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This Master Thesis aims to explore the intricate brain mechanisms involved in the observation of goal-oriented actions, such as grasping an object, as well as actions that are either imitative or not fully executed, such as mimicking a grasp. The central question of our work is whether brain activity in observing such motor events can be used as a reliable predictor of the execution of these movements, providing deeper insights into the operational dynamics of mirror neurons, a group of neurons believed to be pivotal in understanding and mimicking the actions of others. In order to address this issue, a comprehensive approach was utilized, which involved the use of several methods such as time-domain, frequency-domain, and time-frequency domain. Additionally, advanced statistical techniques including t-tests and mass univariate analysis were implemented. Various machine learning methods, including linear classifiers and more advanced algorithms, were employed to confirm and enhance the predictive power of identified neural markers. The investigation revealed a promising predictor - a significant difference between these two conditions, grasping and mimicking a grasp, that consistently appeared around 3 seconds before observing the motor event. In addition to broadening our comprehension of how mirror neurons work, these results may have wider implications for creating neuroprosthetics that are easier to use and for coming up with new ways to treat motor rehabilitation, with an emphasis on how neural systems can adapt and predict responses to upcoming motor actions.
ΕΚΤΕΤΑΜΕΝΗ ΕΛΛΗΝΙΚΗ ΠΕΡΙΛΗΨΗ

ΔΙΕΡΕΥΝΗΣΗ ΤΟΥ ΡΟΛΟΥ ΤΟΥ ΚΙΝΗΤΙΚΟΥ ΣΥΣΤΗΜΑΤΟΣ ΚΑΤΑ ΤΗΝ ΠΑΡΑΤΗΡΗΣΗ ΔΡΑΣΗΣ ΕΦΑΡΜΟΖΟΝΤΑΣ ΑΝΑΛΥΣΗ ΔΕΔΟΜΕΝΩΝ ΗΕΓ

ΚΑΛΟΥΠΤΣΟΓΛΟΥ ΑΘΑΝΑΣΙΑ
ΔΕΛΗΣ ΙΩΑΝΝΗΣ

Αυτή η μεταπτυχιακή διατριβή έχει ως στόχο να διερευνήσει τους περίπλοκους εγκεφαλικούς μηχανισμούς που εμπλέκονται στην παρατήρηση ενεργειών που έχουν συγκεκριμένο σκοπό, όπως το πιάσιμο ενός αντικειμένου, σε σχέση με ενέργειες που είτε τις μιμούνται είτε δεν εκτελούνται πλήρως αλλά παρουσιάζουν υψηλά ποσοστά ομοιότητας κινησιακά, όπως το άγγιγμα ενός αντικειμένου. Το κεντρικό ερώτημα της μελέτης μας είναι αν η εγκεφαλική δραστηριότητα κατά την παρακολούθηση τέτοιων κινητικών συμβάντων, με σχεδόν όμοιο κινησιακό ρεπερτόριο αλλά διαφορετική πρόθεση, μπορεί να χρησιμοποιηθεί ως αξιόπιστος δείκτης πρόβλεψης της εκτέλεσης αυτών των κινήσεων, παρέχοντας βαθύτερη γνώση της λειτουργικής δυναμικής των κατοπτρικών νευρώνων, μιας ομάδας νευρώνων που θεωρείται κομβική για την κατανόηση και τη μίμηση των ενεργειών των άλλων. Προκειμένου να εξεταστεί αυτό το ερώτημα, πραγματοποιήθηκε έρευνα που περιλαμβάνει τη χρήση διαφόρων μεθοδολογιών σε όλες τις διαστάσεις, συμπεριλαμβανομένων του πεδίου του χρόνου, του πεδίου της συχνότητας και του πεδίου του χρόνου-συχνότητας. Επιπλέον, εφαρμόστηκαν προηγμένες στατιστικές τεχνιques, συμπεριλαμβανομένων των t-tests και της μαζικής μονομεταβλητής ανάλυσης. Επιπρόσθετα, χρησιμοποιήθηκαν διάφορες μέθοδοι μηχανικής μάθησης, συμπεριλαμβανομένων γραμμικών ταξινομητών και πιο προηγμένων αλγορίθμων, για την επιβεβαίωση και την ενίσχυση της προβλεπτικής αξίας των εντοπισμένων νευρωνικών δεικτών. Η έρευνα ανέδειξε έναν πολύ αξιοσημείωτο παράγοντα μεταξύ των δύο ενεργειών που εμφανίζονταν σταθερά περίπου 3 δευτερόλεπτα πριν από την παρακολούθηση του κινητικού συμβάντος. Εκτός από τη διεύρυνση της κατανόησης του τρόπου λειτουργίας των κατοπτρικών νευρώνων, τα αποτελέσματα της έρευνας μπορεί να έχουν ευρύτερες συνέπειες για τη δημιουργία νευροπροσθετικών που θα είναι πιο εύχρηστα και για την εξεύρεση νέων τρόπων αντιμετώπισης της κινητικής αποκατάστασης, με έμφαση στον τρόπο με τον οποίο τα νευρικά συστήματα μπορούν να προσαρμόζονται και να προβλέπουν τις αντιδράσεις στις επερχόμενες κινητικές ενέργειες.
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1 Introduction

