *with the mean of the train*).

Once our data is collected, we fit the model with the characters we've specified and train it. It computes the accuracy, f1 score, recall score, and precision after the test.

The average of the accuracy, f1 score, recall score, and precision of these 100 iterations/epochs is computed, and the results are printed.

6. Results

Below, we will show the topographies of the strongest correlation coefficients between the spectral powers in the five frequency bands and participants' ratings on well-being and emotionality for the two conditions (EC/EO).

6.1. Statistical analysis.

6.1.1 WELL-BEING in the EC condition:

- Strong correlations (of all the data) in the **theta** band are present in the posterior part of the brain, with significant values[14]. In general, the p-value in the posterior section of the brain is less than 0.01, while in the temporals and parietals, the p-value is more significant, being less than 0.005.

- ***Beta*** also pops up in the temporals area with a general correlation and a p-value minor than 0.01 (general correlation). There are no significant values between the two groups.

- ***Delta*** has significant values (p-value minor than 0.05) in the posterior part of the brain in the p-value between the two groups being 5.5 the threshold.

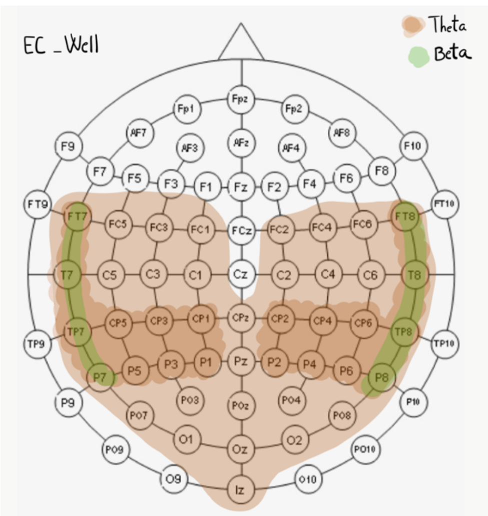

Figure 24 EC Well-Being 4.0 threshold

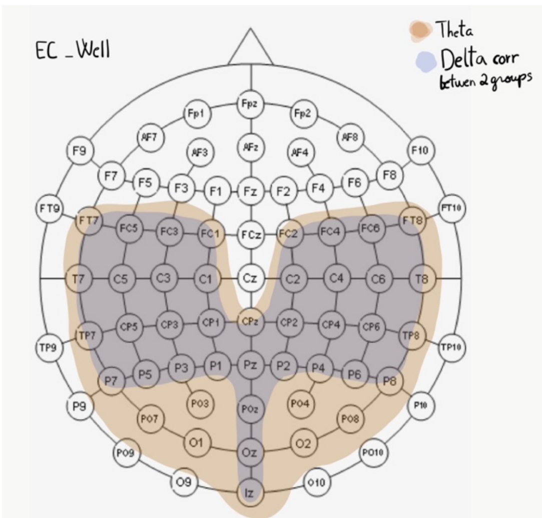

Figure 25: EC Well-Being 5.5 threshold

[14] It is considered significant values if the p-value is minor than 0.01; and if the value is minor than 0.005 it will also be indicated.

6.1.2 WELL-BEING in the EO condition:

- In the <u>correlation of all the data</u>, ***theta,*** is present in the posterior part of the brain, with significant values (less than 0.01 in p-value). ***Beta*** also pops up in the temporals area, left-central, left-parietal, left-occipital, right-occipital, and posterior-middle with a <u>general correlation</u> and a p-value minor than 0.05.

- There are no significant values between the two groups.

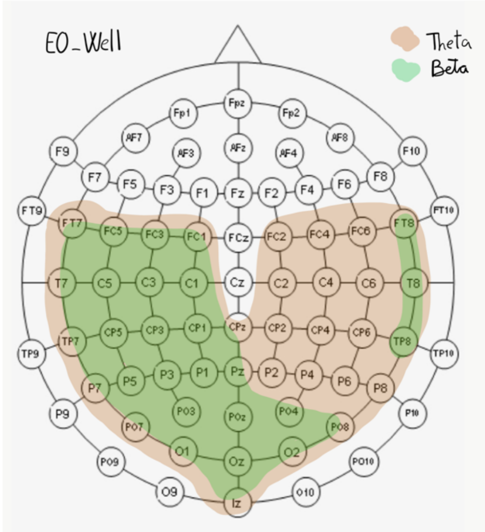

Figure 26: EO Well- Being 4.0 and 5.5 threshold

6.1.3 EMOTIONALITY in the EO condition:

- In the <u>correlation of all the data</u>, **theta**, is present in the frontal part of the brain, with significant values (the p-values were considered significant if they are minor of 0.05). **Beta** also pops up in the left-frontal with a <u>general correlation</u> and a p-value minor than 0.01.

- There are no significant values between the two groups.

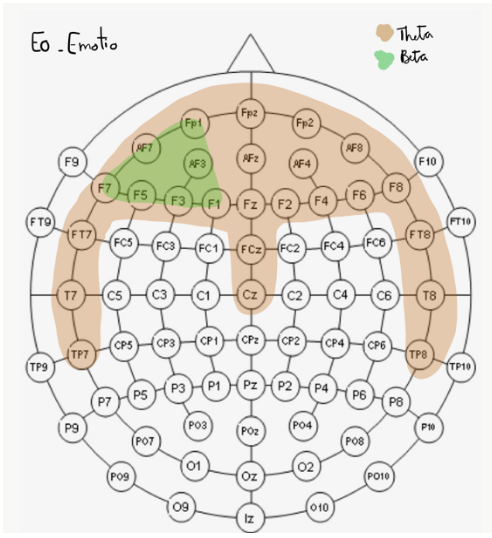

Figure 27: EO Emotionality 4.0 and 5.5 threshold

6.1.4 EMOTIONALITY in the EC condition:

- No general correlation or between groups.

6.2. Classification

In the classification part .

	NNC[15]	RFC[16]	XGBClas.	GNB[17]
EO – Well-being – 5.5				
Accuracy	0.50	0.49	0.50	0.47
F1 score	0.54	0.53	0.54	0.56
Recall Score	0.58	0.54	0.58	0.67
Precision	0.53	0.53	0.54	0.52
EC – Well-being – 5.5				
Accuracy	0.53	0.50	0.52	0.50
F1 score	0.58	0.53	0.57	0.60
Recall Score	0.61	0.55	0.60	0.72
Precision	0.58	0.53	0.55	0.53
EO – Emotionality–5.0				
Accuracy	0.53	0.56	0.54	0.53
F1 score	062	0.63	0.62	0.69
Recall Score	0.70	0.69	0.67	0.89
Precision	0.59	0.61	0.59	0.56

Table 2: Machine learning results

Rand.* = Random, the numbers predicted were completely wrong.

[15] Nearest neighbors classification
[16] Random forest classifier
[17] Gaussian nb

7. Conclusions

Some of the results supported the hypothesis. The pattern of resting electroencephalographic (EEG - With EO) recorded in the **frontal areas** was significantly associated with **emotionality**. A surprising fact was that alpha was not the principal wave in emotionality as predicted in the hypothesis. Instead, **theta** and **beta** were the predominant waves.

With regard to **well-being**, the **temporal area** is the one which shows more significant associations with the the rs-EEG activity as derived from the the p-value analysis.

In a big picture, we can see stronger associations when considering well-being than in emotionality, being the p-value always lower than 0.01 in the significant values.

In terms of the spectral information, overall, theta is the band that shows the strongest correlations, followed by beta. Theta waves fit the hypothesis, the theta activity has been found in information processing beyond our ordinary consciousness, where we accommodate our own fears, troubled history, and nightmares. Beta is the opposite of theta, is the waves that dominates our normal conscious and awake states. Also, Beta is a "quick" activity that occurs when conducting activities which require concentration.

However, in our study we cannot discriminate between populations on the basis of emotionality/well-being punctuation. Only in the statistical analysis of the well-being in the eyes closed condition, in the delta band we have found a significant p-value in the areas of Posterior Midline, left central, right central, left parietal and right parietal. When dealing with the machine learning approach, the feature domain has turned out to be unable to provide a landscape in which populations could be discriminated.

7.1 Limitations and improvements to do in future projects.

Throughout the project's evolution, various areas were examined in order to discover new approaches to understand the relationship between the brain and well-being and the brain and emotionality. One of these was an alternate feature extraction of EEG data by extracting the dimensions of motivation, arousal, and valence. The other was to extract the relationship between the EEG data features retrieved in this experiment and the well-being/emotionality while making comparisons across age and gender groups.

7.1.1 Motivation, Arousal, and valence

Alternative feature extraction. This **model** suggests that emotions are distributed in a three-dimensional space, containing **motivation**, **arousal**, and **valence** dimensions.

- Motivation: Feeling that stimulates a person to act and behave to achieve a desired goal.

- Arousal: Arousal, level of autonomic activation that an event creates, and ranges from calm (or low) to excited (or high).

- Valence: Valence, level of pleasantness that an event generates and is defined along a continuum from negative to positive.

StarLab provided us with the preprocessed LEMON data (the 61 channels, not the 12 brain regions arrangement), 4 files:

- Feature_array_EC_norm = Eyes closed normalized features
- Feature_array_EO_norm = Eyes open normalized features
- Feature_array_EC_no_norm = Eyes closed raw features
- Feature_array_EO_no_norm = Eyes open raw features

Each file contains 3 columns with the Valence, Arousal, Motivation for each subject (EO and EC separated).

