A method for measuring trust and attractiveness of presented faces based on brain activity measurements and machine learning

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Warsaw 2023

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Abstract

Social trust is the confidence that other people, groups or institutions will act fairly, responsibly and as expected. It is the belief that other people will treat us with respect and fairness, and will abide by the rules and norms that govern social interactions. Trust is one of the most important qualities that determines the success of further interpersonal relationships. Deeming someone trustworthy or untrustworthy depends on many factors. When judging others, people are most often attentive to their face and general appearance. A lot of important information can be read from one's face to identify a person and determine his or her traits. The study investigated whether the evaluator's personality traits matter for judging another person based on his or her face alone. It was examined which brain areas are most relevant when making a trust decision. The logistic regression model used obtained results in excess of 70 %, therefore, it can be concluded that it is able to indicate with high probability the correct trust/distrust decision based on brain activity.

Abstract

Zaufanie w społeczeństwie to pewność, że inni ludzie, grupy lub instytucje będą działać w sposób uczciwy, odpowiedzialny i zgodny z oczekiwaniami. To wiara, że inni ludzie będą traktować nas z szacunkiem i uczciwością, a także będą przestrzegać zasad i norm, które rządzą naszymi interakcjami społecznymi. Zaufanie jest jedną z najważniejszych cech, która determinuje powodzenie dalszych relacji międzyludzkich. To czy ktoś zostanie uznany za godnego zaufania czy nie zależy od wielu czynników. Najczęściej oceniając innych ludzie patrzą na twarz i na ogólny wygląd. Z twarzy można wyczytać wiele ważnych informacji, które umożliwiają identyfikację osoby i określenie jej cech. W badaniu sprawdzono czy cechy osobowości osoby oceniającej mają znaczenie dla oceny drugiego człowieka tylko na podstawie jego twarzy. Sprawdzono, które obszary mózgu mają najistotniejsze znaczenie podczas podejmowania decyzji dotyczącej zaufania. Wykorzystany model regresji logistycznej uzyskał wyniki przekraczające 70 % przez co z dużym prawdopodobieństwem jest w stanie wskazać prawidłową decyzję zaufał/nie zaufał na podstawie aktywności mózgu.

Chapter 1

Introduction

People have always formed relationships, and with the development of civilization, ways of establishing connections and interactions have changed. However, regardless of the era, individual personality, behavior and appearance have always been factors in the success of these relationships.

Nowadays, one of the most important factors influencing interpersonal relationships is the first impression, that is, the evaluation of another person based on his or her outward appearance. Research shows that face and clothing are two most evident components of appearance that influence our evaluation of others.

Studies show that people are able to make quick judgments and decisions about trust and possible cooperation based on another person's face. Face is one of the most evident components of appearance, and holds many key pieces of information, such as gender, age, level of attractiveness, trustworthiness and emotions conveyed. Based on this information, people evaluate others and decide whether it is worthwhile to interact with them [55] [72] [100]. It also turns out that facial appearance can play an important role in assessing a person's health. Supple skin, glow in the eyes and a natural facial color can indicate good health. In contrast, pallor, skin discoloration or wrinkles can suggest illness or fatigue.

Today, physical appearance has become a very important part of our lives. Appearance and body language can have a big influence – both positive and negative – on how we are perceived by other people. We often hear the saying that pretty has it always easier, whether in private or professional life. Unfortunately, this saying has merit, as many studies confirm the impact of physical appearance on our lives. The bottom line, however, is that the evaluation of external appearance is not objective and depends on individual preferences and social stereotypes. What is attractive to one person may be completely unattractive to another. This is because everyone has his or her own beauty criteria, which are formed as a result of different life experiences. Nevertheless, research confirms that people are more likely to trust people who they find attractive and who convey positive emotions [87]. It seems that our perception of appearance and body language is embedded in our instincts, and sometimes not even realized. What is more, the study reveals that we show more trust towards women and people with gentle and even childlike facial features [13] [101]. However, this does not mean that people with more masculine facial features or a slightly sharper glance are unable to gain trust.

Judging a person based on first impression or without closer acquaintance is a phenomenon that affects future events and decisions made regarding that person. Studies show that people often base their decisions on first impression. For example, in a study conducted by Ballew and Todorov (2007) [5], researchers found a US presidential candidate's appearance can influence the outcome of an election. Those with a face considered more trustworthy were more likely to win the election than those with a less trusted face.

Similarly, a study by Ancāns and Austers (2018) [3] and Wilson and Rule (2015) [94] found that people with a face considered more sympathetic and trustworthy were more likely to receive a lenient court sentence. These results indicate that a person's appearance can influence the decisions made by judges.

In addition, a study by Zebrowitz and Montepare (2008) [100] found that people with a trustworthy face were more likely to establish a professional relationship. These results suggest that appearance can influence decisions made in professional matters.

In an experiment called the trust game, subjects are usually asked to choose a partner which they will bet money on, and the amount depends on individual trust level assessment. Studies by Chang et al. (2010) [17] and Van't Wout and Sanfey (2008) [90] found that people with a face considered more trustworthy were chosen as partners more often than those with a less trusted face.

1.1 Motivation

Modern societies are becoming increasingly diverse in many aspects, including cultural and technological. Rapid technological development and universal access to the Internet have made it possible to partially move life to the online realm. The worldwide COVID-19 pandemic has contributed to a reduction in human contact. Despite the need for isolation in many parts of the world, people organized meetings through various communication platforms. This proves that humans are social creatures, and are able to find alternative solutions in the face of various difficulties.

Every day, we pass many strangers on the street, meet our family and friends, share the workplace with other employees. Every day we look at different faces that may be new to us or long familiar. Every day, we face opportunities to meet new people, to establish new relationships. Regardless of the contact method, face to face or online, human interactions are very often based on an analysis of appearance, which determines the success of the relationship. In the first place, one looks at the other person's face and draws initial conclusions. It is from the face that basic characteristics can be assessed, such as gender, age, emotional state or health. Social judgments are then formed on the basis of this information. Human interactions are based on a number of different factors that determine their quality and success. Some of the most important ones are trust and attraction.

Trust is the foundation of every area of life. Unfortunately, in recent years, the spread of fake news and misinformation has become a serious social problem. The rapid pace at which information spreads through digital media makes it difficult for people to distinguish truth from falsehood. Any scandals involving financial fraud, abuse of power or corruption further exacerbate the crisis of public trust. The concept of attractiveness is deeply rooted in society and plays an important role in everyday life. Nowadays, people attach a lot of attention to their appearance. Among societies, there are many beauty stereotypes, that make people feel pressured to conform to due to the fear of rejection. Through advertising, thriving digital media reinforce stereotypes that have been established for years. One such stereotype states: "What is beautiful is good." Beauty is associated with positive qualities and behaviors, while anything ugly is mostly discarded. Attractive people are more likely to get employed and promoted at work, find a partner, and gain the trust of others.

1.2 Research goals

The main issues addressed in the dissertation concern the assessment of trust in other people, based on the photos of their faces and the evaluation of the attractiveness of the faces presented. In this respect, the following goals were set:

1. Pilot experiment
   - Building a classification model that predicts trust ratings based on the face evaluator's personality traits.
   - Building a classification model that predicts attractiveness ratings based on the face evaluator's personality traits.
   - Determining which personality traits have the greatest impact on trust and attraction-related decisions.
2. Main experiment
   - Building a classification model that predicts trust ratings based on the collected EEG signal.
   - Building a classification model that predicts attractiveness ratings based on the collected EEG signal.
   - Determining which brain areas are active when making trust decisions and evaluating attractiveness.

1.3 Research hypotheses

The research objectives set allowed us to formulate the following hypotheses:

H1 It is possible to predict trust ratings based on the survey participant's personality traits.

H2 Attractiveness ratings can be predicted based on the survey participant's personality traits.

H3 There are personality traits that have a significant impact on both trust and attractiveness ratings.

H4 One can predict the trust decision regarding the presented faces based on the average electrical charge of the brain.

H5 It is possible to predict the attractiveness rating of the presented faces based on the average electrical charge of the brain.

1.4 Face recognition

Face perception, is an important part of social communication. Neuroanatomical studies conducted since the 1960s have provided interesting data on the formation of these skills in the process of individual development. According to the hypothesis formulated based on the results of these studies, the newborn has the basic ability of face perception [25] [32]. This is evidenced by observations showing that just a few hours after birth, newborns turn to face-like images more often than to other similar shapes [49]. In the weeks and months following birth, the baby learns to recognize faces, as evidenced by its preference for the mother's face in an experimental situation involving alternating presentations of the mother's face and an unfamiliar woman's face [74] [14]. The results of numerous studies have shown that the source of this type of reaction in newborns is the subcortical pathway, consisting of the superior colliculus, diencephalon and amygdala [48]. During the first two years, there occurs a process of specialization of cortical structures involved in face recognition, e.g. lateral occipital cortex and fusiform gyrus, which enables the development of the ability to distinguish faces [69].

The face perception process is very complex and depends on many factors, such as culture and the degree of familiarity with the other person. Research indicates that eye fixations on important details, such as the eyes, the nose and the mouth, are crucial to the process of face perception. Early perception studies have shown that the facial recognition process occurs by repeatedly focusing the eye on the facial elements that form a triangle consisting of the eyes and mouth [91] [45]. The way the face is perceived differs between cultures. In Far Eastern cultures, the gaze is more often focused on the central part of the face (mouth, nose), while in Western cultures it is mostly focused on the eyes [11]. It is also important to note that the way a face is perceived depends on the degree of familiarity with the person. Studies have shown that when viewing a familiar face, subjects focus longer on the inner area (eyes, nose and mouth), whereas when viewing an unfamiliar face - on the outer area [84]. It follows that the inner area of the face is more significant in identifying a person than the outer area.

1.5 Face perception - a neuroanatomical approach

The topic of face perception is one of the key issues in the field of neuroscience and cognitive psychology. Over the past few decades, there has been increasing evidence that different brain structures are involved in face perception processes than during the recognition of other objects. Evidence supporting these findings can be seen in the observation of faces and objects by newborns. Bruce and Young (1986) [12] showed that the recognition of a person's basic features and the determination of his or her identity is carried out through different systems compared with objects. Another example indicating differences in brain center activity can be diseases that lead to impaired face recognition and leave unchanged the mechanisms for recognizing elements other than the face [82].

The areas that mainly specialize in face perception have been specified as the central face perception system. Among them, one can distinguish the fusiform gyrus responsible for reading invariable information from the human face, the superior temporal gyrus, which is responsible for recognizing variable information, e.g. the direction of gaze, and the inferior occipital gyrus, where information is initially processed [44]. In addition to the central perception system, there is also an extended system that encompasses structures related to the face recognition function. Owing to them, the brain is able to identify a face and indicate basic information about a given person, if it is familiar with that person (front part of the temporal cortex), determine the focus of the other person's gaze (interparietal sulcus), indicate accompanying emotions (amygdala). [43].

1.6 Trust

Trust is an important factor in many areas of life, such as interpersonal relations, business, politics, medicine, technology and many others. It is the foundation of lasting and successful relationships, and it enables effective cooperation, builds loyalty and helps achieving goals. Trust can be defined as the belief or feeling of certainty that a person, organization, system or information is credible, honest and can be relied upon to perform certain actions, fulfill duties or keep promises. It is a willingness to put oneself in someone else's hands, an expectation that the other party will act in accordance with our expectations, interests and will not cause harm [19]. Trust involves the belief in the other party's good intentions and responsibility, and the expectation that they will abide by established norms, rules, agreements or standards. It is also the belief that the other party has the competence, knowledge or experience to perform the assigned task or meet expectations.

Trust is the emotional aspect of relationships between people or organizations. It can be built through long-term interactions, positive experiences, behavior consistent with values and commitments, and honesty in actions. Trust can also be at risk and can be violated by actions contrary to expectations, fraud, broken promises or loss of credibility. Nowadays, the issue of trust is important in society for several reasons:

- Socio-political turmoil: Modern society faces many challenges, such as political crises, pandemics, disinformation, fraud and corruption scandals. In such a context, trust becomes a key factor in building stability and social harmony. A society based on trust fosters cooperation, mutual respect and effective functioning of institutions.

- Erosion of trust: There is a decline in trust in society. Repeated examples of fraud, manipulation and broken trust by individuals or institutions can lead to a loss of faith in other people. This can lead to the weakening of social ties, the decline in civic engagement and the deterioration in the functioning of a democratic society.

- Social impact of technology: The introduction of new technologies, especially social media and the Internet, has changed the ways we communicate and establish relationships. However, easy manipulation of information, fake accounts or spreading hatred online can lead to a decrease in trust between people. There is, therefore, a need to understand how these technologies affect social trust and how it can be effectively managed.

1.7 Brain activity and trust

Brain activity during trust assessment is an interesting area of neurological research.It has been shown that when a face is assessed as trusted, alpha and beta waves tend to be stronger, whereas in the opposite case, the gamma band activity increases [71]. Studies using, among others, functional magnetic resonance imaging (fMRI) and electroencephalogram (EEG) identify specific brain areas associated with trust and social decision-making. Among the brain areas active during trust assessment, the following are distinguished: the prefrontal cortex, the inferior frontal gyrus, the inferior temporal gyrus, and the amygdala. The prefrontal cortex is thought to play an important role in decision-making and social judgment. Activity in this part of the brain increases when a person evaluates a face as trustworthy [29]. The inferior frontal gyrus activity is related to the anticipation of other people's actions whereas the inferior temporal gyrus is responsible for recognizing facial emotions. The amygdala plays a key role in the processing of emotions, including trust-related emotions. Research indicates that its activity increases in response to trusted faces.

1.8 Facial attractiveness and neural correlates

Attractiveness is a term used in the context of the physical and social attraction. It is a subjective assessment that may vary by individual and cultural context. Attractiveness is usually associated with positive qualities that make an individual appealing to others. Attractiveness plays an important role in social relationships. Research shows that attractiveness has a significant impact on a person's professional and emotional life. People considered more attractive are more successful, find partners more easily [77] [67], and have a higher earning potential [35].There are many indications that face attractiveness plays an important role in the choice of a partner [34].

Brain imaging studies confirm that the human brain has regions that respond to attraction. Attractive women's faces have been shown to activate reward areas in men more than men's faces or unattractive faces of both women and men [1]. Increased activity in response to attractive faces was recorded in the medial areas, inferior prefrontal cortex (iPFC) and medial prefrontal cortex (mPFC) [18] [20], whereas unattractive faces activated the lateral areas [20]. The orbitofrontal cortex (OFC) indexes the reward value of stimuli and shows more activity in response to reward than punishments. [56]. Other reward-related brain areas that are activated when exposed to attractive faces include the ventral tegmental area (VTA) [1], ventral striatum [52], caudate nucleus [51], nucleus accumbens (NAcc) [1] [51]. Some research suggests that facial attractiveness may be an even stronger rewarding incentive than money. For example, seeing attractive women can lead to a greater lateral parietal cortex (LPC) response than winning money. This suggests that attractive potential partners represent a higher reward than financial gain [102].