The complex interaction between the human motor system and the mirror neuron system has been closely examined and found to be highly intriguing in the fields of cognitive neuroscience and psychology. This study aims to investigate the brain mechanisms that are active in the motor system's coordination of intricate, purposeful activities and the mirror system's involvement in understanding and internally reproducing observed behaviors to provide a comprehensive framework for comprehending the foundations of human cognition.

Comprehending the complexities of the nervous system and its influence on human behavior and cognition is a challenging task that necessitates a multidisciplinary approach. Specifically, investigating the motor mirror nervous system and its interaction with electroencephalogram (EEG) analysis offers a captivating opportunity for exploration. This research aims to provide an overview for examining the complex workings of the motor mirror nervous system using EEG analysis by investigating EEG data collected during mimic and grasp actions revealing information about the spatial and temporal dynamics of brain activity.

Although there has been much study on the roles of motor control and imitation, our understanding of the neurological mechanisms behind these activities, specifically in terms of predictive signals in the brain, is still limited. Our investigation focuses on determining whether there is detectable brain activity in performing grasp and imitate actions. The hypothesis of this study suggests that distinct brain patterns arise prior to motor execution, which can be detected through a thorough analysis of EEG data. The study used a comprehensive methodology, combining time, frequency, and time-frequency analyses, along with statistical techniques like t-tests and mass univariate analysis. The resilience of the predictive neural patterns is additionally assessed by employing diverse machine learning models, establishing a methodological basis that bolsters the exploration of the brain precursors of motor action.

The importance of this research rests in its ability to provide new understanding of the time-related aspects of motor planning and the brain basis of preparation states. The findings of this study, which identify the patterns of brain activity that can anticipate future events, could have important implications for improving the design of neuroprosthetics. Additionally, these findings could provide a more comprehensive knowledge of the underlying causes of motor disorders and contribute to the development of rehabilitation programs for individuals with impaired motor function. Furthermore, the experiment enhances our understanding of mirror neurons, offering empirical proof to support theoretical frameworks related to comprehending and imitating actions. This thesis expands the existing knowledge in cognitive neuroscience and also opens up possibilities for practical use in clinical and technical fields.

The first section provides an introductory overview of the nervous system, clearly outlining its central and peripheral components. This text presents a comprehensive summary of the central nervous system, which consists of the brain and spinal cord, as well as the peripheral nervous system, encompassing the somatic and autonomic divisions. Furthermore, it provides a more detailed exploration of the structure and subdivisions of the cerebral cortex and proceeds to a thorough analysis of the fundamental components of the nervous system, the neurons focusing on their morphology and functions. It aims to understand the categorization and structure of neurons, as well as the functions of axons, dendrites, and the electrical charge...
across the cell membrane, offering a valuable understanding of the mechanisms that drive neural communication and information processing. In addition, the section culminates in exploring the fascinating world of mirror neurons which are believed to have a vital function in comprehending and replicating the behaviors of others.