The process of the statistical analysis was the same as the section 5.3.

Table 3: Motivation, Arousal, Valance results table.

		Arousal	Motivation	Valence
Eyes Open				
Well-Being All data				
	Correlation	0.13	0.08	0.08
	P-value	0.09	0.31	0.33
Well-Being 2 groups division				
	Rank-sum Statistic	-0.27	-1.27	-1.49
	P-value	0.78	0.20	0.13
Emotionality All data				
	Correlation	0.08	0.08	-0.01
	P-value	0.30	0.30	0.88
Emotionality 2 groups division				
	Rank-sum Statistic	-0,18	-1.63	0.63
	P-value	0.85	0.85	0.52
Eyes Closed				
Well-Being All data				
	Correlation	0.17	0.01	-0.07
	P-value	0.03	0.84	0.37
Well-Being 2 groups division				
	Rank-sum Statistic	-0.82	0.09	0.83
	P-value	0.41	0.92	0.40
Emotionality All data				
	Correlation	0.04	0.02	-0.09
	P-value	0.58	0.79	0.24
Emotionality 2 groups division				
	Rank-sum Statistic	-0.57	-1.14	1.39
	P-value	0.56	0.25	0.16

As we can see in Table 3, there are no significant values; only in the eyes closed, well-being condition can we discern a symbolic value; nevertheless, this may be a random guess.

7.1.2 Age, gender.

Out of the remaining 187 participants, 145 were males, and 82 were females. As can be observed, the available data is not gender-balanced. As can be seen, females are less represented than males, given that when we divide the participants into two groups (by the punctuation they have in the test), in the best scenario only 41 will be in each group.

In this dataset, the subject who underwent the TeiQue-SF questionnaire were arranged in 9 groups of age; '20-25': 79, '25-30': 60, '60-65': 19, '30-35': 13, '70-75': 22, '65-70': 25, '75-80': 4, '55-60': 4, '35-40': 1.

To simplify the structure of the data and understand better the demographics of the data we have rearranged the subjects according to the Ericson mental ages groups:

- Group 1 (20-40): 79+60+13+1 = 153
- Group 2 (40-65): 19+4 = 23 <- Not indicative
- Group 3 (65+): 22+25+4 = 51

Table 4: Information of the remaining patients.

Gender/Age	20-40	40-60	60-80	
Male	93	12	18	123
Female	34	7	23	64
	127	19	41	187

In the analysis of the age division, the data was processed without delating the outliers. In the following table 5, we can see a brief resume of the results of the correlation and the p-value of all the data (no correlation was found so the results refer a significant p-values found).

Table 5: Gender and age results.

	EO - Emotionality	EO – Well-Being	EC – Well-Being
Men	-	**Alpha and low gamma** all over the brain. **Delta and theta** in the parietal occipital and temporal.	**Alpha and low gamma** all over the brain. **Delta and theta** in the parietal occipital and temporal.
Women	**Alpha** in the frontal-central-temporal	**Theta** in the Posterior part	**Theta** in the Posterior part and Alpha anterior.
20-40 age group	-	**Delta** (all) and **theta** posterior part.	**Delta** and **theta** posterior part.
40-60 age group	Left temporal **alpha**	**Theta** posterior part.	**Alpha theta** posterior part.
60-80 age group	**Theta** in the posterior brain.	-	**Alpha** - temporal and frontal

7.1.4 Improvements

The mechanism for selecting attributes in the Machine Learning technique should be improved. Another option is to use Deep Learning to detect nonlinear patterns, or to use an EEGNet (Compact Convolutional Network for EEG) to work with pre-processed data.

As previously said, the LEMON data set provides a wealth of information on these participants, and some relation between the well-being and emotionality values could be analyzed to see whether they influence.

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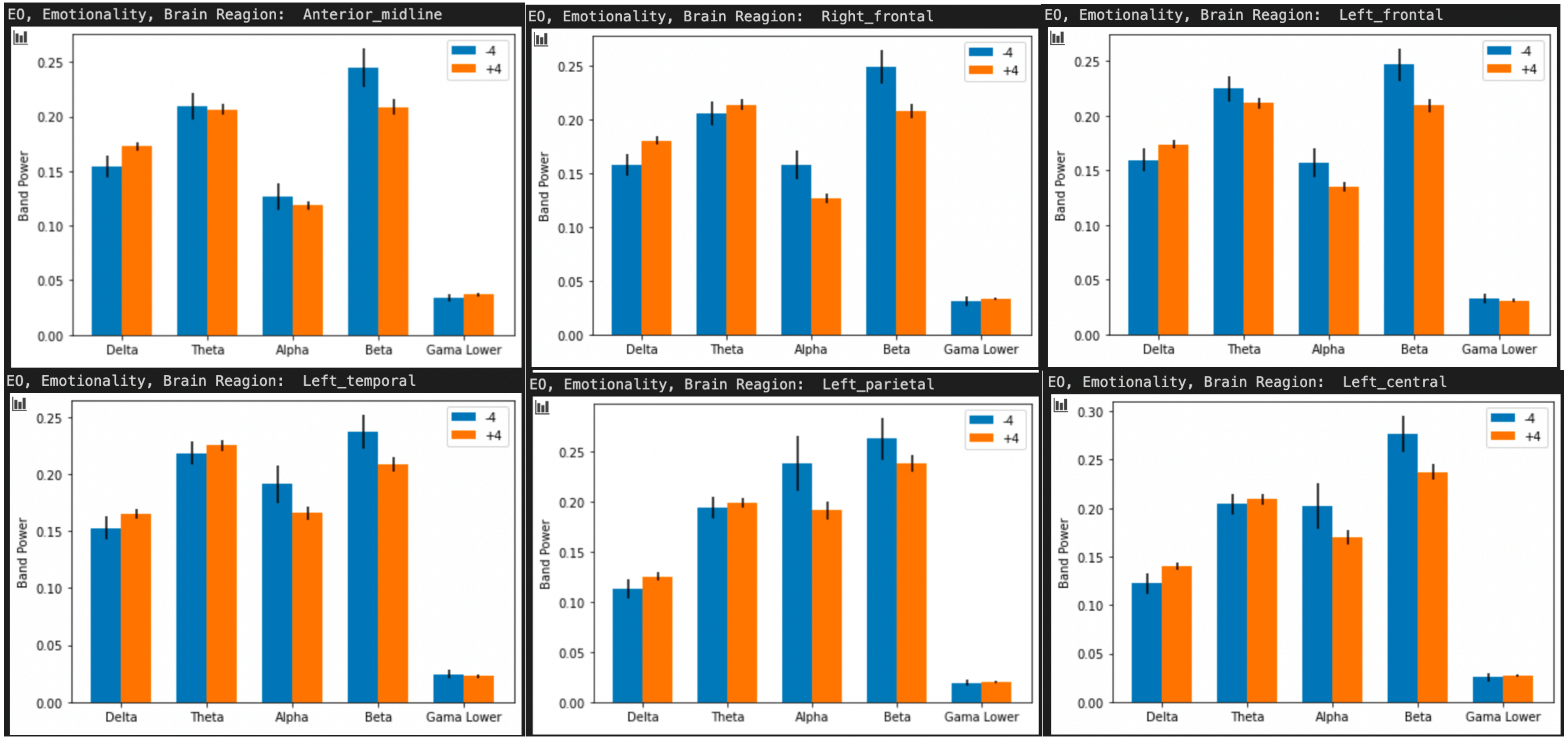
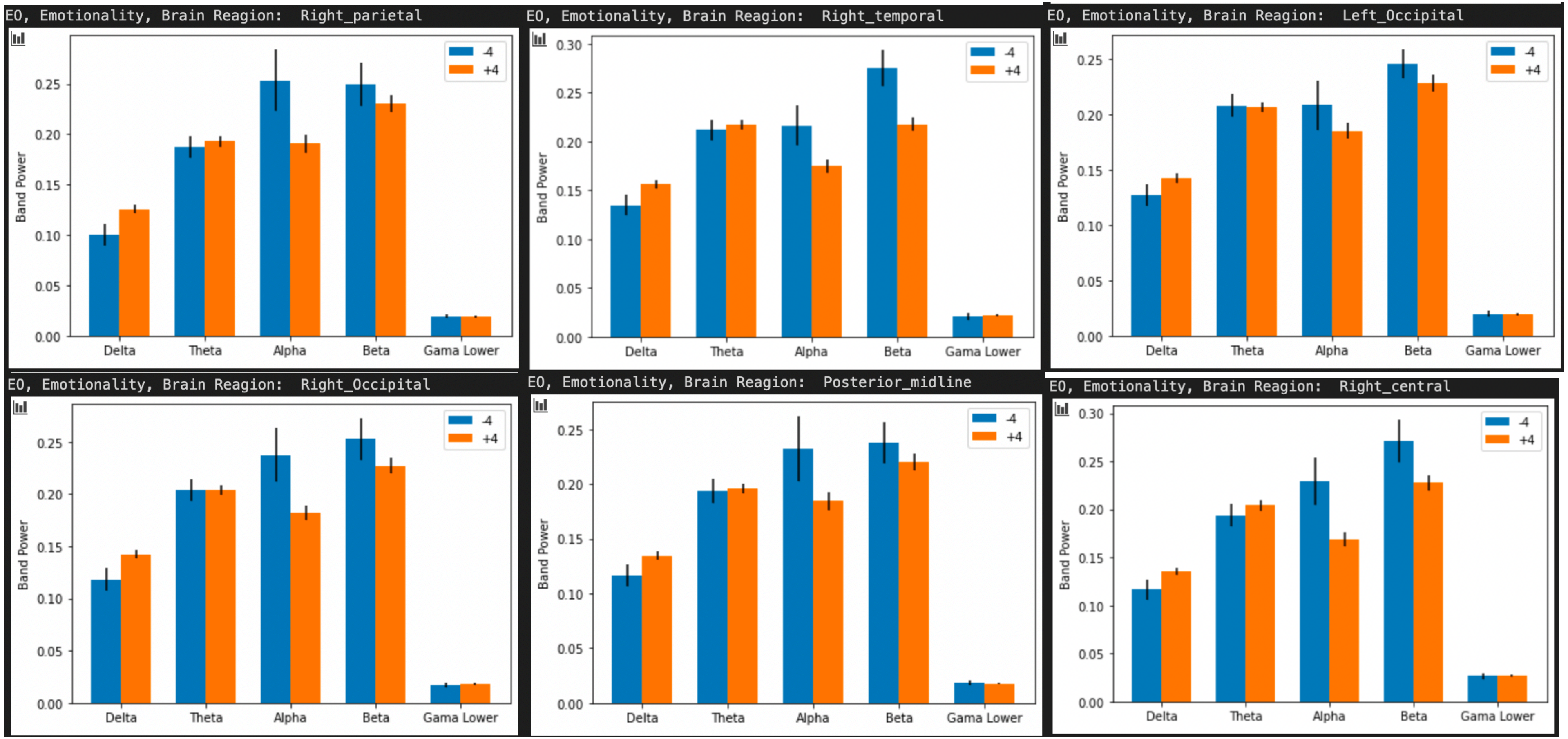
Annex A: Tables and results