Chapter 2

Electroencephalography

2.1 Brain anatomy

The human body consists of many organs that have different functions. Some of them are necessary for sustaining life, others can be removed and replaced, for example, with pharmacology. Organs can be more or less complex, exchangeable by transplantation or non-replaceable. Despite all their differences, organs form one integral organism, whose management center is the brain. It is undeniable that the brain is one of the most important and complex organs of the human body, which cannot be replaced or replaced, and remains a mystery despite many studies. It is located within the skull and is surrounded by the meninges and cerebrospinal fluid. The brain structures – the forebrain, the midbrain, and the hindbrain are formed from the anterior portion of the neural tube around the 28th day of fetal life. Taking into account the anatomical structure and functions performed, the brain is divided into three parts the brainstem, the cerebrum and the cerebellum [24] [23].

The cerebellum is located at the top of the brainstem, under the hemispheres. It is responsible for processing motor signals. It is also involved in cognitive functions.

The brainstem is a structure that includes the midbrain, the pons, and the medulla oblongata. Numerous nerve centers controlling vital functions are located here. It consists primarily of nerve fibers that are responsible for the transmission of electrical impulses between the higher centers of the forebrain and the spinal cord.

The brain is an oval-shaped organ. It is composed of the telencephalon and the diencephalon, which consists of the thalamus, the hypothalamus and the suprathalamus. The brain is flattened in the inferior section, and convex in the lateral and superior sections. It is divided into almost equal parts, which are called hemispheres. The surface of the hemispheres has numerous gyri separated by sulci. The three largest sulci (central, lateral, parieto-occipital) divide the cerebral cortex into four lobes occipital, parietal, temporal and frontal each being responsible for different functional centers [60]. Hence, the occipital lobe receives visual stimuli, the parietal lobe receives sensory stimuli and is responsible for spatial functions, the temporal lobe receives auditory stimuli and is responsible for memory and speech, whereas the frontal lobe manages cognitive processes, and movement planning and initiation [33]. The outer part of the forebrain is gray matter corrugated cerebral cortex of thickness varying between 2 and 5 mm. This is where the largest concentrations of neurons are found. The inner layer, called white matter, is the center of nerve fibers.

The nervous system is a system that consolidates the functioning of human organs and tissues. The fundamental unit of the nervous system is the neuron (nerve cell). When electrically stimulated, it receives, processes and sends information. It consists of a cell body with a nucleus, numerous branches called dendrites and an axon. Depending on the location of the receiving cell, the neuron, may have different sizes. The cell body diameter reaches 100 µm, whereas the axon diameter can decrease by up to six times, and its length can reach 1 m [65]. The neuron operates based not only on electrical impulses, but also chemical signals. Information processing occurs in the soma. The information sent by the axon is received through the dendrites. Nerve cells communicate with each other via synapses (Fig 2.1). It is estimated that the nervous system consists of approximately 100 billion neurons, with each neuron connected to approximately 10 000 other neurons [66].

Neurons communicate with each other using stored energy, which consists of physical and chemical gradients. The electrical impulses transmitted by axons propagate along nerve fibers. Depending on the size of the potential difference occurring on both sides of the neuron's cell membrane, we can distinguish the action potential and the resting potential. The action potential is a state of sudden depolarization of the cell membrane. It is formed as a result of the movement of Na^+ i K^+ ions through cell membrane channels. Single impulses that appear are able to cause a

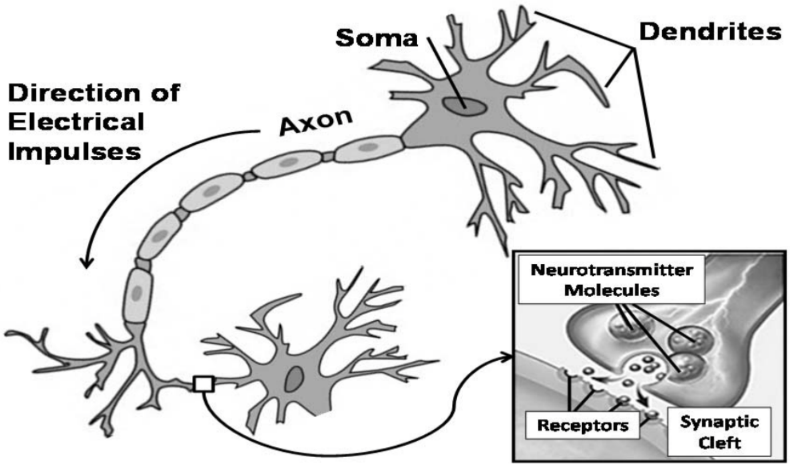

Figure 2.1: Inter-synaptic information transfer diagram [66]

slight local depolarization (pre-depolarization). If the so-called threshold potential is reached, sodium channels open rapidly, allowing Na^{+} ions to enter the cell. If the threshold potential is not reached, no action potential is generated. Sodium ions flowing into the cell intensify cell membrane depolarization and enable the opening of new sodium channels. The intracellular potential becomes more positive than the extracellular potential. Depolarization activates potential-dependent channels, through which K^{+} ions enter the extracellular environment. The increase in the amount of potassium ions outside the cell begins of the repolarization phase, where there is a decrease in intracellular potential.

The environment outside and inside the cell after the action potential has a slightly disturbed ionic economy. The state of the resting potential is brought by the activated sodium-potassium pump, which restores the initial membrane potential. The intracellular electrical potential is lower than the extracellular one at rest of the neuron, and the difference between them is about -70 mV. The components affecting the resting potential are described by the Goldman equation:

$$E = \frac{RT}{F} ln(\frac{P_K[K^+]_z + P_{Na}[Na^+]_z P_{Cl}[Cl^-]_w}{P_K[K^+]_w + P_{Na}[Na^+]_w P_{Cl}[Cl^-]_z}) \tag{2.1}$$

where:

- E - resting potential,
- R- gas constant,

- T- absolute temperature,
- F- Faraday's constant;
- P_X relative membrane permeability to the X ion,
- $[X]_z$ extracellular concentration of X ion,
- $[X]_w$ intracellular concentration of X ion.

Groups of neurons that are synchronously and coherently active generate electrical potential changes that are possible to be detected and amplified using electroencephalographic equipment.

2.2 History of electroencephalography

Electroencephalography is one of the oldest branches of in neuroscience. The first electrical signals were recorded in the 1870s by English physicist Richard Caton [16]. He conducted his research on animals, and used a Kelvin galvanometer to record the signal. The results of his discoveries were published in 1875 in the British Medical Journal. Polish scientists Napoleon Nikodem Cybulski and Adolf Beck [9] conducted their research in similar years. Using a simple amplifier prototype, they obtained the bioelectrical signal from dogs and rabbits [8]. The end of the 19th century was the time of the greatest achievements. It was proved that light has an effect on the brain's electrical activity, which is higher on the opposite side of the eye exposed. Conducted research allowed to locate brain areas that are particularly sensitive to auditory and visual stimuli, and other sensory function areas. Alpha and beta waves were recorded. Theories of conditioned and unconditioned reflexes were developed. These findings laid the foundation for the first human studies.

In the 1920s, German psychiatrist Hans Berger recorded the electrical activity of the human brain for the first time [10]. He initially conducted studies on patients with skull bone defects, and then on people being prepared for the brain tumor removal surgery. He was the first to record brain waves of frequency of 10 cycles per second, which he called alpha waves. He also located the electrode area with the best recorded signal, and indicated the reference electrode. After a series of studies conducted in 1930, Berger published a paper in which he defined the beta wave, determined the relationships between the beta wave and attention focus, and enumerated differences between the alpha and beta waves. After a year-long research on the registered signal, he published another paper in which he discussed brain waves and their amplitudes during sleep and in people with medical conditions such as epilepsy, multiple sclerosis, head injuries, and mental illnesses. He showed that weak electrical currents generated in the brain could be recorded without opening the skull and presented in graphic form. With time, having more modern equipment at his disposal, he expanded his research to include children as well. Berger was the first to use the word "electroencephalogram" to describe the electrical potential of the human brain. Simultaneously with Berger, a young scientist, Gray Walter, conducted his EEG research. Inspired by Berger's achievements, he built his own electroencephalographic apparatus and defined the other two brain wave types, which are delta and theta waves, and proved that delta waves can be used to determine the location of brain tumors.

The 1930s was a time of many EEG experiments. Research conducted by scientists from the Cambridge Laboratory showed the relationship between photostimulation and changes in the alpha rhythm and presented the bioelectrical activity of the cerebellum.

2.3 Electrode arrangement

Electroencephalography (EEG) is a technique that allows for recording the electrical activity produced by brain structures. The EEG test involves recording changes in electrical potential, produced by neurons, with the use of electrodes placed on the surface of the scalp [96]. Throughout the examination, the signal-collecting electrodes only come into contact with the skin through conductive substances (such as gels or salt solutions), which makes electroencephalography a non-invasive diagnostic method of the brain.

Electrical potentials are local (they occur at a specific location), while the potential obtained from the electrodes is the resultant of all surrounding potentials, i.e. electrophysiological signals (e.g. blinks) and signals emitted by the electrical grid. The EEG method allows to represent the resultant electrical activity at a given moment is represented, which is the sum of electrical currents produced by a large number of neurons located in close proximity to the electrode.

The brain is surrounded by tissues (meninges, cerebrospinal fluid, skull), which, among other things, have a protective function. They are also a natural signal attenuation barrier. It is assumed that the amplitude of the EEG signal ranges from 1 μV to 100 μV, and the frequency spectrum is less than 100 Hz (usually up to 50 Hz).

Electrodes for measuring the EEG signal cover the two hemispheres and the four lobes of the brain. The location of the electrodes is standardized according to a global standard called the 10-20 system, which specifies the distances between key electrodes. The designation "10-20" denotes the proportional distances (in percent) between the root of the nose (nasion) and the occipital protuberance in the anterior-posterior plane (inion) and between two ear sections in the dorso-ventral plane. 10 percent of the total distance in centimeters is calculated and a reference point is set at the root of the nose, while the distances between the electrodes amount to 20 percent [68]. Within the 10-20 system, names of the electrodes are related to their location. The electrodes placed over the right hemisphere have even values, and the electrodes placed over the left hemisphere have odd values. The further the electrode is placed from the centerline, the greater its value. In addition, according to the standard system, it is easy to determine the lobe over which a specific electrode is located, because they have appropriate designations such as O-occipital, P-parietal, T-temporal and F-frontal (Figure 2.3). Centerline electrode designations have an additional letter "z". The basic arrangement of the 21 electrodes of the 10-20 system is shown in the figure 2.2. Based on the principles of the 10-20 system, the 10-10 system and the 10-5 system were introduced as extensions to further promote standardization in high-resolution EEG studies [50].

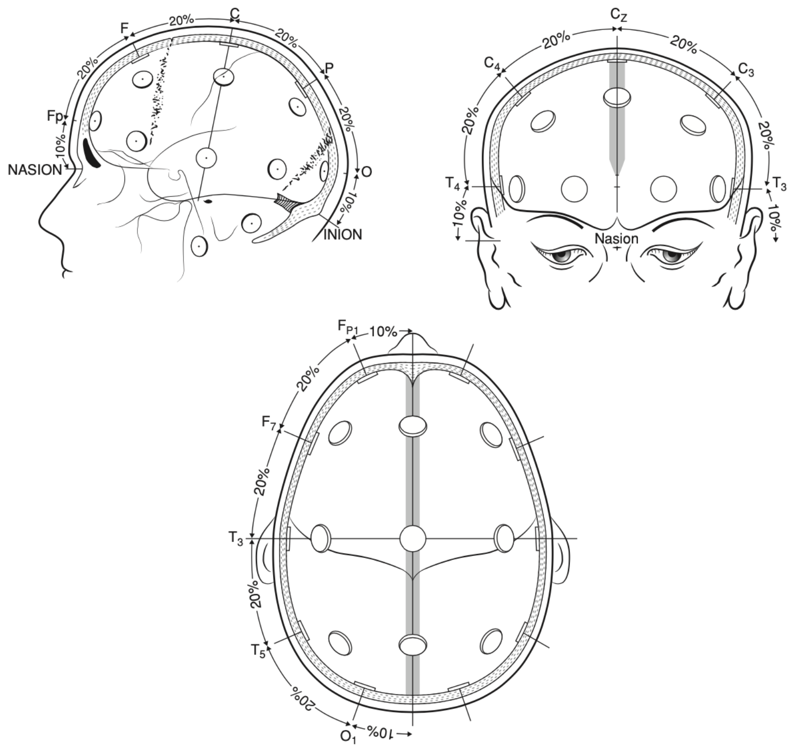

Figure 2.2: 10-20 system of electrode arrangement [83]

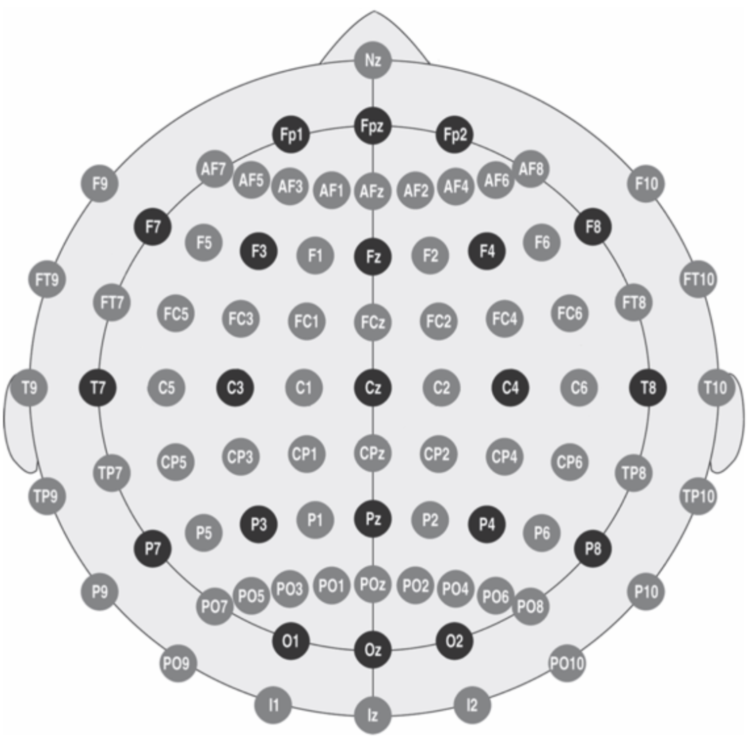

Figure 2.3: Electrode arrangement diagram [62]

2.4 EEG signal bands

Many years of research and analysis of the EEG signal have shown that there are characteristic patterns called rhythms in the electroencephalogram. Their course, i.e. amplitude and frequency, depends on the state of the examined person (for example, during sleep, brain activity is different than in the state of focus), age and other brain disorders [70]. We can distinguish alpha, beta, gamma, delta and theta rhythms (Figure 2.4.

The alpha rhythm is one of the first rhythms identified in the EEG by Hans Berger. It is a rhythmic activity with a frequency of 8 to 13 Hz, which occurs in the posterior head regions, on both the right and left sides. The wave's amplitude varies between 20 and 200 μV, with slightly higher values recorded on the non-dominant side of the brain. This rhythm is most common when a person rests with his or her eyes closed, and as concentration increases, the alpha wave level decreases [42].