The second section presents the fundamentals of an EEG analysis. By incorporating EEG analysis into the investigation of the motor mirror nervous system, a distinct opportunity is presented for the examination of neural processes that underlie social behavior and cognition. The EEG analysis section explores the historical background and functional aspects of EEG, which serves as a potent instrument for investigating brain activity. This section examines the different arrangements and qualities of EEG recordings, contrasts EEG with other brain imaging techniques such as structural and functional imaging and investigates the concept of event-related potentials (ERPs) and the different approaches used to analyze them.

In the third section through the utilization of EEG analysis alongside with experimental data, the goal is to decode the complex dynamics of the motor mirror nervous system and its impact on human behavior and cognition. Within this particular framework, the given empirical data, which encompasses EEG recordings during the observation of purposeful grasping actions and imitating touch actions, offers a structure for investigating the neural correlates of these actions and their nature. The methods and results of this study are being presented thoroughly. This part integrates the concepts of time, frequency, and time-frequency domain studies, along with the statistical and machine learning results, to create a full understanding of how mirror neurons may predict and react to observed events.

In the fourth section, we contextualize the results within the current neuroscientific discourse. We acknowledge the limitations and propose future directions for research to enhance our comprehension of brain systems, particularly mirror neurons during the observation of actions.

In the final section, the outcomes of this comprehensive EEG analysis offer a complete perspective on the operation of mirror neurons. Based on the temporal and spatial patterns discovered in our investigation, we examine the significance of these patterns in understanding how mirror neurons function in action observation.
2 Preliminaries

2.1 Nervous system

The nervous system is a complex network of specialized cells that transmit electrochemical signals from sensory receptors to the site where a response takes place. Every living organism possesses the ability to perceive alterations occurring within themselves and their surroundings. Adjustments to the external environment encompass variations in light, temperature, sound, motion, and smell, while adjustments to the internal environment include adjustments to the head, limbs, and internal organ positions. Upon detection, it is imperative to analyze and respond to these internal and external alterations in order to ensure survival. As life on Earth progressed and the environment grew more intricate, the ability of organisms to adapt to changes in their surroundings became crucial for their survival. A crucial determinant for survival was a prompt and agile reaction or response. Due to the insufficient speed of chemical communication between cells for survival purposes, a more efficient system was developed to enable faster reactions. That system was the nervous system, which relies on the rapid conduction of electrical impulses along specialized nerve cells called neurons to transfer information across the body\textsuperscript{1} (Lentz & Erulkar, 2024).

The field of neuroanatomy pertains to the organization and arrangement of the nervous system's physical structure. To comprehend the functioning of the nervous system, it is imperative to acquire knowledge about the structural organization of the nervous system. The nervous system comprises interconnected subsystems that operate in a coordinated manner. Beginning with a basic division, the nervous system is anatomically and functionally divided into two major components, namely the central nervous system and the peripheral nervous system. It is proposed to further segment the central nervous system and the peripheral nervous system into additional components\textsuperscript{2} (Brain Basics: Know Your Brain, n.d.).

2.1.1 Central nervous system

The Central Nervous System (CNS) refers to the complex network of nerves and tissues that are responsible for receiving, processing, and transmitting information throughout the body. It is comprised of the brain and spinal cord, which work together to regulate and coordinate various functions. The CNS plays a critical role in maintaining homeostasis and responding to internal and external stimuli. The central nervous system is comprised of two distinct components, the brain, and the spinal cord\textsuperscript{3} (Betts, 2022).

2.1.1.1 Brain

During the developmental stage, the brain undergoes a remarkable growth rate. During certain stages of brain maturation, the rate of neuronal proliferation can reach 250,000 new neurons per minute. The postnatal development of the brain involves a period of growth that extends beyond the immediate postpartum period. The human brain attains approximately 80% of its adult size by the age of 2 years. The typical weight of the human brain in adults ranges
from 1.3 to 1.4 kilograms, which is roughly equivalent to 3 pounds. It comprises approximately 86 billion neurons, the fundamental building blocks of the nervous system, and numerous other cells that are of greatest significance in upholding and preserving the comprehensive structure and operation of the nervous system, the glial cells. A thorough analysis of neurons will be covered later on (Zuckerman, 2021; Ackerman, 1992b).