All the programs can be found in: https://github.com/LaiaNO/EEG (Open Source)

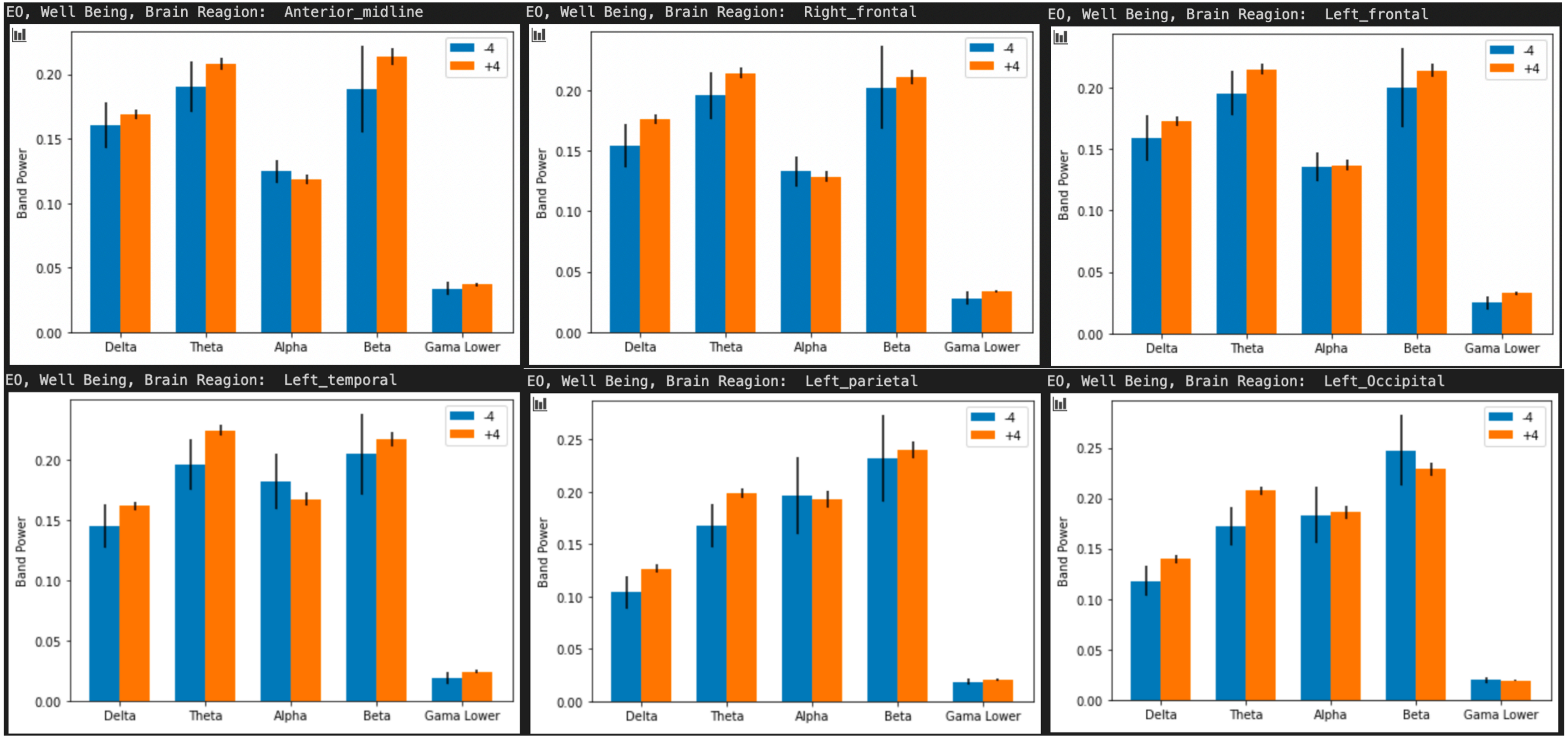
Emotionality – EO – GT[18] 4.0 Divisions, comparison low – high values

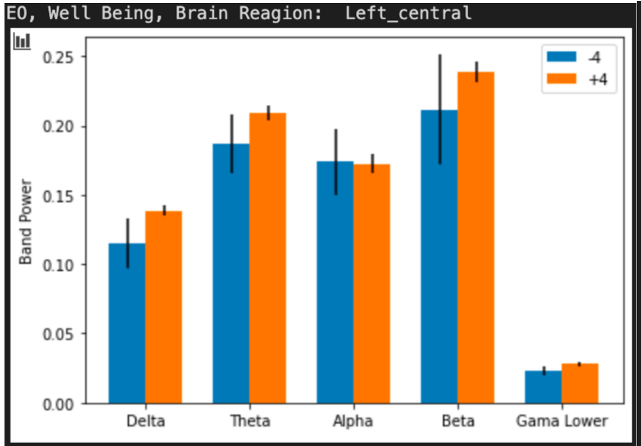


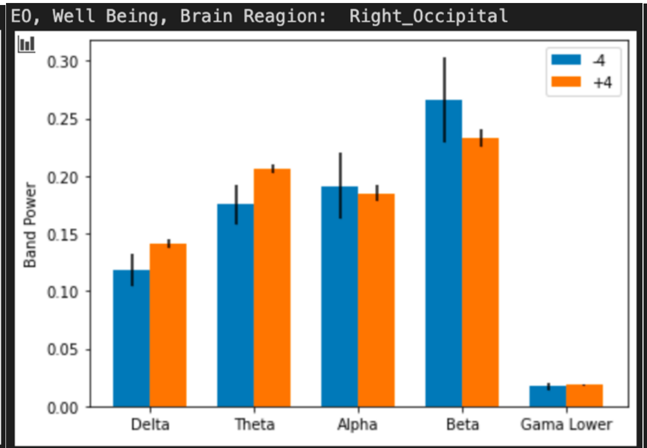
[18] GT = General threshold.

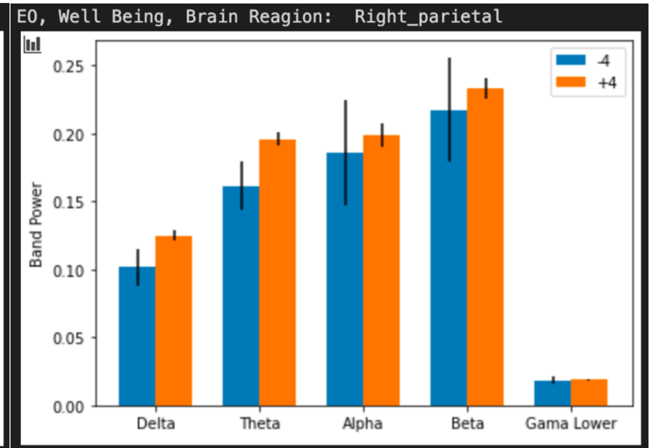

EO, Emotionality, Brain Reagion: Right_parietal
EO, Emotionality, Brain Reagion: Right_temporal
EO, Emotionality, Brain Reagion: Left_Occipital
EO, Emotionality, Brain Reagion: Right_Occipital
EO, Emotionality, Brain Reagion: Posterior_midline
EO, Emotionality, Brain Reagion: Right_central
Band Power
-4
+4
Delta
Theta
Alpha
Beta
Gama Lower
0.00
0.05
0.10
0.15
0.20
0.25
0.30