The beta rhythm is a brain signal whose frequency ranges from 13 Hz to about 25 Hz. It is usually recorded in the frontal and central part of the brain, on both sides, in a symmetrical pattern. The wave's amplitude is usually between 5 and 10 μV. Beta waves are often divided into SMR, $\beta 1$ and $\beta 2$ for a higher specificity. Beta activity is primarily an excitatory mechanism associated with various mental states, such as active concentration, task engagement, arousal, anxiety, attention, or alertness [66]. Beta waves are usually rhythmic and are observed in every age group [57].

The gamma rhythm has a fairly high frequency in the range of 25-70 Hz, but usually reaches slightly over 40 Hz during mental activity in healthy people. It is often associated with stimulatory and perceptual binding mechanisms, that is, with the integration of different aspects of the stimulus into a coherent overall perception. It reflects the mechanism of consciousness. The wave's amplitude is usually between 1 and 2 μV [66]. There are opinions that the gamma rhythm is a sub-effect of neural processes and therefore does not represent cognitive processing [2].

The delta rhythm is a very low frequency wave of 1 to 4 Hz located in the thalamus. It usually associated with deep unconscious sleep in healthy people. The delta wave is measured to assess the depth of sleep. An increase in the delta wave indicates deeper sleep. The amplitude of this wave is usually between 20 and 200

μV. This type of wave is also associated with pathological neural conditions, such as loss of consciousness or coma. In general, delta activity decreases with age [66].

The theta rhythm is characterized by a frequency in the range of 4 to 8 Hz and is associated with meditation and daydreaming. Theta waves are also associated with tasks that require focus and attention, and the more difficult the task, the higher the wave level. Very low theta levels represent a thin line between waking up and sleeping. High theta levels are considered abnormal in adults [42].

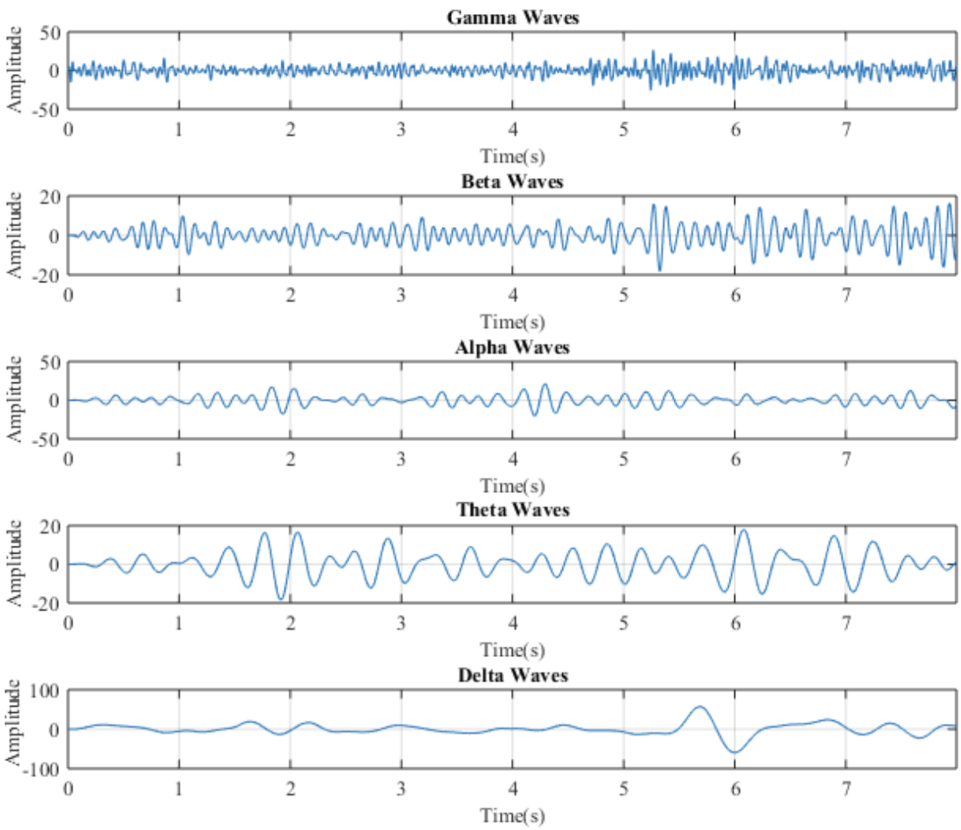

Figure 2.4: Inter-synaptic information system diagram [46]

Chapter 3

Signal processing

A necessary step before preceding data analysis is performing EEG signal preprocessing. This involves applying multiple methods to prepare the EEG signal for further analysis by removing noise and improving the signal's quality.

3.1 Artifacts in the EEG signal

An artifact in the EEG signal can be defined as any information present in the recording that does not come from the brain, is not desired and may adversely affect the quality of the EEG signal [36]. Unfortunately, during signal acquisition, artifacts cannot be completely eliminated, but only reduced. Noise in the EEG signal can be divided into two types depending on its origin. Artifacts that originate from external factors are called non-physiological, while those generated by the electrical activity of organs other than the brain are called physiological [85].

One of the most popular non-physiological artifacts is the network artifact, which is related to the operation of the power grid. It corresponds to the mains frequency, which is 50 or 60 Hz depending on the frequency in a given country. The network artifact has an adverse effect on the gamma band. One way to eliminate this artifact is to use high-pass filters [88]. Another problem that occurs during recording is the influence of electrical devices operating in the vicinity of EEG recording equipment. This issue is caused by the radiation emitted by everyday devices such as mobile phones, radio and television transmitters. Such type of problem can be reduced by appropriate preparation for the test, through switching off all devices that may negatively affect the collected signal. Another problem that negatively affects the signal and can be limited at the preparation stage is insufficient electrode contact with the skin. In order to counteract this type of interference, it is necessary to properly prepare the scalp before the examination, correctly select the size of the cap based on head circumference measurements, and ensure that the electrodes are properly prepared and correctly placed on the head.

Physiological artifacts include artifacts originating from ocular (electrooculography, EOG), muscular (electromyography, EMG) and cardiac (electrocardiography, ECG) (Figure 3.1). Eye movements generate electrical signals that are recorded by EEG electrodes placed on the skin in the area of the frontal and prefrontal cortex area. These artifacts have a distinctive wave pattern that may resemble brain activity. Eye artifact frequency is found in the 0.1-10 Hz band. Eye movements create positive or negative potentials on the electrodes. This is due to the potentials present in the eyeball, and more precisely from the cornea which is positively charged in relation to the fundus. Approaching the electrode increases the potential, and moving away - decreases it. Increasing the potential causes upward eyeball movement, closing of the eyes, and leftward or rightward gaze depending on the hemisphere. Potential is reduced by movements that are antagonistic to potential-increasing movements. These artifacts can cause erroneous EEG results and make it difficult to interpret brain activity.

Muscle artifacts originate primarily from facial, head, and neck muscle activity. These include disturbances related to, among others, facial expressions, tongue movement, jaw clenching or swallowing. Considering the fact that individual muscle groups are characterized by different frequency spectra, it is difficult to identify a specific band that distinguishes this type of artifact. The frequency spectrum for the facial and skeletal muscles ranges between 0-200 Hz, with the frequency for frontal muscles amounting to 20-30 Hz and the frequency for temporal muscles amounting to 20 Hz and 40-80 Hz. Different muscle groups will be observed in different areas of the electrodes. Frontal muscles will be stronger in the frontal electrode area, jaw and temple muscles - in the temporal electrode area, and neck muscles - in the occipital electrode area.

The heart's electrical activity is another example of interference in the recorded

EEG signal. The frequency of these disturbances amounts to about 1 Hz. A characteristic feature of a healthy heart's activity is the regular repetition of the QRS complex, which makes it easier to detect this artifact in the EEG signal (electrical artifact). The heart makes blood flow through the blood vessels. The blood vessel network is distributed throughout the human body, including the head. Electrodes placed over pulsating blood vessels can register these disturbances, called mechanical disturbances [37]. They are regularly spaced and most common in the temporal and frontal electrodes. Recordings of cardiac activity artifacts are time-shifted compared to the ECG signal.

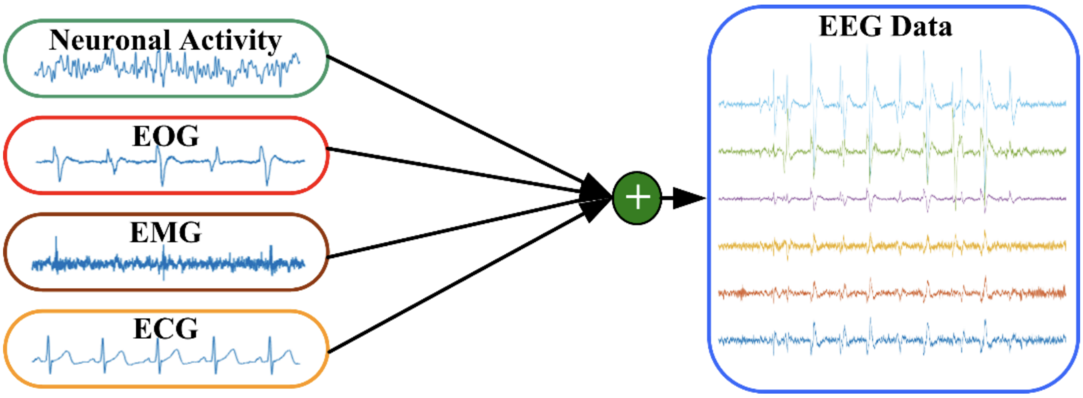

Figure 3.1: Physiological artifacts in the EEG signal

Disturbances are inevitable in the process of recording the EEG signal. Unfortunately, they cannot be completely eliminated, but they can be partially reduced even at the stage test of preparation. It is worth implementing a few basic steps that could contribute to the recording of a less polluted signal. When inviting test participants to the laboratory, it is worth providing them with basic information on how to prepare for the test, including specifying which products should not be used on the day of the test, what is allowed during the examination (e.g. chewing gum is not allowed) and what movements should be limited (if possible and the conditions of the examination allow it), so as to reduce signal contamination. Other important steps include correct cap selection, correct electrode placement on the head of the test participant and grounding the electrodes. These few good habits can minimize the amount of interference in the EEG signal and the data loss during the processing of the recorded signal. Please note that some artifacts cannot be eliminated from the signal because they result from body physiology.

3.2 Preprocessing

EEG signal preprocessing is the processing of the signal recorded by the electrodes placed on the scalp with the aim to prepare raw data for further analysis. The EEG signal is often affected by various artifacts such as eye movements, muscle activity, and electromagnetic interference. Therefore, before analyzing the EEG data, the signal must be pre-processed.

3.2.1 Filtering

The EEG signal is a representation of a complex signal that changes over time and can be represented as a collection of sine-like waves at different frequencies. EEG signal filtering is a process that removes from the EEG signal unwanted noise, such as muscle artifacts, eye movement artifacts, electrode noise, and signals from external sources such as the power grid. EEG signal filtering can be done at different frequencies, depending on the type of interference that we aim to remove, with the use of low-pass and high-pass filters. A low-pass filter is a type of filter that removes the higher frequency components from the EEG signal, leaving only the lower frequency components. This filter acts as a suppressor of high tones, which are usually generated by muscle artifacts. The high-pass filter is antagonistic to the low-pass filter - it removes the lower frequency components and is commonly used to filter [28] eye artifacts. As a standard, a bandpass filter with a range from 1Hz to 40Hz is used in the research to process EEG signals. This is due to the lack of significant information below 1Hz and above 40Hz, which has been reported in the literature. In addition, EEG signals above 40Hz may be subject to interference from the power grid and other devices that operate in a similar frequency range.

3.2.2 Segmentation

EEG signal segmentation is the process of breaking down a long-term electroencephalographic signal into short, more manageable fragments called segments. This process is essential because long-term EEG signals can be very complex and difficult to analyze. Segmentation makes it possible to study shorter fragments of the signal, facilitates identifying characteristic patterns or events over time. For example, when analyzing EEG signals for specific events, segmentation allows for extracting and studying individual episodes. At the design stage of the experiment, tags are defined, which are then applied to the EEG signal at the right moment during the test. Tags enable the identification of events and the division of the signal into shorter fragments.

EEG signal segmentation can be performed using various methods. One technique for signal segmentation is time-based (constant) segmentation, where a long signal is divided into equal or predetermined fragments of fixed length. For signal analysis, segments ranging from 200 ms before the onset of the stimulus to 1000 ms after the onset of the stimulus are typically selected. This allows to obtain several dozen or several hundred segments with a length of 1200 milliseconds, which contain information about both the stimulus presentation and the brain response. The rest of the signal, which is not relevant in this context is deleted or omitted. Another approach to splitting a signal is adaptive segmentation, which divides the signal into segments of variable length, adapted to the signal's characteristics. In contrast to fixed segmentation, where all epochs are of equal length, adaptive segmentation takes into account the differences in the duration of different parts of the EEG signal [4]. Adaptive segmentation methods in EEG can be based on various criteria, such as amplitude analysis, frequency, signal variability or the use of machine learning algorithms. The essence of these methods is to automatically determine the boundaries of the segments based on the signal's characteristics in order to obtain the best match to the variability of brain activity.

3.2.3 Baseline correction

Baseline correction is essential for the precise analysis and interpretation of changes in the amplitude of ERP (Event-Related Potential) signals, which enables the extraction of significant electroencephalographic patterns and stimulus-related events. Experiments involving ERP are one of the most often used in experimental psychology [61]. When analyzing ERP signals, it is important to measure the size of the signal in relation to the baseline, which is defined based on the period preceding the event. This method is based on the assumption that baseline values are similar in different people and under different conditions. To meet this assumption, it is necessary to perform a baseline correction by calculating the average value for the base period and subtracting it from the signal before and after the event. As a result of this process, the average baseline value for each sample is set to zero, allowing the signal segments to be averaged and compared independently of the baseline activity level.

3.2.4 Averaging

Signal averaging is widely used in electroencephalography (EEG). Signal registration using electrodes placed on the scalp is difficult to interpret mainly due to the fact that the signal is the sum of the activity of billions of brain cells. The EEG test provides limited information about the activity of particular brain areas. However, when a specific part of the brain is stimulated with specific stimuli, it evokes a response in the area of the brain responsible for processing information for a given sensory system. By summing the signals evoked after multiple stimuli and dividing by the total number of stimuli, the average evoked response is obtained. During the signal averaging process, sets of signal time epochs are summed with superimposed random noise. Correct summation of the signal waveforms depends on proper synchronization of the time epochs. In contrast, uncorrelated noise will be averaged over time. This process is designed to improve the signal-to-noise ratio (SNR).

Signal averaging, despite its simplicity and effectiveness in noise reduction, has some limitations that should be taken into account. The signal waveform should be repeatable, which means that the signal must occur more than once, although not necessarily at regular intervals. Noise, on the other hand, should be random and uncorrelated with the signal. In the context of averaging, randomness means that noise has no periodicity and can only be described statistically. Accurate knowledge of the temporal position of each signal waveform is also of significant importance. Signal averaging is inapplicable when investigating rare events that cannot be assigned a specific point over time.