2.1.1.1.1 Encephalization: Evolutionary brain growth and complexity process

Encephalization corresponds to the evolutionary mechanism of cerebral expansion and maturation, resulting in an augmentation of brain magnitude in proportion to bodily dimensions. The ectoderm, an embryonic tissue, is responsible for the development of the nervous system. This process begins with the emergence of the neural plate, followed by the subsequent maturation of the neural tube. The initial indication of the maturing nervous system is the neural plate, which becomes discernible around the 16th day of embryonic development. In the subsequent days, a neural groove is generated as a result of the formation of a "trench" within the neural plate. On the 21st day of embryonic development, the convergence of the neural groove edges results in the formation of a neural tube. The anterior portion of the neural tube undergoes differentiation into the encephalon, while the remaining portion of the neural tube undergoes differentiation into the spinal cord. The neural crest cells undergo differentiation to form the peripheral nervous system (Narayan & Verma, 2019).

During embryonic development, the neural tube undergoes differentiation into distinct regions including the forebrain, midbrain, and hindbrain. The neural tube's anterior portion gives rise to three primary cerebral regions, namely the prosencephalon (forebrain), mesencephalon (midbrain), and rhombencephalon (hindbrain). During the seventh week of embryonic development, the aforementioned three regions undergo further division. This phenomenon is commonly referred to as encephalization.

One may inquire as to the mechanisms underlying the continued growth of the brain, given that the majority of neurons are present at birth. The solution lies within the glial cells. The process of glial proliferation persists. Glia performs a multitude of crucial roles in facilitating optimal brain function, such as various functions within the brain, including providing structural support, insulating neurons, maintaining the chemical environment, and contributing to immune responses. Postnatally, the neurons in the brain undergo synaptogenesis, resulting in the formation of numerous novel connections (Allen & Lyons, 2018).

2.1.1.1.2 Cerebral cortex

The cerebral cortex, also referred to as the neocortex, constitutes the outermost region of the brain and is characterized by a high degree of convolution, comprised of neural cell bodies that lack myelin sheaths, also known as gray matter. The brain is known to have a crucial involvement in a variety of advanced cognitive processes, including but not limited to sensory perception, motor coordination, linguistic ability, memory retention, and sensory perception.
The cerebral cortex exhibits a modular organization, comprising discrete cortices that are responsible for specific and specialized cognitive processes \[8\],\[9\] (Brain Anatomy and How the Brain Works, 2021; Brain | SEER Training, n.d.).

The etymology of the term “cortex” can be traced back to its Latin origin, where it is derived from the word “cortex,” which refers to the outer layer or bark of a tree. The rationale behind this is that the cortex constitutes a layer of neural tissue that comprises the external surface of the brain. The cortical thickness exhibits a range of 2 to 6 millimeters. The cerebral cortex is bilaterally symmetrical, and its hemispheres are interconnected by a prominent bundle of neural axons known as the “corpus callosum.” In higher-order mammals, such as Homo sapiens, the cerebral cortex exhibits a convoluted appearance characterized by numerous gyri and sulci. A gyrus is a lump or bulge on the brain (the plural of gyrus is “gyri”), while a sulcus is a groove (the plural of sulcus is “sulci”). Lower animals, such as rats and mice, have a limited number of gyri and sulci \[10\] (MSc, 2023).

2.1.1.1.3 Cerebral cortex divisions

2.1.1.1.3.1 Hemispheres

The cerebral cortex is bilaterally symmetrical and comprises numerous cortices. The cerebral cortex is divided into hemispheres of the brain, which are the two symmetrical halves of the brain. The lobes represent the principal anatomical partitions within every hemisphere, while the cortices denote the areas situated within the lobes. The cortical regions situated in the lobes of the brain are responsible for executing distinct functions and processes that are specialized in nature. To explicate, the lobes denote the wider partitions of the cerebral hemispheres, whereas cortices pertain to the areas within those lobes that exhibit discrete functionalities. The cortices are discrete sub-regions within the cerebral lobes that are responsible for processing and integrating sensory, motor, and cognitive information in a more specialized manner.