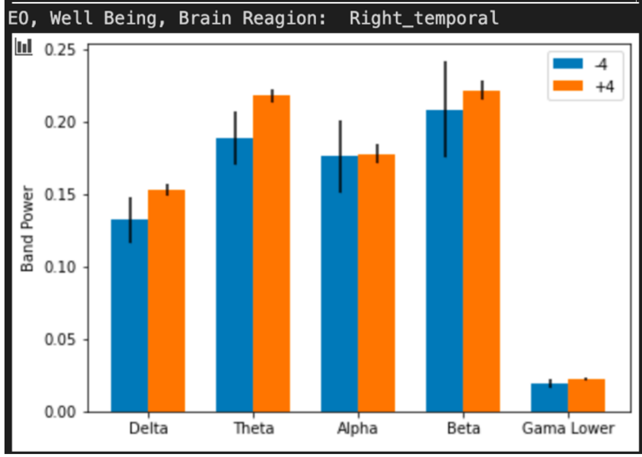
Well-Being – EO – GT 4.0 Divisions, comparison low – high values

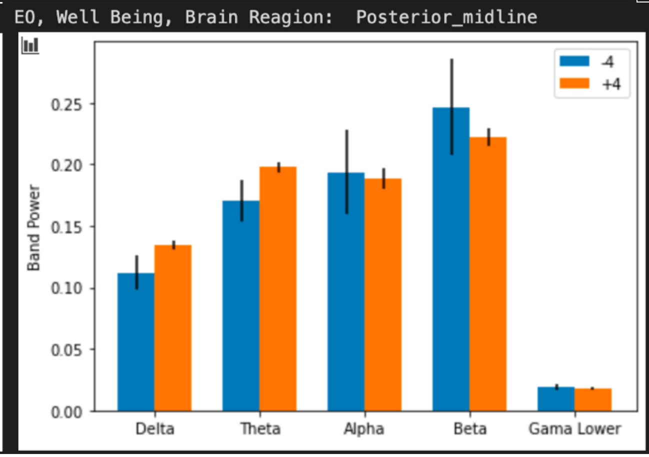


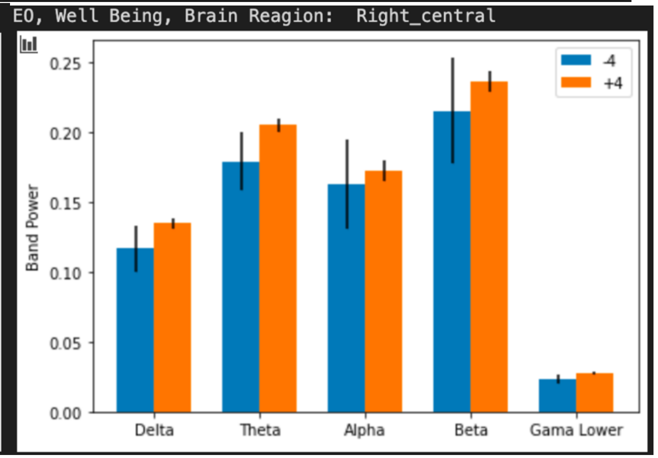

EO, Well Being, Brain Reagion: Left_central
Band Power
0.00
0.05
0.10
0.15
0.20
0.25
-4
+4
Delta
Theta
Alpha
Beta
Gama Lower


EO, Well Being, Brain Reagion: Right_Occipital
Band Power
0.00
0.05
0.10
0.15
0.20
0.25
0.30
-4
+4
Delta
Theta
Alpha
Beta
Gama Lower

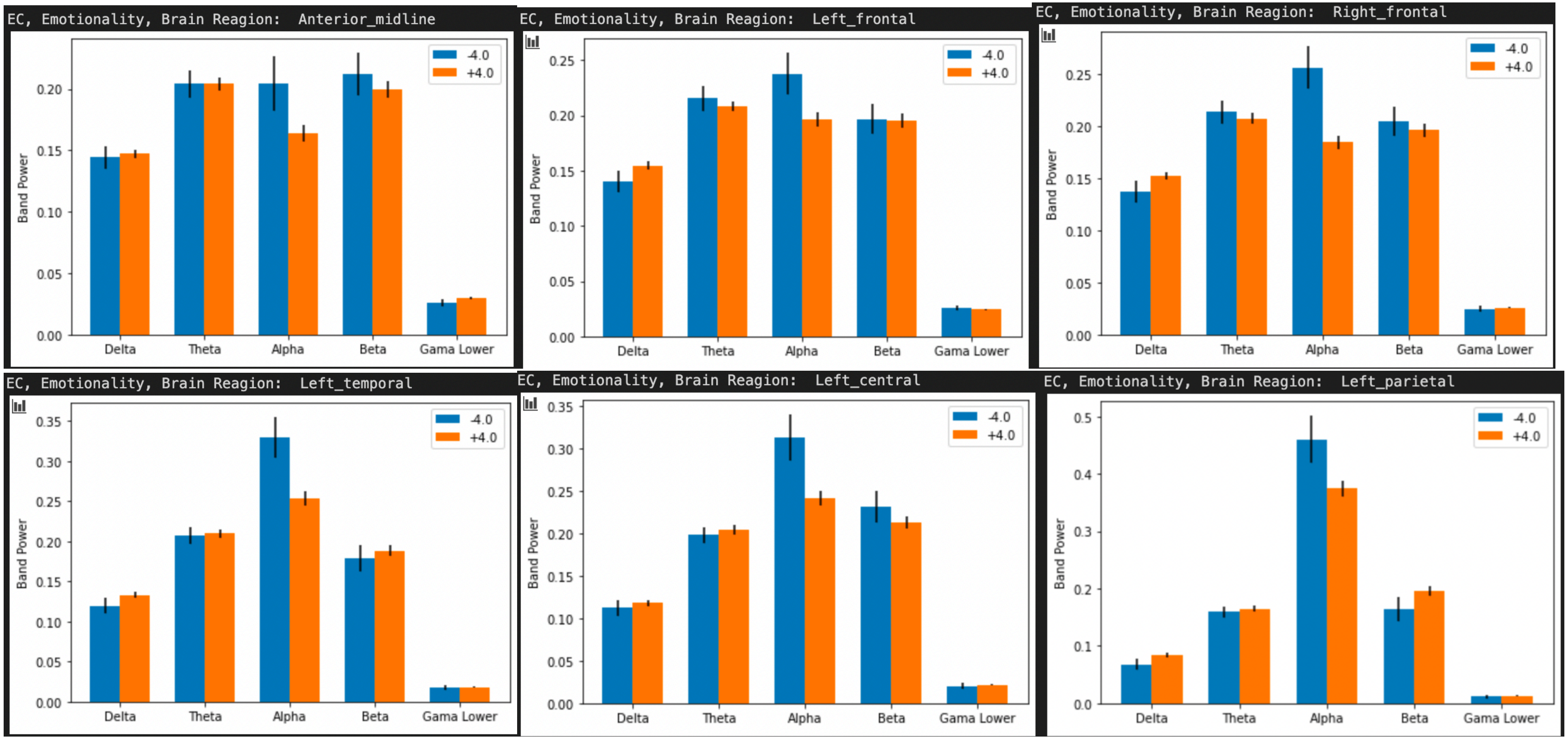

EO, Well Being, Brain Reagion: Right_parietal
Band Power
0.00
0.05
0.10
0.15
0.20
0.25
-4
+4
Delta
Theta
Alpha
Beta
Gama Lower