The key element of signal averaging is epoch time synchronization. Each epoch is precisely synchronized with the previous epochs, which allows for the signal samples from the later epoch to be added to the corresponding samples from earlier epochs. In this way, repeated time-aligned signals S are summed directly with each other, leading to an increase in signal amplitude. For example, after four epochs, the amplitude of the signal increases four times compared to a single epoch. An important assumption in the signal averaging process is noise randomness. The noise should have mean zero and mean effective value N. If this condition is met, the mean effective value of the signal after four epochs is $\sqrt[2]{4N^2}$, or $2N$. After m repetitions, the signal amplitude is mS and the noise amplitude is $\sqrt[2]{m}N$. Therefore, the signal-to-noise ratio (SNR) improves in proportion to the square root of the number of repeats m, which is $\sqrt[2]{m}$ [93].

3.3 Source localization

In recent decades, significant advances in neuroimaging have revolutionized brain research. Neuroimaging is an interdisciplinary field of science that uses a variety of techniques and methods to visualize brain structure, function and activity. It has provided researchers and physicians with extremely valuable tools to unlock the mysteries of the brain, diagnose neurological disorders and monitor the effects of therapy.

One of the most important neuroimaging techniques is magnetic resonance imaging (MRI). MRI uses strong magnetic fields and radio waves to obtain precise images of brain structure. This method allows to study brain anatomy, and locate various areas and structures, which is crucial for understanding brain function. In addition, MRI provides information about brain structure in different planes and allows for the precise study of neurological pathologies. Another important neuroimaging method is functional magnetic resonance imaging (fMRI), which uses changes in blood flow in the brain as an indicator of neuronal activity. fMRI allows for the analysis of brain activation while performing various tasks or during rest. Owing to this method, it is possible to identify brain areas responsible for specific functions, such as speech, perception or memory. fMRI has also found application in research on mental disorders, allowing for the identification of changes in brain activity associated with conditions such as depression and schizophrenia.

Positron emission tomography (PET) is another neuroimaging technique. It involves introducing into the body of tracer substances that bind to specific molecules in the brain. The tracers emit radiation which is detected by PET detectors. This method enables imaging the brain's metabolic activity, as well as analyzing the distribution of receptors and the transport of neurotransmitters. PET is particularly useful in the study of neurodegenerative disorders such as Alzheimer's disease, as it allows for early diagnosis and monitoring of disease progression.

Electroencephalography (EEG) and magnetoencephalography (MEG) are two other important neuroimaging techniques. An EEG test involves recording the brain's electrical activity by placing electrodes on the patient's head. It is a high time resolution technique, which means that it allows for the study of fast-changing neural processes in real time. Modeling the brain's electrical activity is based on the use of a volume conduction model with consideration of current sources. This phenomenon is described by the Poisson equation and the Neumann and Dirichlet boundary conditions [41]. EEG is widely used in epilepsy research due to its ability to detect and monitor epileptic seizures. In addition, EEG is used in research on states of consciousness, sleep, and perceptual and cognitive processes.

Magnetoencephalography (MEG) is a technique complementary to EEG. It measures changes in the magnetic fields generated by the brain's electrical activity. Owing to its high spatial resolution, MEG allows for precise localization of sources of neural activity. It is particularly useful in research on functional connectomics, i.e. the study of connections between different brain areas and their role in information processing.

Other neuroimaging methods include single photon emission computed tomography (SPECT), which, like PET, is based on introducing tracers into the body and imaging their radiation emission, and computed tomography (CT), which uses X-rays to create cross-sectional images of the brain. Although CT provides structural information, it is less precise than MRI.

All of these neuroimaging techniques have their own unique advantages and limitations, and their appropriate use depends on the scientific or clinical question being investigated. Combined, they are powerful tools that enable us to better understand the brain and its complex structure and function. The breakthrough in neuroimaging opened a new era in brain research, contributing to advances in diagnosis, therapy and understanding the very nature of the human mind.

The process of source localization is connected with the concept of forward and inverse problem. The forward problem involves predicting observations based on input data and known model parameters, while the inverse problem involves inferring model parameters based on observations or measurement data (Figure 3.2). In EEG research, simulating electrode potentials generated by brain current sources is called a forward EEG problem, whereas predicting the location of current sources based on measurements of electrode potentials is known as the EEG inverse problem [39].

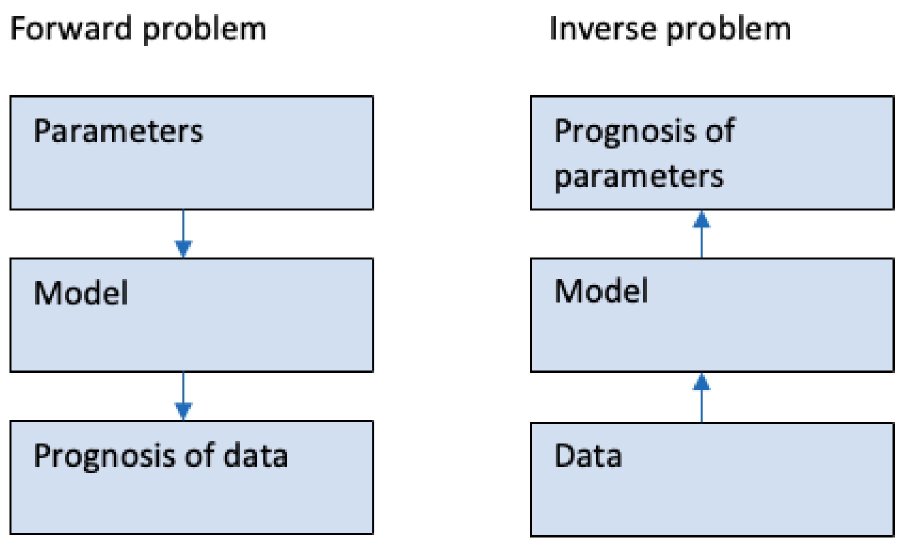

Figure 3.2: Diagram illustrating the forward and inverse problem

The inverse problem is more complex as there are many different sets of parameters that can explain the same measurement data. This is the ambiguity of the inverse problem. Solving an inverse problem often requires additional assumptions, constraints, or additional data to narrow down the range of possible solutions and find the best set of parameters. In practice, various statistical, numerical or optimization methods are used to solve inverse problems in various fields of science and technology.

3.3.1 Inverse solution- the sLORETA

Standardized low-resolution electromagnetic tomography (sLORETA) is one of the most commonly used algorithms for mapping the location of the EEG source generated on the surface of the scalp. It is a reverse technique that allows for the localization of neuronal activity inside the brain based on the recorded EEG or MEG signals. sLORETA was created by Roberto Pascual-Marqui. It is based on the premise that neural activity generates the distribution of electrical currents that can be detected by electrodes placed on the scalp (for EEG) or magnetic sensors (for MEG). This method takes into account the physical conductivity of the brain tissue, which enables estimation of activity sources in three dimensions. sLORETA analyzes EEG or MEG signals from multiple electrodes or sensors, then calculates the spatial distribution of sources of neural activity throughout the brain. The results are presented in the form of a three-dimensional map that shows brain areas where there is neural activity associated with a given EEG or MEG signal. sLORETA allows for precise localization of neuronal activity in the brain, which can contribute to a better understanding of brain function and an improvement in diagnostics and treatment of various neurological conditions [76] [75].

Mathematical description

Current density $\hat{J}$ distribution resulting from neuronal activity is expressed based on scalp potential ϕ. The minimum norm estimate is expressed by the formula:

$$\hat{J} = T\phi \tag{3.1}$$

Based on the formula 3.1, the inverse problem can be solved by the formula:

$$T = K^T[KK^T + \alpha H]^+ \tag{3.2}$$

where α is the regularization parameter and is ≥ 0. The exponent $+$ is the Moore Penrose pseudo-inverse. In order to ensure high localization precision, sLORETA applies standardization by variance of the estimated current density. After transformation, the following formula is obtained:

$$\bar{J}_l = \{[S_{\hat{J}}]_{ll}\}^{-1/2}\hat{J}_l \tag{3.3}$$

where $[S_{\hat{J}}]_{ll} \in R^{3x3}$ is the l^{th} diagonal block of $S_{\hat{J}}$ and $\hat{J}_l \in R^{3x1}$ is the estimated current density at l using the formula 3.1. Matrix representation of the problem:

$$S_d = \begin{bmatrix} [S_{\hat{J}}]_{11}^{-1/2} & 0 & \dots & 0 \\ 0 & [S_{\hat{J}}]_{22}^{-1/2} & \dots & 0 \\ \vdots & \vdots & \ddots & 0 \\ 0 & 0 & 0 & [S_{\hat{J}}]_{MM}^{-1/2} \end{bmatrix} \tag{3.4}$$

3.3.2 MEC

For the sLORETA algorithm, ERP must be determined for each electrode in real time in order to accurately determine electrical activity in the brain. After estimating the ERP signals for each electrode, the MEC can be calculated. The MEC is a measure introduced by Wójcik et al in [99] and reflects the average electrical charge flowing through the brain area placed under the electrodes. The MEC measures were widely used so far by our group [98] [97] [59] [53] [81] [54] [58] [80] [95] The electric current flowing through certain brain areas is expressed by the formula:

$$I(BA, \gamma, t|\Psi\rangle) = \frac{\partial q(BA, \gamma, t, t|\Psi\rangle)}{\partial t} \tag{3.5}$$

where $q(BA, \gamma, t|\Psi\rangle)$ is the electric charge which accumulates in the specified BA for a certain time following stimulation γ stimulation. Vector $\Psi\rangle$ is a set of psychophysiological parameters that describe the electric charge. Electric charge (ι - Iota) that flows through the specified BA is determined by the formula:

$$\forall BA : \iota = q(BA, \gamma, t|\Psi\rangle) = \int_{\gamma+t_1}^{\gamma+t_2} I(BA, \gamma, t|\Psi\rangle)dt \tag{3.6}$$

3.4 Machine learning - regression

Machine learning is a field of artificial intelligence which deals with the development of algorithms and computer models that can learn and make decisions based on input data. The main goal of machine learning is to develop systems that automatically learn from experience and are capable of making predictions, identifying patterns or making decisions without the need for direct human programming.

In traditional programming, a human programmer has to manually write a set of instructions for a machine to perform specific tasks. In machine learning, a model or algorithm is trained on inputs that contain information about correct answers or outcomes. The model analyzes the data, discovers patterns and relationships, and then uses them to make future decisions or predictions.

Regression is one of the fundamental tools used in the field of statistics and machine learning. It is a powerful data analysis tool that allows to model dependencies between variables and predict the value of one variable based on the values of other variables. Regression is widely used in various fields such as social sciences, computer science, economics, medicine, engineering and many others.

It is worth understanding that regression is based on the concept of dependency between variables. We can divide the variables into two categories: the dependent variable (otherwise known as the response variable or the objective variable) and the independent variables (otherwise known as explanatory variables). The goal of regression is to find a mathematical model that best represents the relationship between these variables. A regression model can be linear or non-linear, depending on the nature of the relationship between the variables.

3.4.1 Linear Regression

Linear regression is one of the most basic and widely used statistical analysis techniques. It is employed to model the relationship between the independent variables and the dependent variable using a linear regression equation. The main purpose of linear regression is to predict the value of the output variable y based on the values of the independent variables $x_1, x_2, ..., x_N$. The linear regression formula is expressed as follows:

$$y = \beta_0 + \sum_{i=1}^{N} \beta_i x_i \tag{3.7}$$

where $\beta_0, \beta_1, \beta_2, ..., \beta_i$ are regression coefficients that determine each independent variable's influence on the outcome variable, The least squares method is used to fit the linear regression model to the data (Figure 3.3).

The least squares method is consists in minimizing the sum of squared residuals, i.e. the difference between predicted and actual values. As a result, optimal values of the regression coefficients are obtained that best describe the relationship between the independent variables and the outcome variable.

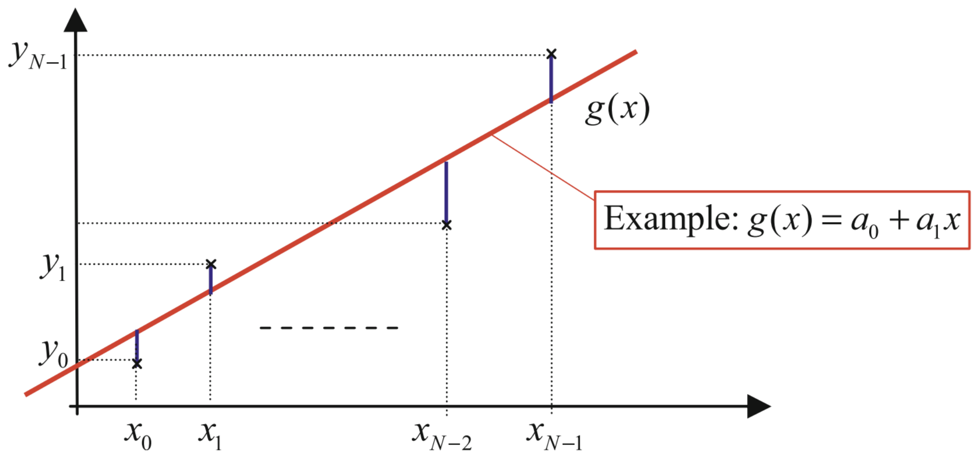

Figure 3.3: Least squares method [89]

3.4.2 Non-linear regression

Nonlinear regression is an extension of linear regression that allows for modeling non-linear relationships between the independent variables and the outcome variable. In contrast to linear regression, where a linear relationship is assumed, nonlinear regression allows for more flexible data adjustment using non-linear functions. The basic assumption of nonlinear regression is that the relationship between the independent variables and the outcome variable can be described by a function other than linear function. This is accomplished by using various nonlinear models, such as polynomial functions, logarithmic functions, exponential functions, etc. Examples of nonlinear regression include:

- Polynomial regression, in which the outcome variable is modeled as a combination of polynomials of the independent variables. This can be achieved by adding to the model the successive powers of the independent variables.

- Logistic regression, which is used when the outcome variable is a binary or categorical variable. A logistic regression model applies logistic function to predict the probability of belonging to a class depending on the values of the independent variables.

- Exponential regression, which is used when there is an exponential relationship between the independent variables and the outcome variable. Examples include modeling population growth and energy flow distribution.

3.4.3 Logistic regression

Logistic regression is a machine learning algorithm mainly used for binary classification problems, i.e. predicting belonging to one of two classes. Although the name suggests regression, logistic regression is actually a classification algorithm. The idea of logistic regression is to predict the probability of belonging to a particular class based on the values of features. The result of logistic regression is a numerical value of the probability of belonging to one of the classes, which is transformed by a logistic (sigmoid) function to a value between 0 and 1.