Observing the brain from a superior perspective makes it apparent that it is partitioned into two distinct lengthwise hemispheres. The human brain is divided into two hemispheres, each of which is responsible for controlling and receiving sensory information from the contralateral side of the body. The dominant hemisphere, namely the left hemisphere, is primarily engaged in the cognitive processes of linguistic comprehension, analytical cognition, and deductive reasoning. Additionally, it governs the motor and sensory functions of the right half of the body. In contrast, the right cerebral hemisphere is commonly linked with spatial cognition, imaginative thinking, and affective regulation, and governs the motor functions of the left bodily hemisphere \[11\] (Bui, 2023).

2.1.1.1.3.2 Lobes

Interhemispheric communication is facilitated by the corpus callosum, which is comprised of a collection of nerve fibers. The anterior commissure constitutes a smaller fiber bundle interconnecting the two hemispheres. The brain’s cerebral hemispheres are divided into four main regions known as lobes through the implementation of sulci and gyri. The sulci, also known as fissures, and the gyri, which are elevated ridges, are observable features of the
cerebral cortex. The convolutions resulting from the sulci and gyri augment the cortical surface area that can be accommodated within the cranium. The aggregate surface area of the cerebral cortex is approximately 324 square inches, which is equivalent to the dimensions of a standard newspaper page. Individuals exhibit distinct configurations of gyri and sulci. The cerebral hemispheres are partitioned into four distinct lobes, namely the frontal, parietal, temporal, and occipital lobes (Lobes of the Brain, 2018).

The frontal lobe is a region of the brain located at the front of the cerebral cortex. It plays a crucial role in a variety of cognitive functions, including decision-making, problem-solving, and social behavior. It is positioned anterior to the central sulcus. This lobe highlights various cognitive and behavioral domains, including reasoning, planning, language, motor function, emotional regulation, and problem-solving.

The parietal lobe is a region of the brain that is involved in processing sensory information, including touch, temperature, and pain. It is located near the top and back of the brain and is responsible for integrating sensory information from different parts of the body to create a coherent perception of the environment. Additionally, the parietal lobe is involved in spatial awareness and perception, as well as in the planning and execution of movements. It is positioned posterior to the central sulcus. This part is responsible for the processing of sensory input related to tactile sensations, including touch, pressure, temperature, and pain.

The temporal lobe is a region of the brain that is located on the lateral surface of the cerebral cortex and is involved in a variety of functions including auditory perception, memory, and language comprehension. It is located on the lateral aspects of the cerebral cortex. This section concerns the process of distinguishing and recognizing auditory stimuli, as well as the capacity for memory retention attributed to the hippocampus, a critical brain region involved in spatial orientation and memory formation.

The occipital lobe is a region of the brain located at the posterior end of the cerebral cortex. It is primarily responsible for processing visual information received from the eyes. Situated posteriorly in the cranium, following the parietal and temporal lobes, lies the structure. The occipital lobe is a vital component in fundamental visual perception, as well as being involved in visual memory and visual attention. The occipital lobe is responsible for the integration of visual information from both eyes, which facilitates depth perception and the capacity to perceive three-dimensional objects (Slide Show: How Your Brain Works, 2016; Bui, 2023).

In summary, the cerebral hemispheres are broadly divided into lobes, which in turn are divided into cortices which refer to the specific regions within those lobes that are characterized by unique functions.

2.1.1.3.3 Cortices

The lobes represent important anatomical partitions that are designated according to their respective position and purpose. Each cerebral lobe comprises several cortices. Cortices refer to distinct areas that are comparatively diminutive in size within the lobes, located within, that exhibit unique and specialized functionalities in the processing and integration of
information pertaining to various sensory, motor, and cognitive processes. The complicated roles and subdivisions of cortices exhibit variability in greater specificity contingent upon diverse brain models and research perspectives. The following categorization of the cortices of the human brain is based on their respective specialized functions (Ackerman, 1992).

The prefrontal cortex, located in the frontal lobe, is a cerebral area linked to executive functions and elevated cognitive processes. The cognitive function in question is of paramount importance in the processes of decision-making, problem-solving, working memory, attentional control, and emotional regulation. Furthermore, it plays a role in social behavior, the manifestation of personality traits, and the amalgamation of information from diverse brain regions to facilitate purposeful actions.