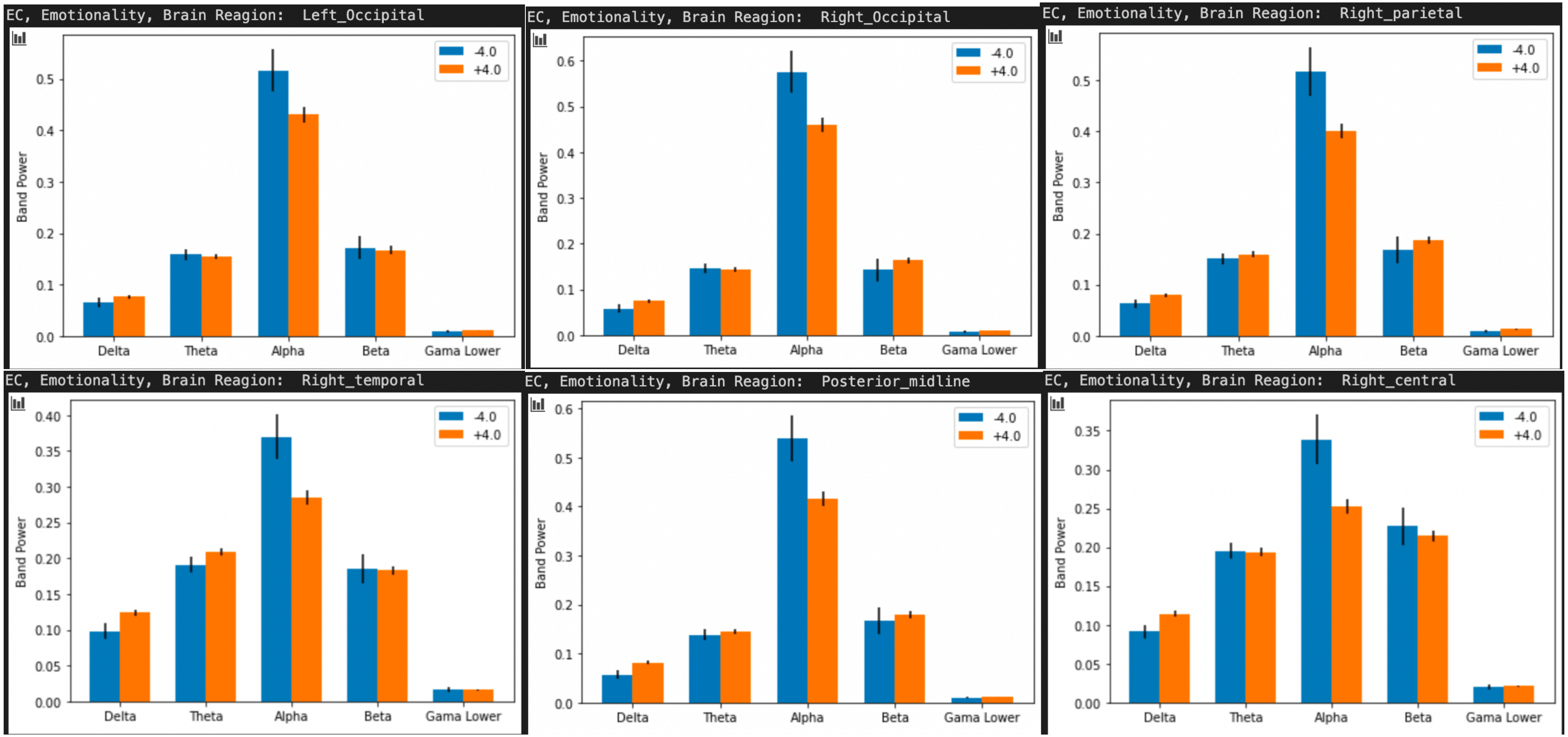

EO, Well Being, Brain Reagion: Right_temporal
Band Power
0.00
0.05
0.10
0.15
0.20
0.25
-4
+4
Delta
Theta
Alpha
Beta
Gama Lower


EO, Well Being, Brain Reagion: Posterior_midline
Band Power
0.00
0.05
0.10
0.15
0.20
0.25
-4
+4
Delta
Theta
Alpha
Beta
Gama Lower

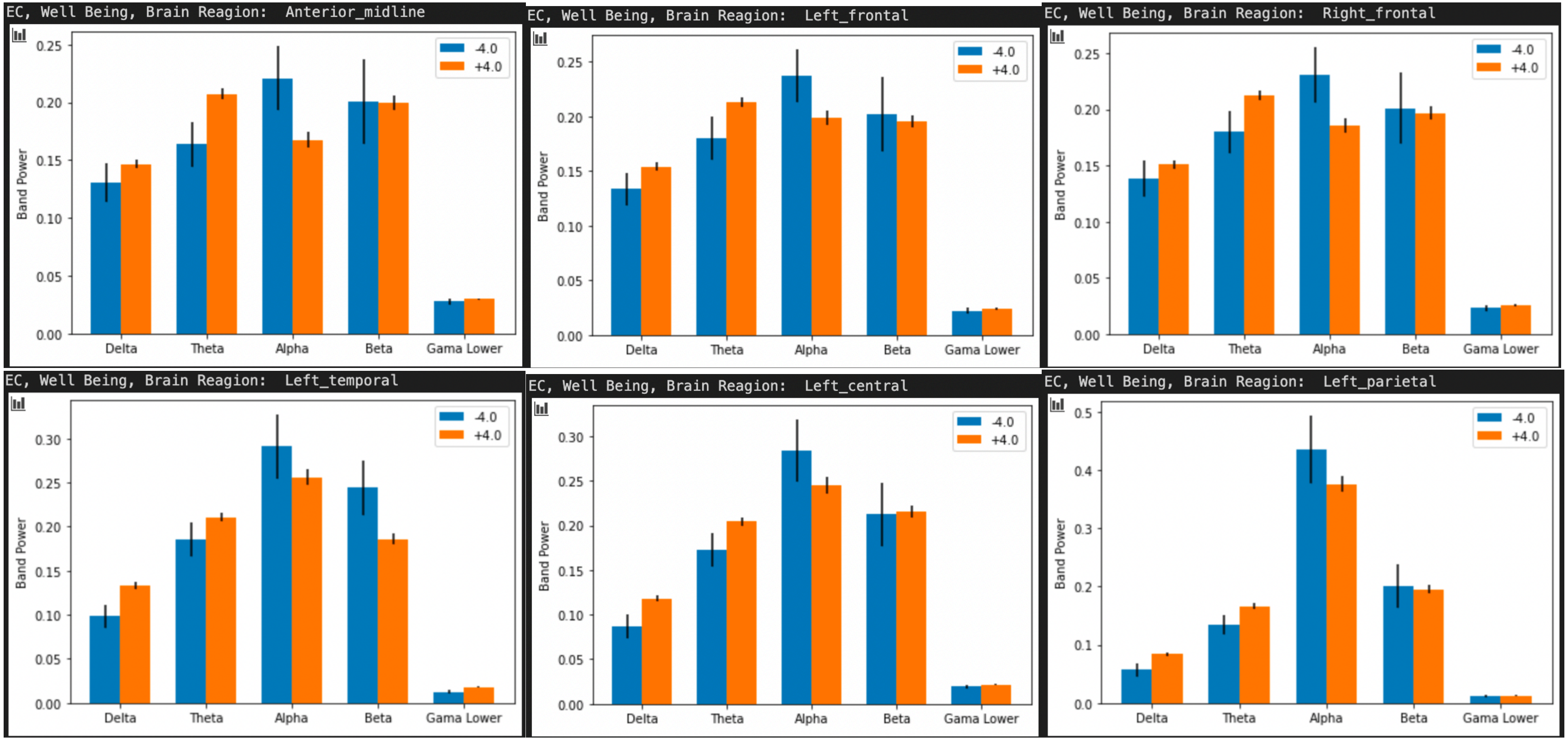

EO, Well Being, Brain Reagion: Right_central
Band Power
0.00
0.05
0.10
0.15
0.20
0.25
-4
+4
Delta
Theta
Alpha
Beta
Gama Lower

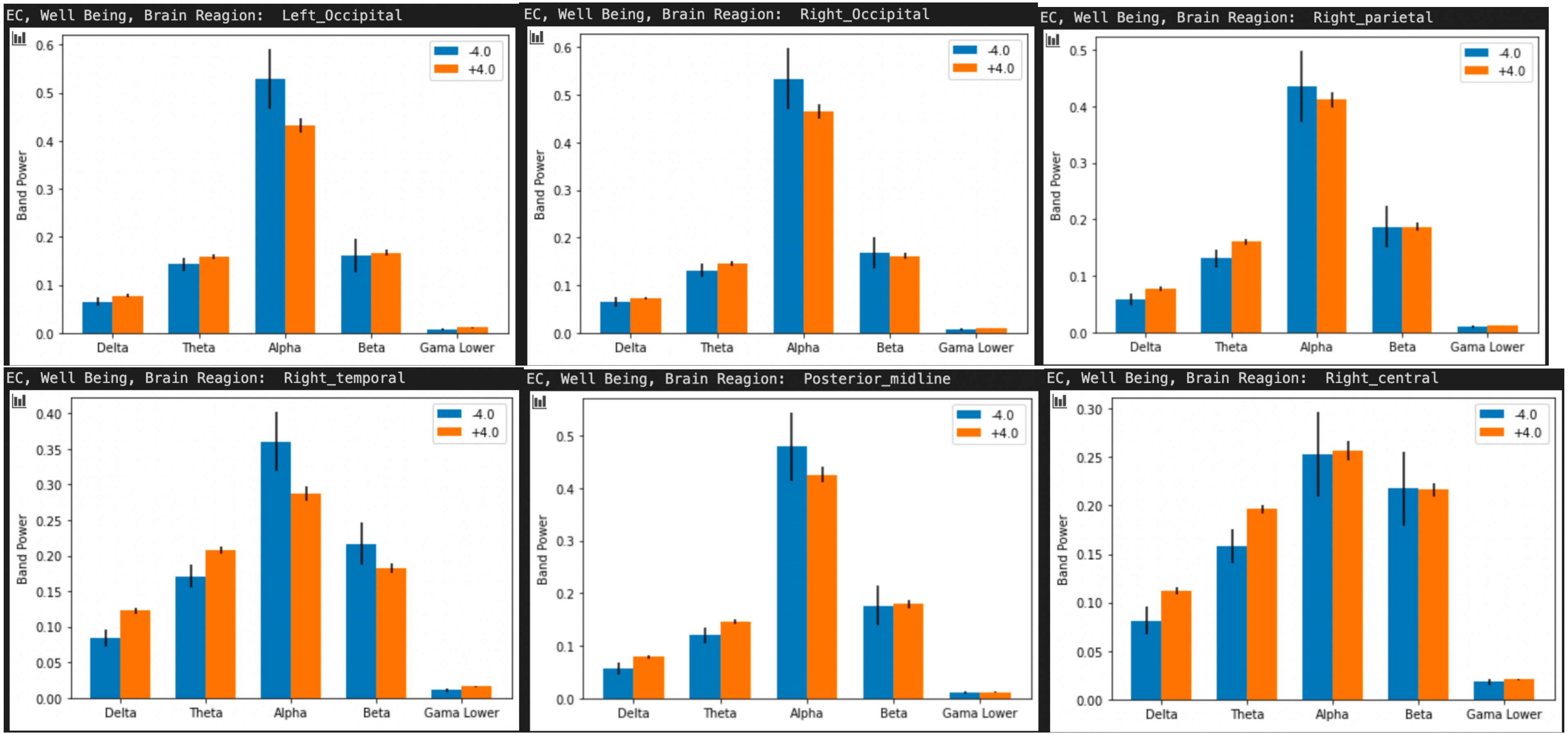
Emotionality – EC – GT 4.0 Divisions, comparison low – high values