In logistic regression, there is a decision limit (e.g., 0.5) above which a sample is predicted to belong to one class and below that to another class. This can also be adjusted to tailor the model to the preferences or requirements of the classification problem. In logistic regression, the so-called logit function (log-odds) is used. It combines the values of features with the weights assigned to these features. The logit is transformed using a logistic function, which takes the following form:

$$f(x) = \frac{1}{1 + e^{-z}} \tag{3.8}$$

where f(x) is the value of the dependent variable, z is the value of the independent variable, and e is the Euler number. The figure 3.4 shows the graph of the logistic function, which shows that the function tends to 1 as z increases, and similarly as z decreases, it tends to 0.

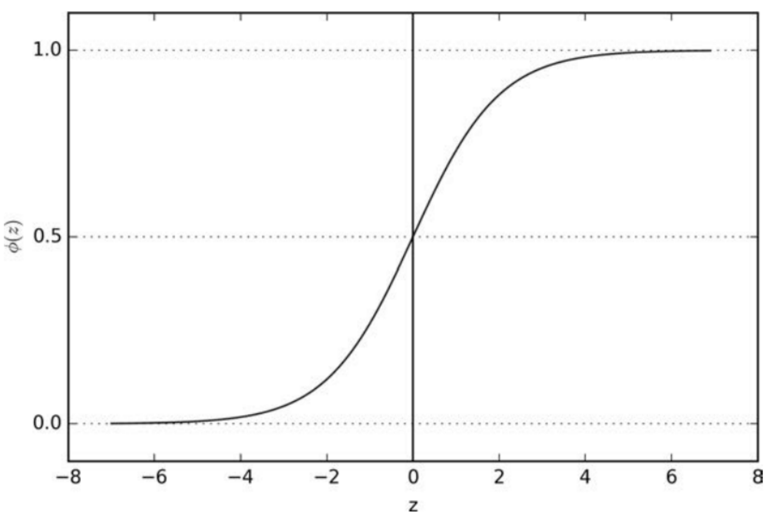

Figure 3.4: Logistic function graph [78]

In the training process of logistic regression, an optimization algorithm such as gradient descent or its more advanced variants is used. The goal is to find optimal weights that minimize the cost function, e.g. cross-entropy, which measures the difference between predicted probabilities and actual class values.

It is also important to include regularization in logistic regression to prevent model overfitting. This can be achieved by adding a regularization term to the cost function that penalizes excessive weights.

3.4.4 Classification effectiveness measures

Classification performance measures are used to assess the quality of classification models that predict the membership of objects in different classes or categories. To assess the quality of two-class classification, a confusion matrix can be used. The confusion matrix provides detailed information on classification errors, which allows to assess how well the model performs in recognizing different classes. The basic table has rows representing actual values and columns indicating the predicted value.

<table>
<tr><td></td><td></td><td colspan="2">Prediction</td></tr>
<tr><td></td><td></td><td>False</td><td>True</td></tr>
<tr><td rowspan="2">Observed</td><td>False</td><td>TN</td><td>FP</td></tr>
<tr><td>True</td><td>FN</td><td>TP</td></tr>
</table>

Table 3.1: Confusion matrix

There are 4 fields in the table 3.1:

- True Negative (TN) refers to a situation in which the model correctly identifies the non-occurrence of a particular phenomenon or condition as negative, when in fact it is not present.
- False Positive (FP) refers to a situation in which the model erroneously predicts the occurrence of a certain event, while in fact this event does not occur. In such cases, efforts are made to minimize these occurrences.
- False Negative (FN) occurs when the model does not identify the occurrence of a certain event, while in fact this event is present. The goal in these cases is to minimize such events.

- True Positive (TP) indicates that the model accurately predicted the occurrence of a phenomenon, as confirmed in practice. When designing the model, our goal is to maximize the accuracy of these predictions.

Based on the confusion matrix, various performance measures can be calculated, such as accuracy, precision, sensitivity, and specificity for each class.

Accuracy

Accuracy determines how well the model predicts the correct class or label for a given test data set. It is calculated as the ratio of the number of correct predictions to the total number of predictions, according to the following formula:

$$accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{3.9}$$

It is usually expressed as a percentage value, where 100% means perfect accuracy, i.e. correct prediction for all samples. Accuracy is one of the simplest and most intuitive indicators for evaluating classification models. However, it is not always an appropriate measure of performance, especially in the case of unbalanced classes (when one class dominates the data set). In such cases, other measures, such as precision, recall and F1-score, may be more informative.

Precision

A measure of the classification model efficiency which provides information about the proportion of truly positive predictions among all positive predictions made by the model. In simple terms, precision measures how well the model copes with identifying real positive cases in relation to all cases that it has classified as positive. Precision can be calculated using the following formula:

$$precission = \frac{TP}{TP + FP} \tag{3.10}$$

Precision values range from 0 to 1, where 1 stands for ideal precision, i.e. all positive predictions are true. Precision does not take into account false negative predictions, i.e. cases in which the model does not identify truly positive cases. Therefore, it is worth taking into account other measures, such as recall and F1-score, to get a more complete picture of the classification model performance.

Recall

The recall indicator, also known as the True Positive Rate (TPR), is a measure of a classification model performance that provides information about the proportion of truly positive cases that have been correctly identified by the model, relative to all actually positive cases in the data set. Sensitivity can be calculated using the following formula:

$$recall = \frac{TP}{TP + FN} \tag{3.11}$$

Similarly to precision, recall takes values from 0 to 1, where 1 indicates perfect sensitivity, which means that all truly positive cases have been correctly identified by the model. Recall is particularly important when the cost of false negative predictions is high. As with precision, sensitivity alone does not provide a complete picture of a classification model's performance. For a more complete view of model performance, it is useful to consider other measures such as precision and F1-score.

Specificity

Specificity, also called True Negative Rate (TNR), is a measure of classification model performance that informs us about the proportion of truly negative cases that have been correctly identified by the model, relative to all actually negative cases in the data set. It is calculated on the basis of the following formula:

$$specificity = \frac{TN}{TN + FP} \tag{3.12}$$

Similarly to precision and sensitivity, specificity ranges from 0 to 1, with 1 being perfect specificity, i.e. all truly negative cases were correctly identified by the model. As a single measure, it does not fully describe the classification carried out and therefore the results of the above-described measures: precision, recall and F1-score should be additionally included.

F1-score

The F1-score is a measure of the classification model performance that combines precision and recall information. It is the harmonic mean of precision and sensitivity that provides a balanced evaluation of the model considering both the ability to identify true positive cases (precision) and the ability to detect the majority of true positive cases (sensitivity). It is calculated according to the following formula:

$$F1 - score = \frac{2 \cdot precision \cdot recall}{precision + recall} \tag{3.13}$$

F1-score takes values from 0 to 1, where 1 means the perfect fit of the model, and 0 means the worst possible performance. It allows for a balanced assessment of the performance of the model, taking into account both precision and sensitivity. F1-score is particularly useful in cases where we want to simultaneously minimize both false positive and false negative predictions.

ROC curve

The ROC (Receiver Operating Characteristic) curve is a graphical representation of the classification model performance, which illustrates the relationship between True Positive Rate (TPR) and False Positive Rate (FPR) depending on various decision thresholds.

The FPR is the percentage of false positives that are misclassified as positive by the model. It is calculated by dividing the number of false positives by the sum of false positives and true negatives, as follows:

$$FPR = 1 - specificity = \frac{FP}{TN + FP} \tag{3.14}$$

In the ROC curve graph, the X axis represents FPR, and Y axis represents TPR. For different threshold values, points (FPR, TPR) are marked on the graph and then connected by a line to form an ROC curve (Figure 3.5).

An ideal classification model would have an ROC curve that is adjacent to the upper left corner of the graph, which would mean it has a TPR of 1 and an FPR of 0 for all thresholds. This would mean that the model is able to correctly identify all positive cases while not making any false positive predictions. The farther the curve is from the random line (the diagonal line from point (0,0) to point (1,1)), the better the model's ability to discriminate between positive and negative cases.

The Area Under the Curve (AUC) is a measure of overall performance for a classification model, which quantifies the area under the ROC curve. The interpretation of AUC is as follows: AUC equal to 0.5 indicates a random performance of

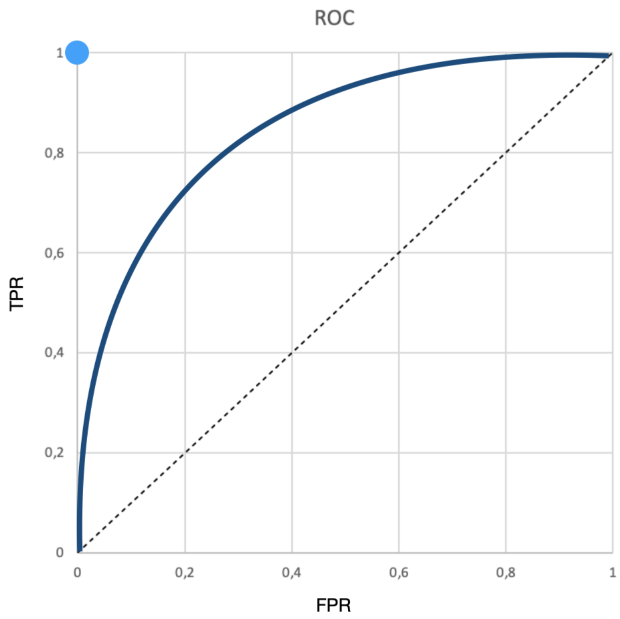

Figure 3.5: ROC curve graph. The blue point on the axis with the values TPR=1 and FPR=0 represents the ideal model

the model, indicating no ability for correct classification. AUC above 0.5 indicates performance better than random, and the higher the AUC value, the better the model's performance.

Chapter 4

Research conducted

The process of data preparation and its analysis has been divided into two stages. Before proceeding with decision-making research in terms of electroencephalographic examination, a pilot study was carried out. It examined whether there are any links between a given personality trait and issuing a trust assessment. In addition, the pilot study takes into account an additional feature of attractiveness. The course of both experiments is presented below. The experiments were carried upon the permission of the University's Bioethical Commission (MCSU Bioethical Commission permission 13.06.2019).

4.1 Pilot experiment

Appearance can affect the success of interpersonal interactions, hence, before proceeding with the work related to the main objectives of the dissertation, a pilot study was conducted with the aim of collecting information about the people participating in the study and their evaluations towards the people featured in the photos. The purpose of the pilot study was to see if there is a correlation between the level of trust towards the person in the photo and the personality trait shown by psychological tests, as well as the level of attractiveness and the personality trait.

4.1.1 Study participants

The pilot study was conducted as an additional activity within one of the classes among first-year students of the Maria Curie Skłodowska University. The participants were students of such faculties as computer science and cognitive science. The age of the participants ranged from 18 to 24 years old, most of whom were under 20 years old. Due to the security of personal data, each participant had a unique code and password for the survey.

4.1.2 Description of research tools

The research collected information on the level of trust placed in the people presented in the photos, the assessment of attractiveness concerning the people in the photos and the personality traits of the respondents. The participants' personality traits were derived from psychological tests they had completed, while the assessments of the people depicted in the photos were obtained through a separate survey/experiment.

Each participant completed two psychological questionnaires. One of them was the NEO-PI-R questionnaire, which enables quite a detailed indication of personality structure. This is a form that is derived from the five-factor model of personality known as the Big Five. The initial NEO PI-R questionnaires consisted of three main dimensions, divided into six subscales each [21]. As a result of further research and observation, the questionnaire was expanded and improved. The current version consists of five constant personality components, which are divided into six component variables (table 4.1) [22]. The division into component constants and variables results from the conditions. Genetically determined components are called constant (basic), while those that are susceptible to any changes under the influence of, for example, the environment are called variables. Characteristics of persons included in particular permanent groups of the NEO PI-R questionnaire are described below:

- Neuroticism - a trait characterized by a tendency to experience negative emotional states such as fear, frustration, anxiety, general dissatisfaction. People endowed with this personality trait have impaired ability to assess the situation, often exaggerate minor situations, do not cope with stress, dwell on situations from the past [92].

- Extroversion - a trait of people whose interest is focused on the people around them. Extroverts are usually self-confident, brave, easily establish contacts with others, like to be in the center of attention, feel comfortable in a group, thanks to which they gain good energy and lose it while being alone. In addition, extroverts easily express their feelings, both negative and positive [40].

- Openness to experience - a feature that characterizes creative and active people who are looking for new stimuli, impressions and skills. Openness translates into a desire to experience new experiences and activities. People displaying it are not afraid of changes, they like to leave their comfort zone, they are open to unconventional patterns of thinking and behavior, thanks to which it is easier for them to question the opinion of others and formulate their own judgments [63].

- Agreeableness - a feature that determines a person's attitude to the social world. Agreeable people are described as patient, cooperative and positive towards others. Other traits include i.e. altruism, high trust, honesty. They do not like disputes, so they agree to compromise. People with a low level of agreeableness are characterized by the fact that they are able to take care of their own interests and are reluctant to agree to proposals that are not very favorable to them. They can draw additional motivation from competition with others [38].

- Conscientiousness - a trait of people prone to self-discipline and persistent in the pursuit of set goals. Conscientious people are focused on action, hard-working, dutiful, punctual. They perform the duties entrusted to them diligently, unfortunately, sometimes they get too involved in work, falling into workaholism. On the other hand, people with low conscientiousness are more spontaneous and easily make quick decisions, do not have specific goals and attach less importance to the duties entrusted to them [79].

Using the NEO PI-R questionnaire, it is possible to determine the general adaptation of the examined person to the environment, their typical behavior and feelings within their personality. The NEO PI-R consists of 240 closed questions/statements, to which the research participant answers using a scale from 0 to 4, depending on how much the participant identifies with particular questions/statements [73] [22].

Neuroticism	Extroversion	Openness	Agreeableness	Conscientiousness
N1- Anxiety	E1- Warmth	O1- Fantasy	U1- Trust	S1- Competence
N2- Angry hostility	E2- Gregariousness	O2- Aesthetics	U2- Straightforwardness	S2- Order
N3- Depression	E3- Assertiveness	O3- Feelings	U3- Altruism	S3- Dutifulness
N4- Self-consciousness	E4- Activity	O4- Actions	U4- Compliance	S4- Achievement striving
N5- Impulsiveness	E5- Excitement seeking	O5- Ideas	U5- Modesty	S5- Self-discipline
N6- Vulnerability	E6- Positive emotions	O6- Values	U6- Tendermindedness	S6- Deliberation

Table 4.1: Components of the NEO PI-R questionnaire

The second test was a questionnaire developed by Hans J. Eysenck and Sybil B. G. Eysenck, which in its final version is called the Impulsiveness-Venturesomeness-Empathy Questionnaire (IVE) [31]. It is used to diagnose adults and adolescents in terms of three dimensions: impulsiveness (characteristic of people who act on the spur of the moment without analyzing possible consequences), propensity to risk (feature of people who are open to new experiences and are not afraid to take new challenges) and empathy (sensitivity to other people's feelings) [30]. The questionnaire has 54 single-choice questions, in which the participant can only answer affirmatively "YES" or negatively "NO". The answers belonging to individual dimensions are summed up and on this basis it is possible to indicate the leading personality traits [15].