The motor association cortex, found in the frontal lobe, plays a role in the organization, synchronization, and implementation of deliberate movements. The process involves the amalgamation of data from diverse sources, such as the primary motor cortex and sensory regions, to produce intricate motor sequences and facilitate motor acquisition. This region of the brain is involved in the facilitation and execution of intentional behaviors and is also implicated in the integration of precise motor movements.

The primary motor cortex, which is located in the precentral gyrus of the frontal lobe, controls how voluntary motions are carried out. The structure in question is responsible for receiving input from the motor association cortex and subsequently transmitting signals to the muscles, thereby facilitating the production of movements that are both precise and coordinated. The organization of the primary motor cortex follows a somatotopic pattern, whereby distinct areas are responsible for regulating the movement of discrete anatomical regions.

The primary somatosensory cortex is located in the postcentral gyrus of the parietal lobe and is responsible for receiving and processing tactile sensory information from various regions of the body. The aforementioned sensory modalities are reliant on their pivotal function in facilitating the perception of tactile, thermal, and nociceptive stimuli. The primary somatosensory cortex exhibits a somatotopic arrangement, whereby distinct cortical regions are specialized in the processing of sensory information originating from discrete bodily regions.

The sensory association area is situated in the parietal, temporal, and occipital lobes and serves to consolidate and construe sensory input from various modalities. The process involves the integration of sensory information from primary cortices with that of higher order processing regions, resulting in the formation of a unified perception of the surrounding environment. The sensory association area is responsible for the cognitive processes involved in the identification and comprehension of intricate sensory inputs, such as auditory, visual, and tactile stimuli, including objects, faces, and sounds.

The visual association area, located in the occipital and temporal lobes of the brain, is accountable for the advanced examination and comprehension of visual data. The aforementioned process involves the reception of input from the primary visual cortex, which is subsequently integrated with other sensory and cognitive processes. The aforementioned region of the brain is of paramount importance in the process of identifying objects, perceiving
spatial relationships, retaining visual information, and comprehending visual cues within a given context.

The visual cortex, located in the occipital lobe, is accountable for the primary reception and interpretation of visual stimuli that are transmitted from the eyes. The visual system is comprised of the primary visual cortex, commonly referred to as V1, as well as various higher-order visual areas. The visual cortex is an essential component in the process of visual perception, encompassing the identification of fundamental visual characteristics, the analysis of motion, and the formation of a visual depiction of the surrounding environment.

Wernicke's Area is a region situated in the left hemisphere of the brain, specifically located in the posterior section of the superior temporal gyrus. Its primary function is associated with the comprehension and formulation of language. The comprehension and interpretation of oral and written communication are significantly reliant on it. Injury or impairment to Wernicke's area can result in deficits in receptive language, which may manifest as challenges in comprehending or generating coherent speech.

The auditory association area, located in the temporal lobe, is responsible for the processing and integration of auditory stimuli that are received from the auditory cortex. The function of this entity pertains to the processing of auditory information at a higher level, encompassing the identification of sounds, retention of auditory information, and the comprehension of intricate auditory stimuli, such as language, melodies, and sounds from the surroundings.

The auditory cortex has a location in the temporal lobe and plays a crucial role in the preliminary processing and analysis of auditory stimuli received from the ears. The auditory system is of utmost importance in the perception of sound, encompassing essential functions such as sound detection, frequency analysis, and spatial localization of sound sources. The organization of the auditory cortex is tonotopic in nature, wherein distinct areas exhibit selective responsiveness to particular sound frequencies.

Broca's Area is a region positioned in the left frontal lobe, specifically in the posterior portion of the inferior frontal gyrus. It is primarily linked to language production and speech articulation. The coordination and planning of motor movements necessary for speech are significantly influenced by it. Lesions to Broca's area may lead to impairments in expressive language abilities, which are characterized by challenges in generating speech that is both grammatically correct and fluent [16][17][18][19] (Pérez, 2018; Queensland Government, 2017; Bastianetto, 2021; “Encyclopedia of the Human Brain,” 2003).

Table 1 presents a concise functional division of the cerebral cortex.