EC, Emotionality, Brain Reagion: Left_Occipital
EC, Emotionality, Brain Reagion: Right_Occipital
EC, Emotionality, Brain Reagion: Right_parietal
EC, Emotionality, Brain Reagion: Right_temporal
EC, Emotionality, Brain Reagion: Posterior_midline
EC, Emotionality, Brain Reagion: Right_central
Band Power
-4.0
+4.0
Delta
Theta
Alpha
Beta
Gama Lower

Well-Being – EC – GT 4.0 Divisions, comparison low – high values




EC, Well Being, Brain Reagion: Left_Occipital
EC, Well Being, Brain Reagion: Right_Occipital
EC, Well Being, Brain Reagion: Right_parietal
EC, Well Being, Brain Reagion: Right_temporal
EC, Well Being, Brain Reagion: Posterior_midline
EC, Well Being, Brain Reagion: Right_central
Band Power
-4.0
+4.0
Delta
Theta
Alpha
Beta
Gama Lower

EO – Emotionality – Statistical analysis results table

Brain Regions	Bands	General Correlation	General P-value	P-val between 2 group 4.0	P-val between 2 group 5.5
Anterior_midline	Delta	0.08270360644960495	0.26175751055372315	0.6170421433505648	0.6695829478180326
	Theta	0.16119453689139948	0.028818263281367308	0.4883149151786641	0.1933615531908751
	Alpha	-0.02637640524406381	0.7252339667287536	0.4417106337597084	0.8587595248423405
	Beta	-0.09978709256901748	0.18015630122577744	0.2806311926671834	0.9567960801891843
	Gama Lower	0.03495818277072803	0.6394231092995637	0.36703081477164035	0.4164367826409565
Left_frontal	Delta	0.08444584554889592	0.25180669928076216	0.7774565459103906	0.5494152345885803
	Theta	0.12063942795676003	0.10475372520457368	0.7979183885810038	0.2826556455933519
	Alpha	-0.03788873562000638	0.6125820882114552	0.4779321366439975	0.6372609966119507
	Beta	-0.09388348623782054	0.20999663803335494	0.38848165956150094	0.5890241874148501
	Gama Lower	-0.03976245359630721	0.5940753015936772	0.6401028522935919	0.9125483453212353
Right_frontal	Delta	0.08919216653673405	0.22603604196376004	0.6056081326369049	0.4409720653426348
	Theta	0.14558770651333647	0.04862003147383035	0.5451839544819658	0.35331617739241894
	Alpha	-0.025641011541054977	0.7318761379358759	0.3832989090384942	0.6884477786208762
	Beta	-0.09206307242927901	0.21643318987832946	0.31129498301640257	0.745145177306482
	Gama Lower	-0.013618831241640601	0.8552133735661094	0.9770314064889177	0.9834916510267931
Left_temporal	Delta	0.07303511335787966	0.32052928655976587	0.8542329038546354	0.5425781285171682
	Theta	0.15299487685464072	0.03866978544839001	0.49616355135084866	0.14648477803741425
	Alpha	-0.03810245663395848	0.607593786114599	0.7636370770184165	0.6270842196592213
	Beta	-0.10657224204190352	0.1521685974290748	0.3526217356571584	0.49324990982861683
	Gama Lower	-0.09612390029176993	0.19927235623920384	0.517047299453553	0.9071114218032899
Left_central	Delta	0.07558913873977842	0.30516663966986823	0.8236546401972135	0.649577048775245
	Theta	0.1341398404967519	0.0694663612506393	0.5415356295641481	0.2347056985283128
	Alpha	-0.021264454431564137	0.7744861587431443	0.7875474996229869	0.5330835324793861
	Beta	-0.14493648385388982	0.05092058290313124	0.4457258837381993	0.2369653853308369
	Gama Lower	-0.06053023487268913	0.41825539557607866	0.995532003730278	0.6504515382737965
Left_parietal	Delta	0.01821886374072485	0.8045296141913089	0.9612126976850621	0.6654997757192617
	Theta	0.0954939670341724	0.1960069504824079	0.5696196720407227	0.7167192119704137
	Alpha	0.04195438656368483	0.5738819160937758	0.4201601007889021	0.16052002968875678
	Beta	-0.08175848551512799	0.27254488547706845	0.9724393629378049	0.4834421726836893
	Gama Lower	-0.08287343428583697	0.2633901618753647	0.688055683118532	0.9800411230189559
Left_Occipital	Delta	-0.0028872812247953033	0.9687163284083175	0.7953499306009101	0.46496070360617703
	Theta	0.09584147388985091	0.1943770525787602	0.982551909733314	0.641796540063424
	Alpha	0.02356104037705039	0.7528914865246366	0.7346958633319978	0.2010689987751456
	Beta	-0.055989579829960216	0.4540793009305223	0.8583278021267132	0.4832514149525057
	Gama Lower	-0.09346941907954501	0.2107404251510947	0.5986212754854984	0.6281285379234219
Right_Occipital	Delta	-0.0039130780520620695	0.9576108442623199	0.884003875279262	0.654474049261548
	Theta	0.05697537930811671	0.4436227951056912	0.8768849114533788	0.9045205177443643
	Alpha	-0.009264242906253994	0.9012178736101749	0.964482698342483	0.22509640720220214
	Beta	-0.07932797830651865	0.28443399470861386	0.9649048364273313	0.44918473342196963
	Gama Lower	-0.07037660606752129	0.3464852532107761	0.724246311653922	0.7900551033636362
Right_parietal	Delta	0.018741596868869545	0.7990387001942617	0.845762983969474	0.749209045395328
	Theta	0.08712702137695465	0.23829169871562017	0.6777583888493237	0.8767718068954964
	Alpha	-0.021459231450302957	0.7743134924425533	0.8577848808912742	0.34769675913486153
	Beta	-0.07348225106777798	0.3255664963920495	0.877994283328841	0.5901912034647168
	Gama Lower	-0.014516213293028976	0.8453644530116513	0.7594332727425663	0.8721018134363955
Right_temporal	Delta	0.0626732419062821	0.39413905711724884	0.9741361365261115	0.6457072721057329
	Theta	0.16664967982812734	0.023760782491410885	0.45778999800279596	0.15299072490443885
	Alpha	-0.03607661721286904	0.6258842477405582	0.8568190300991527	0.5317518344598815
	Beta	-0.12549838851206968	0.08960981814521933	0.31683277691626	0.31546477967580544
	Gama Lower	-0.021812652111653733	0.7706989328492743	0.7921053130624557	0.9256604889628518

Posterior_midline	Delta	0.018423808422261073	0.8023756700482043	0.9225170030674149	0.67437287516924
	Theta	0.05643447701319226	0.44546483682085786	0.8611130669094526	0.9530127496533328
	Alpha	0.016964376035271844	0.8206823563162222	0.941967007303883	0.17648392447773276
	Beta	-0.09309865588889325	0.21002022145381366	0.9080499494872015	0.39756218000494203
	Gama Lower	-0.06165430346711371	0.40574113130887185	0.6719343085196707	0.9029310208864344
Right_central	Delta	0.03214711733900051	0.6631376641317749	0.9220631255218572	0.8804280276375587
	Theta	0.12855473630059244	0.08117205954614835	0.43110127745491156	0.31798634515444524
	Alpha	-0.0019454051428210127	0.9791483452986735	0.670087320793751	0.5122216554581283
	Beta	-0.12115400627332186	0.1042354137648412	0.3613621299207751	0.5977344030571987
	Gama Lower	0.003568758206034796	0.9621845642785598	0.9906999260296308	0.5910373088970388