A separate stage of the research was a survey/experiment in which the respondents' assessments of the people in the photos were collected. Face photos were taken from databases available on the Internet that make their resources available for scientific purposes. From a wide array of resources, two quite numerous collections were selected: Development Emotional Faces Stimulus Set (DEFSS) [64] and Multi-Racial Mega-Resolution (MR2) [86]. During the verification of the usability of each set of photos, it was checked whether the faces do not show any emotions, whether they are presented frontally, whether the photos show real faces (they are not generated by artificial intelligence), whether the whole head is presented, not just the face, whether the photos are of good resolution. The selected sets met the above requirements, and only those faces that did not show emotions were selected from the photos. In addition, the MR2 database contains photos of people of various origins (European, African and East Asian). Most importantly, each of the databases used was tested by the respondents before being published in order to verify, among other things, the existing emotions. Figure 4.1 shows most of the photos used in the pilot study.

Figure 4.1: A fragment of the set of photos used in the study

100 photos were used for the experiment. Fifty photos showed female faces and fifty photos showed male faces. All the faces had a neutral facial expression and depicted the face from the front. Almost half of the photos (49) are of European descent, 31 of African descent and the remaining 20 of East Asian descent. Based on the answers provided by the participants, the set of photos was divided into 4 parts: trustworthy and attractive, not trustworthy and attractive, trustworthy and unattractive, untrustworthy and unattractive. By analyzing all the collected information, the collection was limited to 24 photos (6 photos from each group). The new set will be used to design the main experiment.

4.1.3 Procedure

The first part of the study involved psychological questionnaires, on the basis of which it is possible to determine the personality traits of the participants. At the very beginning, each participant completed the NEO PI-R test sheet, which consisted of 240 questions [22]. The questions/statements in the test refer to how people behave in different situations. The answers to the questions were given on a scale from 0 to 4, depending on how the participant would behave in a given situation.

After completing the first test, each participant took the IVE test [31]. The set of questions in this questionnaire is definitely smaller than the previous one and contains 54 questions. In this case, the participant has a dichotomous scale of answers in the form of YES or NO statements.

In the second part of the study, answers related to the assessment of people in the photos were collected. During the survey, the surveyed person was shown 100 photos from the prepared database. Each time a photo was displayed, three questions appeared in turn: "To what extent are you able to trust the person in the photo", "How attractive is the person in the photo", "What gender is the person in the photo". The participant's task was to answer the displayed questions. To move on, they had to answer the currently displayed question. The questions in which the participant had to assess trust in the person whose face was presented in the photo and their attractiveness had a gradual scale of answers from 1 to 5, where the higher the value, the higher the face was assessed. The last question about the gender of the person in the photo assumes that there can only be two choices. The participant, using the keyboard, selected the "k" key for a female face and "m" in the case of a male face. In total, in this part of the study, each participant answered 300 questions. The research protocol of the pilot experiment is presented in the figure 4.2.

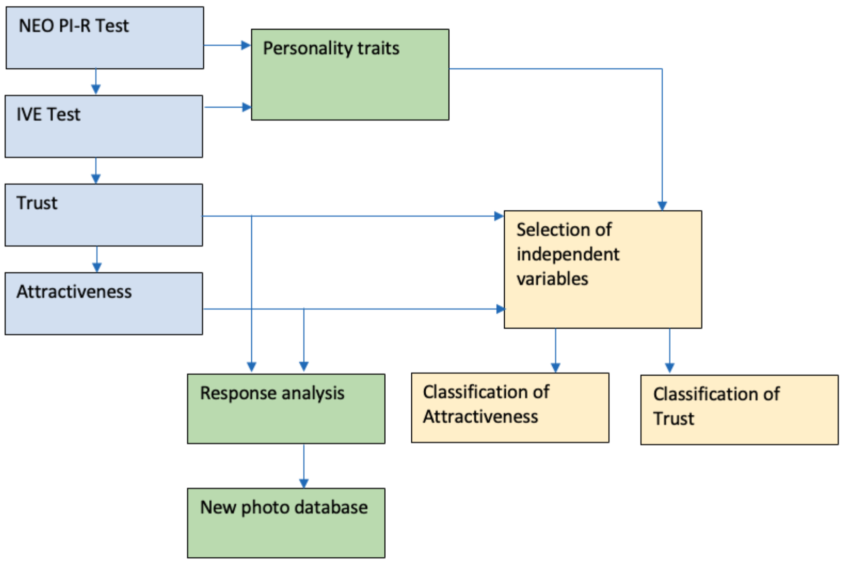

Figure 4.2: Research protocol for pilot study

4.2 Main Experiment

4.2.1 Study participants

The study involved 61 young people, students of computer science at the Maria Curie-Skłodowska University in Lublin. People aged 18-23 were invited. Registration for the study took place via an online form, in which head circumference and time availability had to be provided. To ensure the confidentiality of personal information, each participant was assigned a randomly generated ID number. In order to create the most representative research group, students were recruited according to specific criteria. It was assumed that right-handed people with short hair could participate in the study, because long hair causes more noise in the signal. Due to the low number of short-haired women in computer science, only men were recruited for the study. Only people without permanent or serious health problems within a year that would hinder the conduct of the study or affect the quality of the collected data could participate in the study. As an element of preparation for the study, participants were asked not to consume alcohol for at least three days before the planned study.

4.2.2 Research tool

The study of brain activity during the evaluation of the presented face photos was carried out in the EEG laboratory located in the Department of Neuroinformatics and Biomedical Engineering of the Maria Curie-Skłodowska University in Lublin. During the study, the EEG signal was collected from the surface of the participants' heads. Therefore, the tools necessary to perform the test are: measuring equipment with software and a research experiment.

Measuring apparatus

The laboratory is equipped with high-quality equipment for measuring the EEG signal. The test stand consists of a signal recording stand and a test participant's stand. The signal recording station (Figure 4.3) is equipped with a computer with EGI's NetStation software, which enables the recording of the collected EEG signal and its processing [27].

Figure 4.3: Station for recording the EEG signal

The participant's stand (Figure 4.4) includes a computer and an amplifier with a cap. During the test, the participant sits in front of a computer monitor on which stimuli stimulating the brain are displayed. The computer has OpenSesame software, thanks to which it was possible to design the experiment and its presentation. It is fully compatible with the software of the signal recording station, thanks to which all participant's reactions could be recorded on the EEG signal.

Figure 4.4: Position of the research participant

The research was carried out using a 256-channel EEG amplifier from EGI, recording at a frequency of up to 500 Hz. EGI amplifiers use a technology called "Net Amps" which is integrated with the GSN (Geodesic Sensor Nets) electrode system. The amplifier is directly connected to the electrodes of the HydroCel GSN cap, ensuring high signal quality and minimizing interference.

Signals from the scalp surface were collected using the HydroCel GSN 130 Geodesic Sensor Nets cap by EGI, which is shown in the figure 4.5. The flexible mesh and 256 measuring electrodes ensure that the electrodes fully cover the head, so that important signals are not missed.

Figure 4.5: Cap for measuring the EEG signal from the surface of the scalp

The EEG laboratory is equipped with a photogrammetric station (Figure 4.6), with the help of which, after each examination, pictures of the test participant wearing a cap are taken. The GPS photogrammetric station is a device with 11 cameras in its frame that are able to record high-resolution images. Each of these cameras is precisely calibrated and directed at electrodes located on the scalp. Thanks to this, by taking a series of photos from different points of view, this station collects rich information about the position of the electrodes in space. The process of photogrammetry, i.e. the analysis and interpretation of photos taken by the station, is

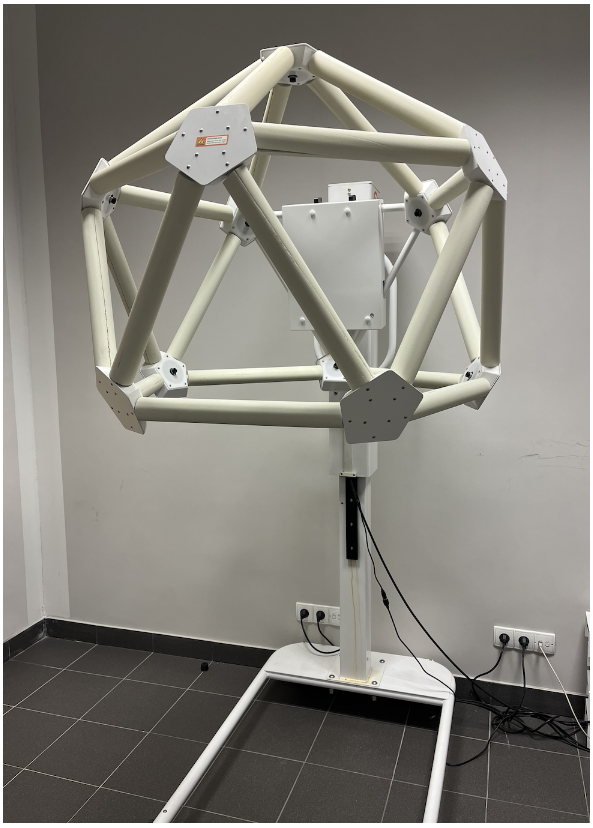

Figure 4.6: GPS photogrammetric station

crucial for determining the exact position of the electrodes. Owing to the advanced algorithms of the software used, the station can precisely locate each electrode on the scalp. These results are then stored in the form of coordinates that can be used in further scientific research.

Research experiment

During the experiment, the participant was stimulated by stimuli in the form of pictures of faces. Faces from the MR2 [86] and DEFSS [64] databases were used to design the experiment. As a result of the statistical analysis of the data collected during the pilot experiment, 24 photos were specified (Figure 4.7) that were used for the study. The photos show faces of men and women of different ages and races.

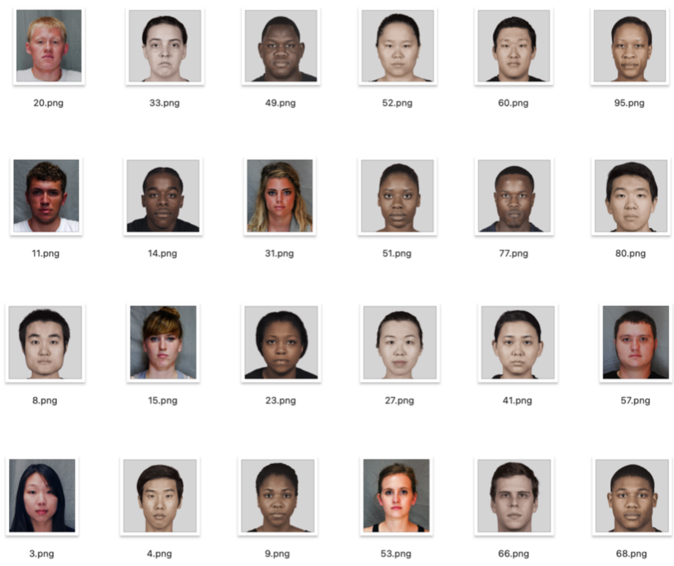

Figure 4.7: A collection of photos used in the design of the experiment

The experiment for the study was created using the OpenSesame program (version 3.2.8), whose window is shown in the figure 4.8. It is a program dedicated to the design of experiments in the field of neuroscience or psychology and is compatible with software recording the EEG signal. In the designed experiment, the participant's task was to assess the person in the photo in terms of trust level and attractiveness level.

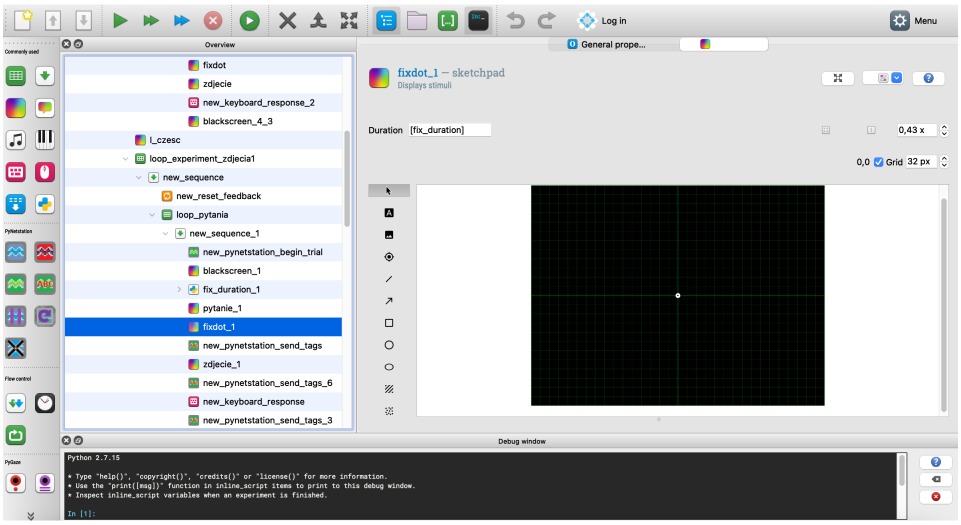

Figure 4.8: The OpenSesame window

Before starting the target part of the study, a training was conducted in which several photos from outside the used photo database were placed. The training was identical to the proper part. This was to train the participant so that he or she could freely and easily answer the questions displayed during the study. No signal was collected from the electrodes during the training.

During the experiment, each time the participant was shown a series of 4 windows presented in the figure 4.9. The black screen displayed for 300 ms was an element of rest for the participant and somehow separated the subsequent screens on which the participant focused. The time of the next screen oscillated between 100 and 1200 ms and contained a small dot in the middle of the screen. The third screen displayed a question that the participant would answer. The question display time is 1200 ms. The last screen showed a photo with the face being judged. The maximum display time of this screen was 20000 ms. During the face presentation, the participant answered the question displayed on the previous screen. Pressing the appropriate key indicating the answer (keys 1 to 5) automatically interrupted the exposure of the last screen and the participant moved on. For each question, a single picture was displayed, i.e. during the experiment, each face appeared twice. The experiment consisted of two parts: the training part and the main part. During the training part, the participant was given a few photos from outside the set of photos used for evaluation. The training part included the same elements as the main part.

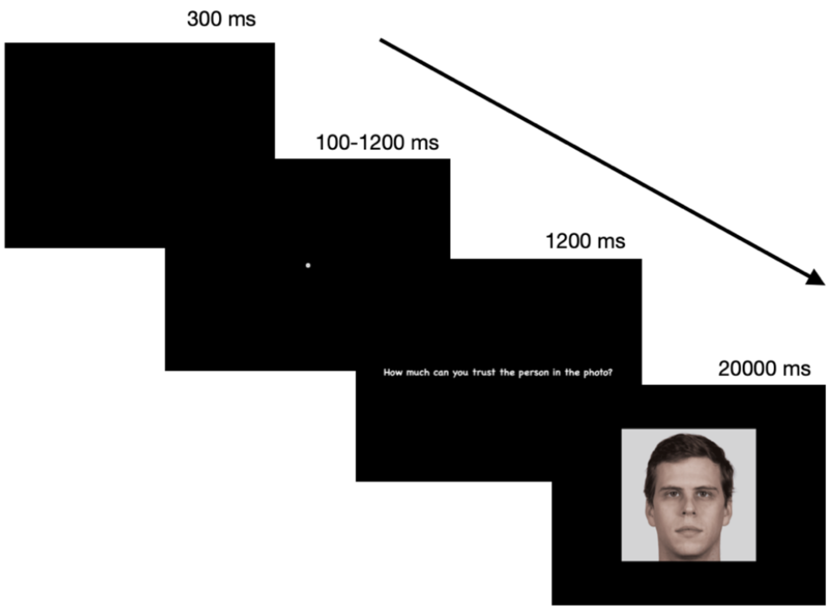

Figure 4.9: Experiment template

4.2.3 Procedure

The conducted research can be divided into two parts. The first part is the preparation for the test, and the second part is the execution of the test. Participants were instructed on how to prepare for the study before applying for the study. At the preparation stage, each participant was familiarized with the purpose of the research and the principles of how they should/should not behave during the research. Putting on the cap and preparing the measurement software are the last elements of the described stage. The ready participant could proceed to the experiment.