<table>
<thead>
<tr>
<th>CORTICAL AREA</th>
<th>FUNCTION</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prefrontal Cortex</td>
<td>Problem-Solving, Emotion, Complex Thought</td>
</tr>
<tr>
<td>Motor Association Cortex</td>
<td>Coordination of complex movement</td>
</tr>
</tbody>
</table>

Table 1. Functional Divisions of the Cerebral Cortex
Primary Motor Cortex | Initiation of voluntary movement
Primary Somatosensory Cortex | Receives tactile information from the body
Sensory Association Area | Processing of multisensory information
Visual Association Area | Complex processing of visual information
Visual Cortex | Detection of simple visual stimuli
Wernicke’s Area | Language comprehension
Auditory Association Area | Complex processing of auditory information
Auditory Cortex | Detection of sound quality (loudness, tone)
Broca’s Area | Speech production and articulation


2.1.1.1.4 Protective barriers to brain

The central nervous system, specifically the brain, has been protected by a multitude of tissue layers, which involve the cranium and meninges. The skin (scalp) comes first. The skull (cranium) of a person is made of bone below the skin. Several bones surround and protect the brain. One frontal bone, two parietal bones, two temporal bones, one occipital bone, one sphenoid bone, and one ethmoid bone make up the eight bones that surround the brain. These eight bones make up the structure of the skull. The meninges, which are three layers of tissue, also shield the brain. The rear of the occipital bone has a sizable aperture known as the foramen magnum. The medulla, which regulates heart rate, breathing, and blood pressure, terminates here, and protrudes from the skull. Nerves and blood arteries may enter and exit the skull via smaller openings known as foramina. Sutures are the points in the skull where the bones join together. In young children, these sutures are flexible, but as they become older, they become set.[20] (The Central Nervous System | SEER Training, n.d.).

The cranium, composed of multiple osseous elements, constitutes a rigid skeletal framework that envelops and safeguards the encephalon. Its function is to serve as a safeguarding shield that provides protection to the brain against external impacts and trauma. The inflexible configuration of the skull offers essential support and facilitates the maintenance of the brain’s form and placement within the cranial vault. In contrast, the meninges refer to a trilaminar set of defensive membranes that envelop the brain and spinal cord. The meninges serve as a safeguarding interface between the brain and the skull, furnishing supplementary cushioning and support to the brain.

Both the skull and meninges serve the purpose of protecting the brain. Three distinct coverings known as meninges are located underneath the skull providing support and securing
the brain. The dura mater, which constitutes the outermost layer of the meninges, is characterized by its considerable thickness and durability. The function of the skull is to restrict the movement of the brain and safeguard it against potential movements that may cause harm or strain to its blood vessels. The arachnoid membrane constitutes the intermediate layer of the meninges and possesses a fragile, intricate, spider-web-like configuration. The function of the structure in question is to provide a cushioning effect for the brain and facilitate the distribution of cerebrospinal fluid, the transparent fluid that envelopes and safeguards the brain and spinal cord. The pia mater, which constitutes the innermost layer of the meninges, is a fragile and slender membrane that is closely adhered to the cerebral surface. It provides sustenance to the brain and helps safeguard its delicate structures (Cipolla, 2009; Abbaoui et al., 2023).

Therefore, the skull and meninges collaborate to protect the brain from external injuries, offer structural reinforcement, and preserve the brain's internal equilibrium.

2.1.1.1.5 Overview of the fundamental structures and functions of the brain

The human brain is an overly complex and intricate organ, consisting of multiple interconnected structures, each with distinct roles and functions. Presented below is comprehensive data about every region of the brain, accompanied by elucidations of their connections and interrelationships, which shed light on the complex mechanisms of the human brain.

The cerebellum is situated at the posterior aspect of the brain stem and exhibits resemblances to the cerebral cortex, such as the existence of hemispheres and a cortical layer that encompasses them. The primary functions of the entity in question pertain to the domains of movement, balance, and posture.

The brainstem is a complex of anatomical structures that are located between the thalamus and the spinal cord. It comprises several components, including the pons, medulla oblongata, tectum, reticular formation, and tegmentum. The regulation of essential physiological processes, including respiration, cardiac function, and vascular pressure, is heavily dependent on its pivotal role.

The hypothalamus, a multifaceted anatomical entity located in the inferior region of the brain, governs a range of physiological processes such as thermoregulation, emotional regulation, appetite and thirst control, and circadian rhythm modulation. The hypothalamus, despite its relatively diminutive size accounting for only 0.33% of the brain's mass, is capable of detecting alterations in the body's temperature and subsequently instigating suitable responses to regulate it. These responses may include the dilation of capillaries in the skin to facilitate the dissipation of heat.