EC – Emotionality – Statistical analysis results table

Brain Regions	Bands	General Correlation	General P-value	P-val between 2 group 4.0	P-val between 2 group 5.5
Anterior_midline	Delta	0.07052556873686794	0.33879537093573847	0.6609418843799644	0.552139608135253
	Theta	0.10406692386510624	0.1620933977386499	0.6242616144786948	0.5937052215477174
	Alpha	0.029792193566829384	0.6897177604755512	0.4506570913124619	0.6933102157822519
	Beta	-0.015143582902238557	0.8392115239125492	0.947064146795262	0.7693845458117694
	Gama Lower	0.054744247265849685	0.46545016882657303	0.20847566323930422	0.2647810039641778
Left_frontal	Delta	0.05355585113606431	0.46783767004787674	0.9283095262787525	0.6726682390558483
	Theta	0.059617743268112845	0.4253190483382019	0.6182126635544656	0.6071770003623197
	Alpha	-0.016921177499833486	0.8201490873678348	0.8421203787139484	0.8872463284224555
	Beta	-0.020557055631137806	0.7829719402480266	0.881248663248299	0.7620878207144952
	Gama Lower	-0.028435896252203552	0.7039511633744616	0.8325427890826991	0.9378348111032833
Right_frontal	Delta	0.07437825102793105	0.31168653099338123	0.884003875279262	0.25104605091642684
	Theta	0.1105996593537277	0.13718537915545906	0.4970947928466033	0.3888161042397086
	Alpha	-0.007346756845735423	0.9209391844297373	0.7845680293396483	0.8500972606733966
	Beta	-0.039145369555864694	0.6008357670264447	0.8368324327609491	0.6183944457865291
	Gama Lower	-0.011982311281178153	0.8724539664233776	0.9494958853673802	0.5469786125092589
Left_temporal	Delta	0.061857215190076545	0.40161724396483156	0.5462976246407893	0.46554089415076516
	Theta	0.10531387399137766	0.15367062656582645	0.6499757428792903	0.26158417902542996
	Alpha	-0.006382065812061747	0.9312931208315558	0.7141284238837333	0.8671289244975761
	Beta	-0.08629574550690347	0.24411234119209463	0.44785815644452054	0.3497761721560996
	Gama Lower	-0.09263753360275678	0.2161369312791335	0.6767428604109513	0.8952773533223094
Left_central	Delta	0.03711333929773099	0.615020788793828	0.4697451914155367	0.7332824734454304
	Theta	0.11092403719552246	0.13386772609435224	0.7166082286360702	0.32767688318996224
	Alpha	0.009833599019451801	0.8943135370218921	0.7511598488185738	0.580932200571965
	Beta	-0.07316798553945372	0.32764547637545355	0.4944934101511903	0.6620632104402052
	Gama Lower	-0.07734864539343653	0.30068690839255663	0.8533902523805695	0.8323479339384758
Left_parietal	Delta	0.019733555712926686	0.7892061836324452	0.6558183981393568	0.7134838490496165
	Theta	0.07472264234180254	0.31341129680247776	0.6719343085196707	0.3915309352729983
	Alpha	-0.0011709840057932833	0.9873097012952888	0.5741378935112809	0.8574421831916195
	Beta	0.022256523212744225	0.766803178782968	0.7212634446722077	0.6531447994367112
	Gama Lower	-0.0646867878601297	0.3843101614799391	0.8594685914647302	0.9153254916795692
Left_Occipital	Delta	-0.008986932300785105	0.9038951017136452	0.37008241271629294	0.7690874522719077
	Theta	0.057377570837379176	0.4404066598156941	0.9558768898501682	0.3666305407250138
	Alpha	0.02734782797986884	0.7102369551904257	0.6267414564428051	0.6283215675567794
	Beta	-0.021766816252105164	0.7705452684179198	0.6480860184763313	0.6708555449344561
	Gama Lower	-0.07466145775924896	0.31514560883065834	0.5914853329344385	0.6547413698404887
Right_Occipital	Delta	0.03647459453172962	0.6249538614418882	0.7471061995484956	0.4635888765518318
	Theta	0.06079232242791493	0.4123494828459767	0.9692894100597967	0.2979348975752425
	Alpha	0.009226629090903778	0.9002631589221485	0.6001789904381414	0.7561437383635798
	Beta	0.000725824677896926	0.992241137190654	0.6926987632821435	0.9606470966690988
	Gama Lower	-0.022836289011628725	0.7596079544660204	0.815157718310354	0.7498615068278098
Right_parietal	Delta	0.03697338787823239	0.6192529041531406	0.9384073632180666	0.5486634432754391
	Theta	0.10447183980559134	0.15814657391589498	0.6401463162524546	0.2590984670633404
	Alpha	-0.0016599599995660097	0.9820112838356693	0.43969648066405465	0.7654205461410506
	Beta	0.0026854171171446922	0.9712993337853689	0.9954056720458865	0.6123712411973865
	Gama Lower	-0.027121667788584897	0.7162783111606228	0.7734168569184623	0.7095317110558184
Right_temporal	Delta	0.06997566538179535	0.3425843417716799	0.7443354867532912	0.41814580943144775
	Theta	0.11372234652363494	0.1232409293445794	0.3470143194812978	0.37011231674609935
	Alpha	-0.008909195636856241	0.9041985936646425	0.7059863367539466	0.726260460899533
	Beta	-0.09449654724164913	0.20574710854178802	0.2848138315737746	0.31805737348945173

	Gama Lower	-0.02479989506299729	0.7403515131340573	0.5754908861897348	0.7235426748499798
Posterior_midline	Delta	0.06102978063803002	0.41052273076846546	0.9229420815759501	0.47441991325583455
	Theta	0.08313092662374241	0.2632227869166002	0.9558768898501682	0.2752908310289375
	Alpha	-0.006329788944565187	0.9314830834849567	0.5852327906382327	0.8886194025901559
	Beta	-0.015572168313108918	0.8342721112404452	0.748282889143565	0.6815382685029076
	Gama Lower	-0.06869853013965849	0.35545466832146744	0.654038088220246	0.8121410526145258
Right_central	Delta	0.08279734863479331	0.2625187627403507	0.7026055709896706	0.29168744069584074
	Theta	0.11092043405351365	0.1338804367314973	0.3788651890266792	0.3481669691849467
	Alpha	-0.003736974916329308	0.9597366816077988	0.6737613860054602	0.6916784820358441
	Beta	-0.06381485193756692	0.3934024482149103	0.5527915835185852	0.8900901754810483
	Gama Lower	-0.018113367599475298	0.8087631330245267	0.6787323348429444	0.8571772912621058

EO – Well-Being – Statistical analysis results table

Brain Regions	Bands	General Correlation	General P-value	P-val between 2 group	P-val between 2 group
Anterior_midline	Delta	0.026013772058808456	0.7245019152061932	0.371264068309193	0.9569333356495573
	Theta	0.12282129513848744	0.09671946431298471	0.4093017900410746	0.2522281691732935
	Alpha	0.04825622156831936	0.5200361843541536	0.7209484802666938	0.7362013291530538
	Beta	-0.09646718513389924	0.19515803794194295	1.0	0.6751684785082503
	Gama Lower	-0.04027684780980634	0.5893075386429238	0.7536456970680775	0.30242123817651045
Left_frontal	Delta	0.07033903572035784	0.3400776292609932	0.12672055878210545	0.39753268548404386
	Theta	0.13647431349865996	0.06620124155723331	0.36029758874298545	0.24251032471186695
	Alpha	0.023646120364795818	0.7520281737517299	0.8479267118167477	0.7252426499855497
	Beta	-0.1279285331380178	0.08700301173091532	0.8702390028977116	0.5004133799102963
	Gama Lower	-0.05552717906219445	0.4565643732964013	0.8543296023272282	0.14544375085335026
Right_frontal	Delta	0.07775243875394561	0.2914933919180809	0.07269473744340221	0.41448029981340717
	Theta	0.12574919092023737	0.08896571570522248	0.4360291586168098	0.24970733534980205
	Alpha	0.042698987330500246	0.5681781975498534	0.6803845246604512	0.5792181679225034
	Beta	-0.12053549849368944	0.10505539410217155	0.8277027315276116	0.5190343431067963
	Gama Lower	-0.12832378146987017	0.08427554855121187	0.41911335640176095	0.06786777217130384
Left_temporal	Delta	0.09404304711463746	0.20046228516270992	0.0986132618706148	0.4179540091233991
	Theta	0.19392256795395693	0.00852899411722328	0.18315288824038933	0.05241456889929568
	Alpha	-0.004628840391557587	0.9502752832202682	0.5524529048817779	0.6765765097004641
	Beta	-0.16440986507645927	0.02656556188285479	0.9830986611086542	0.17406555174082805
	Gama Lower	-0.10374265787890351	0.16577756805297386	0.6120061670886846	0.18944202667454202
Left_central	Delta	0.07990014832741063	0.27832888928252814	0.10983117956128173	0.5189094203552702
	Theta	0.17558249368568146	0.01712388825686153	0.12084629952503333	0.11727905227491327
	Alpha	0.03284246026756951	0.6580693661494695	0.9211265554360596	0.6802049460893682
	Beta	-0.1705209318359064	0.021364210580346224	0.9380860548007779	0.20824120041633665
	Gama Lower	-0.07084718968636866	0.34326211723050437	0.6341741537016201	0.2892385318644821
Left_parietal	Delta	0.06491121718333413	0.3774378241242499	0.06579560169929669	0.952508423746525
	Theta	0.17429655771343872	0.017653200501781735	0.102886787105209	0.09172466312500575
	Alpha	0.016366074388060377	0.8264289258101837	0.7842600584670524	0.5926151968918079
	Beta	-0.16696926426868378	0.024268147998303142	0.9774661922964097	0.11079925357304653
	Gama Lower	-0.10010768989087707	0.17635237505811008	0.9944300941287234	0.08276658732679243
Left_Occipital	Delta	0.05547588173608679	0.4507798160263476	0.11554796309427984	0.990496293996974
	Theta	0.17818950717810317	0.015238314322752213	0.16911833640797602	0.10726440242659249
	Alpha	0.02426502903401547	0.7457573810785795	0.7344825817995349	0.5100491673182193
	Beta	-0.16767378396091553	0.024058809676410185	0.8312710994231186	0.07672664221908505
	Gama Lower	-0.1348773014489716	0.07024959646843139	0.39800805991044585	0.06398163800685205
Right_Occipital	Delta	0.042630344948664745	0.5623760967603896	0.12167533794127841	0.9359175183260562
	Theta	0.1578365943949422	0.0328478815425413	0.2439639465303466	0.16514944641024443
	Alpha	0.031088779337621025	0.676955217779626	0.6594260737939849	0.5312565640984723
	Beta	-0.166585884365292	0.02381519803546357	0.9610258539931581	0.10792691193471456
	Gama Lower	-0.12164478499347613	0.10282942233155004	0.5460411680580718	0.08255458295600308
Right_parietal	Delta	0.05582486421959459	0.4479321795409622	0.07698944987016329	0.997624020827235
	Theta	0.1604232118851082	0.029157525148573945	0.11444868547798272	0.1255660060277501
	Alpha	0.018952016639413732	0.8000908197061265	0.8272133390491893	0.5918884972541015
	Beta	-0.09951509593980905	0.18257312421432045	0.407135508127237	0.174252999482442
	Gama Lower	-0.06367594033091704	0.39179911410829743	0.7896267375247004	0.19325888804715974