The purpose of the experiment was to record the EEG signal while answering questions about trust and attractiveness. The participant answered two questions during the study: "To what extent are you able to trust the person in the photo" and "How attractive is the person in the photo." The faces presented in the experiment were not familiar to the participants. Each time, the participant was given a choice of values from 1 to 5, which allowed him to indicate how much he trusts the person in the photo and how attractive the person is. A value of "1" meant not at all, and the higher the value, the more the participant trusted/thought the person was attractive. The research protocol of the main experiment is presented in the figure 4.10.

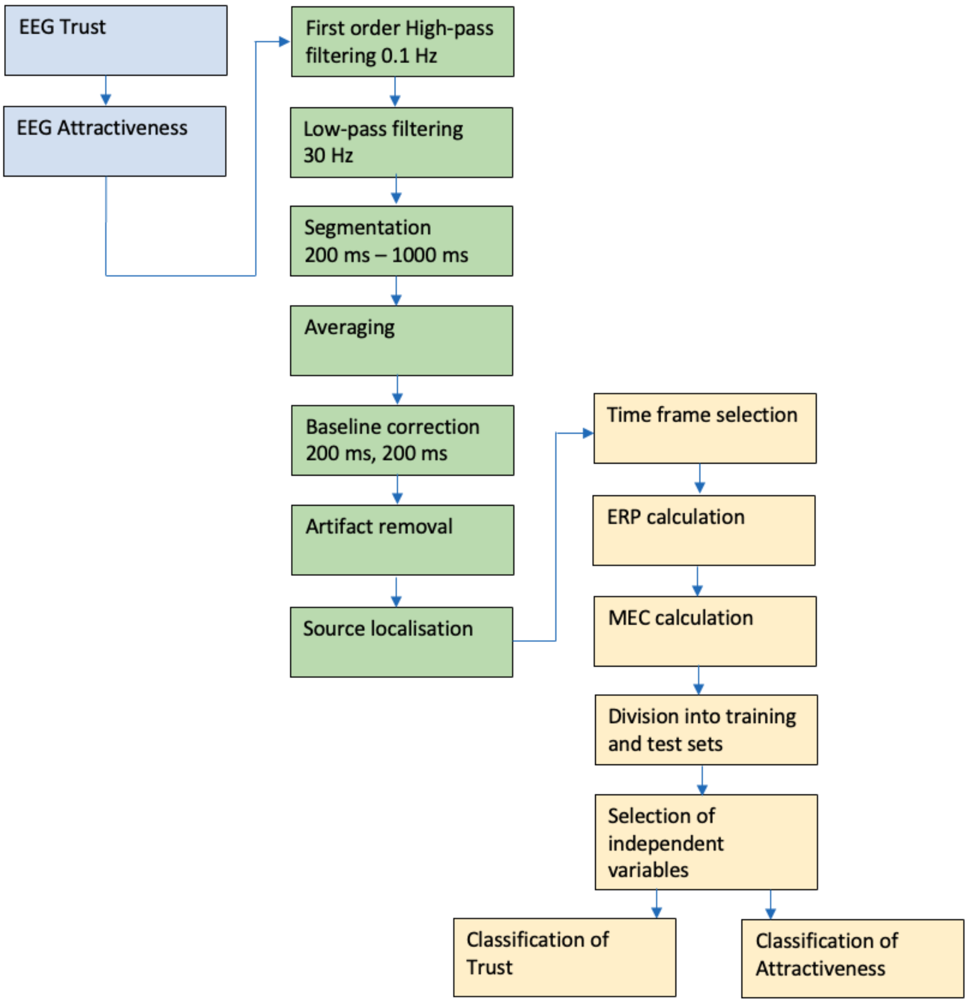

Figure 4.10: Research protocol for main experiment

Chapter 5

Results

5.1 Pilot experiment

The process of statistical evaluation of the data was performed using a logistic regression model. For this purpose, the SPSS statistical calculation program was used. The model was built on the basis of the answers given regarding trust and attractiveness and personality traits. Since the dependent variable should be bivariate, all participants' responses regarding trust on a scale of 1 to 5 were converted to representations of 1- trusted/attractive (responses above 3) and 0- not trusted/attractive (responses below 3). Further in the model, 34 explanatory variables were distinguished, which represented all personality traits that can be determined by the psychological questionnaires used.

A backward stepwise logistic regression model based on the Wald criterion was used. The Wald criterion is used to streamline the regression model by determining the least significant variables. The model was optimized after each step by discarding the least significant variable, i.e. the one with the lowest Wald coefficient. As a result of eliminating the explanatory variables that had the lowest impact on the model, the number of descriptive variables was reduced to 9 (26 steps) for the model assessing trust and to 5 (30 steps) for the model assessing attractiveness (Table 5.1).

Explanatory variables (trust)	Explanatory variables (attractiveness)
N2- Angry hostility	O5- Ideas
N4- Self-consciousness	U3- Altruism
N5- Impulsiveness	S2- Order
E4- Activity	Empathy (IVE)
O4- Actions	sdr- Tendency to risk (IVE)
U1- Trust	-
U3- Altruism	-
Empathy (IVE)	-
Impulsiveness (IVE)	-

Table 5.1: Summary of the components of the NEO PI-R questionnaire after the elimination of the number of descriptive variables

On the basis of the data returned by the logistic regression model, the relationship between the dependent variables and the descriptive variables, which were the individual components of personality traits, was assessed. The correctness of the logistic regression classification was also assessed, which is presented in the tables 5.2 and 5.4. The obtained model for the dependent variable "trust" made accurate classifications in 78.8% of the data, while the classification of data for the variable "attractiveness" resulted in correct matches for 72.6% of the data. Hypothesis H1 was positively verified. Hypothesis H2 was positively verified.

Observed		Predicted		
		trust		Percentage of correct classifications
		0	1	
trust	0	30	10	75.0
	1	8	37	82.2
Total percentage				78.8

Table 5.2: The proportion of accurate classifications in the training dataset for the variable "trust"

The classifier quality measures presented in the table 5.3 i 5.5 confirm that it was possible to build a good quality classifier for predicting the rating of trust and attractiveness based on personality traits.

Accuracy	Precision	Recall	F1-score
0.79	0.79	0.82	0.80

Table 5.3: Classification measures that represent classifier quality for trust

<table>
<tr><td colspan="2" rowspan="3">Observed</td><td colspan="3">Predicted</td></tr>
<tr><td colspan="2">attractiveness</td><td rowspan="2">Percentage of correct classifications</td></tr>
<tr><td>0</td><td>1</td></tr>
<tr><td rowspan="2">attractiveness</td><td>0</td><td>46</td><td>6</td><td>88.5</td></tr>
<tr><td>1</td><td>9</td><td>23</td><td>71.9</td></tr>
<tr><td>Total percentage</td><td></td><td></td><td></td><td>82.1</td></tr>
</table>

Table 5.4: The proportion of accurate classifications in the training dataset for the variable "attractiveness"

Accuracy	Precision	Recall	F1-score
0.82	0.79	0.72	0.75

Table 5.5: Classification measures that represent classifier quality for trust

Optimizing the number of explanatory variables by eliminating them on the basis of significance led to the listing of several most influential variables for each dependent variable. Hypothesis H3 was positively verified. Optimization results are presented in the table 5.6, in which additionally it was color coded whether the variable is significant only for one dependent variable or for both.

Type of test	Personality factors	Component factors
Neo-Pi-R	Neuroticism	N2- Angry hostility
		N4- Self-consciousness
		N5- Impulsiveness
	Extroversion	E4- Activity
	Openness	O4- Actions
		O5- Ideas
	Agreeableness	U1- Trust
		U3- Altruism
	Conscientiousness	S2- Order
IVE	Empathy	
	sdr - Tendency to take risks	
	Impulsiveness	

Table 5.6: The impact of individual personality components/personality traits on trust level and attractiveness assessment as well as trust level and attractiveness assessment at the same time. Green indicates the impact on the trust variable (favorable - light green, unfavorable - dark green), yellow on the attractiveness variable and blue on both variables at the same time (favorable - light blue, unfavorable - dark blue)

		trust					attractiveness				
		B	Standard error	Wald	Relevance	Exp(B)	B	Standard error	Wald	Relevance	Exp(B)
Step 26	U1	0.709	0.331	4.599	0.032	2.032	-	-	-	-	-
	N2	1.153	0.442	6.8	0.009	3.169	-	-	-	-	-
	U3	1.041	0.371	7.859	0.005	2.833	-	-	-	-	-
	N4	-0.721	0.333	4.703	0.03	0.486	-	-	-	-	-
	E4	-0.753	0.398	3.579	0.059	0.471	-	-	-	-	-
	O4	0.694	0.357	3.776	0.052	2.001	-	-	-	-	-
	N5	-0.605	0.374	2.609	0.106	0.546	-	-	-	-	-
	impulsiveness	-0.717	0.368	3.794	0.051	2.047	-	-	-	-	-
	empathy	-0.592	0.351	2.846	0.092	0.553	-	-	-	-	-
	constant	0.096	0.273	0.124	0.725	1.1	-	-	-	-	-
Step 30	S2	-	-	-	-	-	-0.741	0.303	6	0.014	0.477
	U3	-	-	-	-	-	0.961	0.32	9	0.003	2.615
	O5	-	-	-	-	-	0.501	0.298	2.82	0.093	1.65
	sdr	-	-	-	-	-	0.535	0.299	3.208	0.073	1.707
	empathy	-	-	-	-	-	-0.471	0.292	2.608	0.106	0.624
	constant	-	-	-	-	-	-0.678	0.263	6.675	0.01	0.507

Table 5.7: Estimating the values of the logistic regression model parameters for the dependent variable - attractiveness and trust. The table shows the statistics for each of the predictors in the model. As a result of gradual elimination of the predictors in the light parts of the table (step 26 for the confidence dependent variable, step 30 for the attractiveness dependent variable), the variables furthest away from the dependent variable are presented

Among all the explanatory variables, altruism (U3), which is one of the elements of agreeableness in the NEO PI-R questionnaire, had the greatest influence on the decisions regarding the level of trust and the assessment of attractiveness. People with a high level of altruism are more than 2.5 times more likely to give a positive rating to a person in a photo than people with a low level of altruism (table 5.7). In general, variables belonging to the groups of neuroticism and agreeableness of the NEO PI-R (U3, U1, N2) have the greatest positive impact on trust, for which the probability of giving a positive assessment increases two or even three times for people with a high level of these features. Traits such as empathy from the IVE test and components of extroversion (E4 and E5) have a negative impact on trust. In these cases, the probability of giving a positive opinion drops by more than 40%.

5.2 Main Experiment

5.2.1 Preparation of data for classification

After the preparation of raw data with the use of such activities as filtration, segmentation or localization of sources, the collected data should be properly developed so that it can be used by the classification model. The process of preparing data sets is presented in the diagram below 4.10, which included selection of the time interval, calculation of the MEC value, division into training and test sets, and selection of describing variables.

The first step was to determine the appropriate time frame based on the average activity of brain areas over time. The signal of each participant in the study was analyzed and the range in which brain activity was the highest was selected. The analysis of the signal in time allowed to select the interval from 250 to 350 ms from the occurrence of the stimulus. On this basis, data sets were obtained for both dependent variables.

Determination of the average electric charge of the MEC, based on the ERP signal, was the next step for the predetermined time interval. 5ms intervals are included in the calculation of the MEC value. Details on the determination of the MEC were presented by Wójcik in his work [99]. The final dataset contained the MEC values for each brain region over the time period. This step was aimed at obtaining representative values for the classification analysis.

Splitting the data into training and test sets is the next step in data preparation. The experiment involved 60 people, for whom two events were determined for each dependent variable: trust (trusted, did not trust) and attractiveness (attractive, unattractive). The final dataset consisted of approximately 120 results for each dependent variable. A standard division of the data into training (80%) and test (20%) sets was used to perform the classification analysis.

The reduction of the number of independent variables is the last element of data preparation. At the initial stage of the analysis, the data contained 68 variables describing brain regions according to the Desikan-Killiany atlas (table 5.8): 34 right hemisphere regions and 34 left hemisphere regions.

To reduce the number of independent variables, the Recursive Feature Elimi-

Desikan-Killiany region name	Desikan-Killiany region name
Banks of Superior Temporal Sulcus	Parahippocampal
Caudal Anterior Cingulate	Pars Opercularis
Caudal Middle Frontal	Pars Orbitalis
Cuneus	Pars Triangularis
Entorhinal	Pericalcarine
Frontal Pole	Postcentral
Fusiform	Posterior Cingulate
Inferior Parietal	Precentral
Inferior Temporal	Precuneus
Insula	Rostral Anterior Cingulate
Isthmus Cingulate	Rostral Middle Frontal
Lateral Occipital	Superior Frontal
Lateral Orbitofrontal	Superior Parietal
Lingual	Superior Temporal
Medial Orbitofrontal	Supramarginal
Middle Temporal	Temporal Pole
Paracentral	Transverse Temporal

Table 5.8: Desikan-Killiany brain regions available in Brainstorm

nation with Cross-Validation (RFECV) method was used. This algorithm allows recursive elimination of the least significant features, using cross-validation, in order to select the optimal subset of variables. RFECV was used to find the most important brain areas of decision importance in the classification analysis.

The data preparation and variable selection steps described above are critical to the performance of a logistic regression model and its ability to accurately predict classification.

5.2.2 Logistic regression model

Two types of variables appeared in the study: independent variables (explanatory variables) related to brain regions and dependent variables related to trust and attractiveness. Both dependent variables are presented in a dihotomic (two-state) form: trusted or distrusted and attractive or unattractive. During the study, participants answered the question using a scale from 1 to 5. The obtained ratings were converted to 0/1 (not trusted/trusted, unattractive/attractive) by determining the average of the ratings 1-5. Values greater than or equal to 3 were assigned as positive, while values below 3 were considered negative. As a result, a variable in a dichotomous form was obtained, which could be used for statistical analysis.

A logistic regression model was used to carry out the analysis, which allows to describe the relationship between explanatory variables and dependent variables. The model's first data set was about trust, and included information about individual brain regions as explanatory variables and whether the study participant trusted or distrusted as the dependent variable. When performing the analysis, the logistic regression model tried to find relationships between these variables. The second dataset looked at attractiveness and also included the same explanatory variables for brain areas. However, in this case, the dependent variable was related to the description of the attractiveness of the person in the photo.