Right_temporal	Delta	0.08112798314286909	0.26968413054292245	0.12167533794127841	0.51238560893736
	Theta	0.1814152841006593	0.01371846402059755	0.16367799658827942	0.09074538089297271
	Alpha	0.004953005480471256	0.9466517952133595	0.8055821526327376	0.7995644034705085
	Beta	-0.16962503184371927	0.02133897484231812	0.9944300941287234	0.1027166098364383
	Gama Lower	-0.06363816619690532	0.394716330016866	0.8758339783954964	0.27541773810614834
Posterior_midline	Delta	0.053087262963131814	0.4705411751975223	0.07379270712421826	1.0
	Theta	0.14427669798770199	0.05007320663714219	0.18818369117710132	0.18998936504786257
	Alpha	0.05225014722887785	0.4848263878768039	0.7959637737167683	0.48844658057045776
	Beta	-0.17014613058978154	0.021293523531158536	0.8772466824886326	0.09770261028077817
	Gama Lower	-0.09854853166920319	0.18321879440470784	0.6399846954165942	0.13166181163399884
Right_central	Delta	0.07464952811073831	0.3112348805910873	0.07695444785511343	0.5645986341133834
	Theta	0.15557059764213454	0.03446930055970443	0.13031149373829462	0.16842647813783573
	Alpha	0.016271211603604972	0.8269467774619568	0.865565973261327	0.708559917523555
	Beta	-0.10235123321304022	0.17035674115439756	0.4790566412142775	0.4053942381640324
	Gama Lower	-0.07893494293226375	0.2935716066739452	0.7628031448933182	0.22073761935216962

EC – Well-Being – Statistical analysis results table

Brain Regions	Bands	General Correlation	General P-value	P-val between 2 group 4	P-val between 2 group 5
Anterior_midline	Delta	0.04004425395543963	0.5873591571041685	0.4373747225428286	0.7889369714749781
	Theta	0.10820252085093998	0.14596112402945402	0.1213463174230489	0.2592492595336141
	Alpha	0.04434479530264589	0.5522348132668131	0.6886840573038957	0.9826867420260784
	Beta	-0.08671344551814905	0.2444393588431831	0.7506639068628811	0.815372178020513
	Gama Lower	-0.08155657905064222	0.27642405491518324	0.869488628584685	0.15263399299699967
Left_frontal	Delta	0.08021566105302927	0.2764292933573225	0.09738016898720686	0.4630126355516019
	Theta	0.11369161127012922	0.12753054583862036	0.15743151184997295	0.14103324008411214
	Alpha	0.024779619473555715	0.7391594299464225	0.6350114844533559	0.8716881363270294
	Beta	-0.11882288439149039	0.11012558988337208	0.8654236871637409	0.6196238574453306
	Gama Lower	-0.0509056067216413	0.4961490004576064	0.8590687886122218	0.13494069729904376
Right_frontal	Delta	0.08463599276622562	0.24944967830518444	0.07698944987016329	0.4010460730284293
	Theta	0.12013381058368626	0.10622777910867409	0.23199043828638766	0.1619466073097774
	Alpha	0.03806199164819446	0.6069887039568564	0.7802858631316455	0.9842850540355434
	Beta	-0.12566085339193106	0.09187878859185619	0.7817853985892138	0.6268767118526606
	Gama Lower	-0.00654387522030031	0.930135478716221	0.8102617199786648	0.33434310720086946
Left_temporal	Delta	0.12460979502908445	0.0901502237452857	0.03126441337292732	0.3859218194474222
	Theta	0.19542344598996067	0.007680918528256867	0.08140432266397334	0.020521461807283606
	Alpha	-0.021491871861416677	0.7715306705244734	0.6961482726765746	0.7059699723855037
	Beta	-0.19544499854080719	0.007842674927397247	0.3658179226206877	0.07306404643925696
	Gama Lower	-0.08641719490644645	0.24870920182946618	0.7696008854428127	0.0650697123034141
Left_central	Delta	0.12920557957030265	0.07881134350553567	0.03230321645690978	0.21201163272355106
	Theta	0.18716421522938403	0.010957873625552783	0.046933915284419335	0.039897266361287154
	Alpha	-0.0036967222405718753	0.9601700169174393	0.7304093905082728	0.850580628811157
	Beta	-0.11605686405331793	0.11974851129862965	0.6253496177806441	0.30086546544501314
	Gama Lower	-0.0693248204397244	0.35375799898982135	0.6443286177542743	0.09909648795770852
Left_parietal	Delta	0.1153974111330406	0.11677715824212194	0.02785124446076573	0.41276655353030267
	Theta	0.19612711482072112	0.007625152146451477	0.05993379507602404	0.021501087091272533
	Alpha	-0.023070475867251083	0.7539689066660129	0.9715271253594974	0.9596255399654813
	Beta	-0.0614570236336118	0.41246512423225484	0.637288914020012	0.46618159826210837
	Gama Lower	-0.08242773190427209	0.26729649258213745	0.6582586729022215	0.18514012455325657
Left_Occipital	Delta	0.09685570137215295	0.19212093569079078	0.11950986861036472	0.5113226164070204
	Theta	0.17262791578816283	0.019447659695307044	0.2806636835274241	0.04246535402422949
	Alpha	-0.016939063571712498	0.8180128574290422	0.6945976760574677	0.907544555998771
	Beta	-0.11345248380967846	0.12727403846022362	0.4208183459165036	0.12911763954682967
	Gama Lower	-0.07842669077552351	0.2912912249763486	0.9272763926375316	0.1752183028140747
Right_Occipital	Delta	0.10334435899760223	0.165043933454627	0.1454854537988447	0.4238127137333856
	Theta	0.17990374799392483	0.014538539759799098	0.2480199437931342	0.04617973760154979
	Alpha	-0.02402467182020858	0.7441393582438459	0.7187161510509346	0.855858181086511
	Beta	-0.09860045289027042	0.18541765260822804	0.45842094220196783	0.2230586512402738
	Gama Lower	-0.03689410555046592	0.6209758579934471	0.7830123797443732	0.42645821629449 02
Right_parietal	Delta	0.09253184009229833	0.21282129613053166	0.035620941544546654	0.4917106289374763
	Theta	0.19510983381396682	0.007951563204783596	0.043393658829285524	0.035944392286306
	Alpha	-0.011083362918255612	0.8803298524157583	0.8992981334468594	0.8093954083395067
	Beta	-0.059775842755226696	0.4227952956555925	0.6821268519260132	0.39013134356089285
	Gama Lower	-0.04113911850047937	0.5813549263718418	0.8543296023272282	0.3580236696699234
Right_temporal	Delta	0.133223213526944	0.06986837313375133	0.01981132767311752	0.2787879922722448
	Theta	0.19045621619812325	0.009411317921868806	0.07368901125743259	0.032525984624222966

	Alpha	-0.019928507078709114	0.7877399541052422	0.7107605856340574	0.8190331759026772
	Beta	-0.16750070739806544	0.024207089724403438	0.6341741537016201	0.06178336068744068
	Gama Lower	-0.04221604410352642	0.5725666203672392	0.4908663282044383	0.3774290213374848
Posterior_midline	Delta	0.10767284472543849	0.1457176996255367	0.03881829501581097	0.38755564595595404
	Theta	0.18142892371735347	0.013973601908884692	0.05377862194870402	0.03855314978929071
	Alpha	-0.021069157446294322	0.7747124522885571	0.987055604024671	0.9501368649955882
	Beta	-0.08642058149143697	0.2447309605769751	0.6181415049940004	0.3789230766048929
	Gama Lower	-0.06384951502109183	0.3905069634021879	0.8938788855117626	0.3270462779616008
Right_central	Delta	0.11884128045541878	0.10714152389648936	0.021051929807359995	0.24395604367401258
	Theta	0.16157889595721905	0.028434033130198176	0.02397457778982207	0.09611243594793405
	Alpha	-0.02001462257502047	0.786844643596433	0.8464721011376886	0.785585589212298
	Beta	-0.08779825268127346	0.23987781525952556	0.4513043273711278	0.5372293926740261
	Gama Lower	-0.008789252833656249	0.9065190440360092	0.4019848144297996	0.6455384373692827