In order to build the logistic regression model, Python version 3.9.9 was used, using the scikit-learn library version 1.2.2.

5.2.3 Data classification

The study performed descriptive variables elimination to identify the most important brain areas that influence the participant's trust decision. The descriptive variable initially had 68 areas that could be marked using the Desikan-Killiany atlas. These areas cover both hemispheres of the brain. Then, using the feature elimination algorithm, it was possible to reduce the number of variables to 10 areas. Optimization results are presented in the table5.9 and in the figure 5.1, which represents the spatial location of individual areas.

Region name	Hemisphere
Banks of Superior Temporal Sulcus	L, R
Frontal Pole	L
Fusiform	R
Lateral Orbitofrontal	R
Medial Orbitofrontal	L, R
Middle Temporal	L
Pars Opercularis	R
Rostral Anterior Cingulate	L

Table 5.9: Brain areas obtained in the process of data optimization of the trust variable

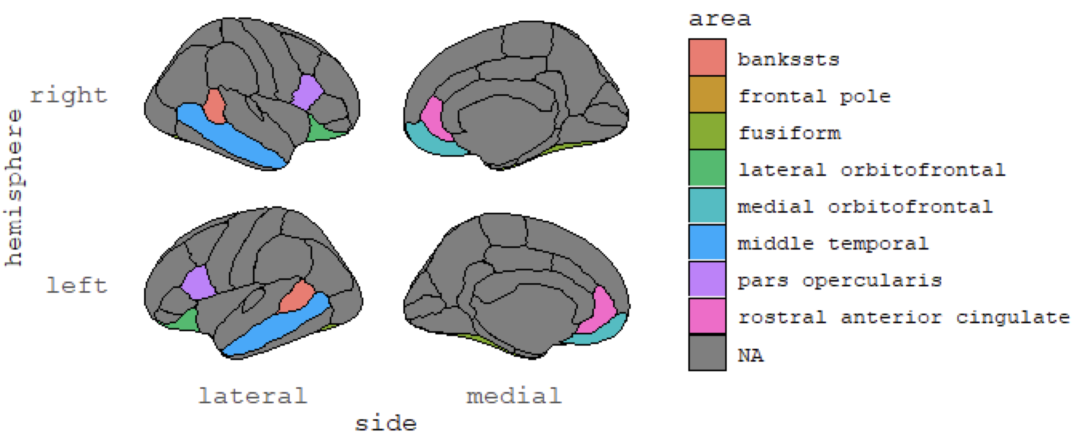

Figure 5.1: Representation of brain areas after optimization of the number of variables describing the trust variable, divided into hemispheres (l-left, r-right)

Based on the selected 10 most important brain areas, logistic regression classifier that achieved satisfactory efficiency in predicting the participant's decisions was constructed. The accuracy of the obtained model is 0.78, which means that it is able to correctly classify the trust/distrust decision in 78 cases out of 100 possible. The basic measures of the classifier's quality showed that the built model predicting trust based on the average electrical charge of the brain is of good quality and is able to correctly indicate the answer in most cases (Table 5.10). Hypothesis H4 was positively verified. The quality of the conducted classification is shown in the figure 5.2 using the ROC curve for the trust model and the confusion matrix in the figure5.3.

Accuracy	Precision	Recall	F1-score
0.78	0.92	0.73	0.81

Table 5.10: Classification measures that represent classifier quality for trust

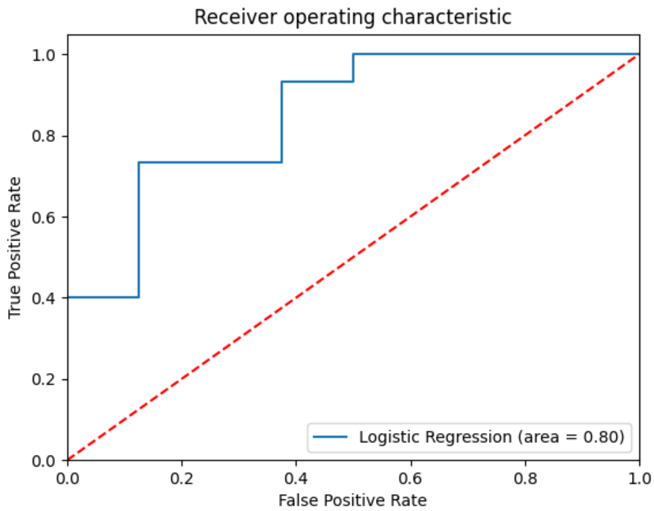

Figure 5.2: ROC curve characterizing the trust classification model

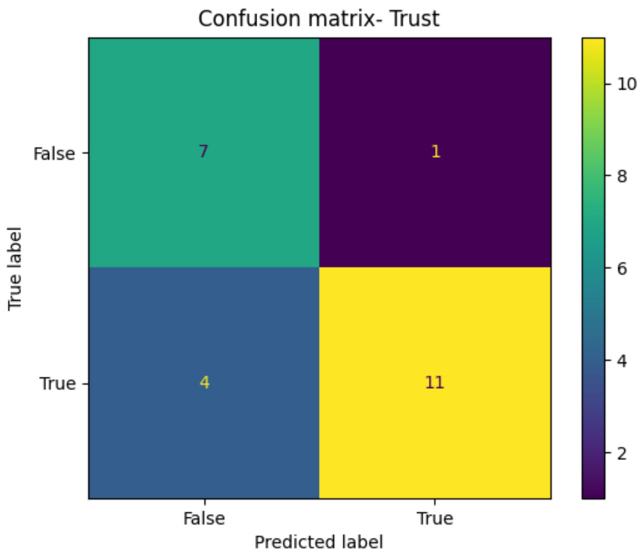

Figure 5.3: Confusion matrix of the dependent variable trust

In the process of eliminating features for the model based on the dependent variable "attractiveness", 8 areas significant for this variable were identified, which are presented in the table 5.11. The spatial arrangement of the areas is shown in the figure 5.4

Region name	Hemisphere
Banks of Superior Temporal Sulcus	R
Cuneus	R
Entorhinal	L
Fusiform	R
Inferior Parietal	R
Inferior Temporal	L
Lateral Occipital	L
Supramarginal	R

Table 5.11: Brain areas representation after optimization of the number of variables describing the attractiveness variable, divided into hemispheres (l-left, r-right)

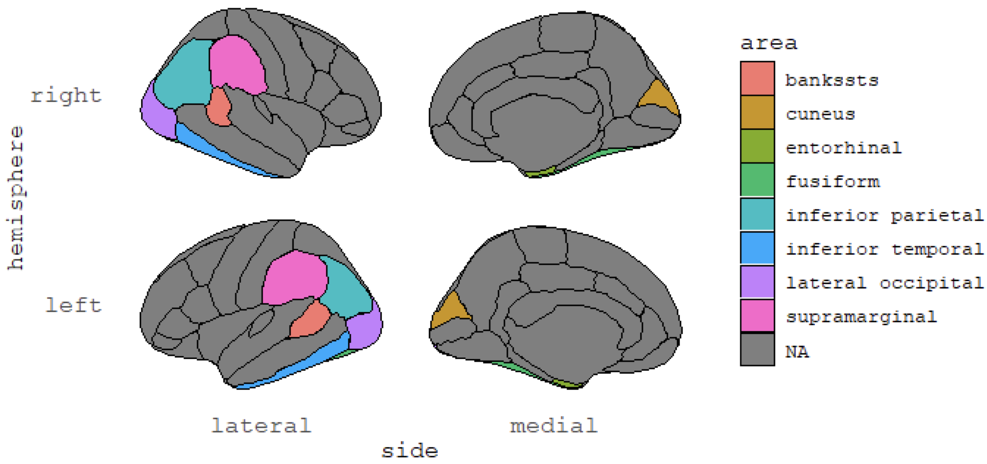

Figure 5.4: Spatial representation after optimization of areas for attractiveness variable

On the basis of limited descriptive variables, logistic regression classifier was constructed, which achieved accuracy (ACC) at the level of 0.76. This means that the model is able to correctly classify 76% of cases related to attractiveness. The basic measures of the classifier's quality showed that the built model predicting attractiveness based on the average electrical charge of the brain is of good quality and is able to correctly indicate the answer in most cases. (Table 5.12). Hypothesis H5 was positively verified. The characteristics of the model are shown in the figure 5.5 i 5.6.

Accuracy	Precision	Recall	F1-score
0.76	0.85	0.73	0.79

Table 5.12: Classification measures that represent classifier quality for attractiveness

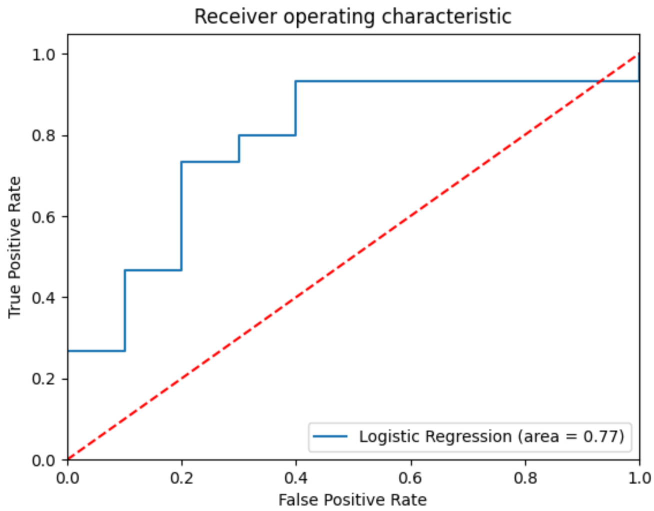

Figure 5.5: ROC curve characterizing the attractiveness classification model

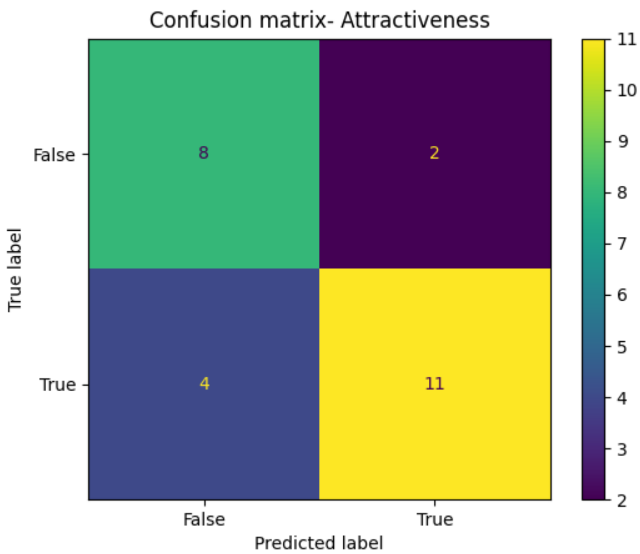

Figure 5.6: Confusion matrix of the dependent variable attractiveness

As a result of the data reduction process carried out for both dependent variables, i.e. both for decisions regarding trust and attractiveness, brain areas important for making these decisions were distinguished. The banks of superior temporal sulcus and fusiform regions appeared in both models, suggesting that these are active brain regions for both trust and attractiveness decisions.

Chapter 6

Discussion

6.1 Pilot experiment

The study was aimed at examining the relationship between personality traits and trust and attractiveness assessment of faces presented in photos. For this purpose, a survey was conducted to assess whether faces inspire trust and whether they are attractive, and two psychological tests were used: the IVE Impulsivity Questionnaire and the NEO PI-R Personality Inventory. The IVE test enabled the determination of three personality traits: impulsiveness, risk-taking and empathy. The NEO PI-R test was used to diagnose five personality traits: neuroticism, extroversion, openness to experience, agreeableness and conscientiousness. Each of these features also had six elements.

In order to select the significant features that influenced attractiveness and trust, a stepwise backward logistic regression model was used. Using the Wald coefficient, the least significant descriptive variables from the model were eliminated one by one. The procedures available in the SPSS program were used to learn and train the model. Analysis based on backward stepwise logistic regression confirmed hypothesis H3 and showed that altruism has the greatest impact on perceived attractiveness and trust [7]. In both cases, this trait had a beneficial effect on the dependent variables, which means that people with higher levels of altruism were more likely to evaluate others positively. Overall, it was found that trust is mainly determined by the traits of agreeableness and neuroticism.

After collecting data from the respondents, along with determining personality traits that influence the decisions made, a set of photos was selected for further electroencephalographic (EEG) tests. The set of 100 photos was divided into four groups, taking into account different combinations of dependent variables: attractive and trustworthy, unattractive and untrustworthy, attractive and untrustworthy, unattractive and trustworthy. Each group contained a different number of photos. The largest groups included high attractiveness with high trust and low attractiveness with low trust. The reason for such a division was the relationship between attractiveness and trust. It is assumed that attractive people are more trustworthy, and less attractive people are similarly considered less trustworthy [72], [87]. On the basis of the highest average scores for each photo and gender from each group, 6 photos were selected and used in EEG studies. This set of images was used to further analyze and study the electroencephalographic responses related to assessing facial trust and attractiveness.

6.2 Main Experiment

The main experiment presented in the paper was designed to analyze brain activity recorded during an EEG study in which participants assessed faces. Through stimulation with stimuli in the form of pictures presenting male and female, the participants had to assess the level of trust in the presented faces and assess their attractiveness.

Based on the main experiment, the most important areas of the brain involved in face perception in terms of trust and attractiveness were identified [6]. In both cases, eight regions were identified, with some regions active in two hemispheres during the confidence assessment. When assessing confidence, the following regions have the greatest influence on the classification: banks of superior temporal sulcus, frontal pole, fusiform, lateral orbitofrontal, medial orbitofrontal, middle temporal, pars opercularis, rostral anterior cingulate. While assessing the attractiveness of the face, the activity of the following regions was demonstrated: banks of superior temporal sulcus, cuneus, entorhinal, fusiform, inferior parietal, inferior temporal, lateral occipital, supramarginal. The banks of superior temporal sulcus and fusiform regions have an impact both in the assessment of trust and in the assessment of attractiveness. The activity of the same regions when evaluating different features (trust, attractiveness) may result from the fact that both of these features are interdependent. In addition, these areas may show increased activity during facial processing tasks as they are part of the perceptual facial processing system [43]. The orbitofrontal cortex is thought to be involved in various cognitive and emotional processes, including trust decisions [26]. The middle temporal region, in the literature, is presented as an area that increases its activity when assessing trust in known and unknown faces [47]. During the attractiveness assessment, increased activity was recorded in the lateral occipital region, which is involved in the visual processing of objects, especially in facial processing and is part of the perceptual facial processing system [43].

Based on the above-mentioned brain areas, there were constructed machine learning models able to predict trust assessment concerning presented people and their attractiveness with satisfactory quality. Accuracy was achieved at the level of 0.78 for the model where the dependent variable was trust and 0.76 for the model with the dependent variable attractiveness.

In the present thesis, the IT input involves the data processing process and the construction of classification models using data collected during EEG experiments. The main experiment used a research design that integrated the Mean Electric Charge (MEC) of specific brain areas and evoked potentials. The indicated approach has not been described in the literature so far in the context of assessing the trust and attractiveness of faces presented in photos.

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