The thalamus functions as an intermediary hub for sensory stimuli, collecting afferent signals from various neural regions and relaying them to the cerebral cortex. The processing of sensory information and its correlation with movement is of utmost importance (Professional, n.d.).

The limbic system is a complex network of brain structures that are involved in various functions such as emotion regulation. The limbic system, which comprises anatomical
structures such as the amygdala, hippocampus, mammillary bodies, and cingulate gyrus, is involved in various cognitive processes such as emotional regulation, motivational drive, learning, and memory consolidation. The hippocampus, situated in the limbic system, plays a crucial role in the process of memory consolidation.

The basal ganglia are a group of nuclei located in the brain that play a crucial role in motor control, which are situated in the depths of the cerebral hemispheres, and encompass various structures such as the globus pallidus, caudate nucleus, subthalamic nucleus, putamen, and substantia nigra. They participate in the coordination of motor activity.

The midbrain comprises various anatomical structures, including but not limited to the superior and inferior colliculi and the red nucleus. This is correlated with functions pertaining to visual perception, auditory perception, oculomotor control, and motor coordination [24] (Raikar, 2023).

The aforementioned structures exhibit interrelated connections within the central nervous system. Although individual structures within the brain have distinct roles, they also work in conjunction to facilitate comprehensive brain function. The following is a series of relationships and connections:

- The cerebellum is a neural structure that receives afferent projections from diverse brain regions, including the brain stem. The cerebellum is involved in the coordination of motor activities and serves as a recipient of sensory inputs from the brain stem, which it utilizes to regulate balance, posture, and movement.
- The medulla, located in the brain stem, plays a crucial role in regulating vital physiological processes such as respiration, heart rate, and blood pressure. The hypothalamus, situated in proximity to the brain stem, collaborates with it to oversee and regulate diverse physiological functions such as thermoregulation, appetite, hydration, and circadian rhythms.
- The thalamus and limbic system are integral components of the human brain. The thalamus functions as a crucial relay station, receiving sensory information from diverse regions of the body and transmitting it to the relevant areas of the cerebral cortex for further processing. Furthermore, it exhibits associations with the limbic system, facilitating the amalgamation of sensory stimuli with affective and mnemonic procedures.
- The limbic system, with a specific emphasis on the hippocampus, is known to exert a substantial influence on the process of memory consolidation. In contrast, the basal ganglia, which encompasses the caudate nucleus and putamen, is recognized for its involvement in the regulation of motor function and coordination. These structures collaborate to facilitate cognitive processes such as learning, memory retention, and motor-related functions.
- The basal ganglia are a group of nuclei that receive afferent projections from the midbrain, including the substantia nigra, which is responsible for the production of dopamine, a neurotransmitter that plays a critical role in motor control. The coordination of motor activities and regulation of movement is a collaborative effort between the midbrain and basal ganglia [25] (Thau, 2022).
In general, these structures constitute a varied network within the brain, interlinked via neural pathways, facilitating inter-regional communication and coordination. The combined action of various functions allows for the regulation of essential physiological processes, the processing of sensory stimuli, the management of motor activities, and the provision of support for cognitive and affective functions within the brain.

2.1.1.2 Spinal Cord

In contrast to the brain which is the regulator of the nervous system and is situated inside the cranial cavity, the spinal cord is a long, cylindrical bundle of nerves that runs from the base of the brain to the spinal column. The central nervous system is composed of the brain and the spinal cord, which collaborate closely to enable efficient communication between the brain and the body. Specifically, the spinal cord functions as a channel for passing on sensory information from the body to the brain, as well as carrying signals related to motion from the brain to the body to facilitate voluntary movement and reflex responses.

The length of the spinal cord in adult females is approximately 43 centimeters, while in adult males it is approximately 45 centimeters. The weight of the spinal cord is estimated to be between 35 and 40 grams. The vertebral column, which contains the spinal cord, is approximately 70 centimeters in length. Hence, the length of the spinal cord is comparatively shorter than that of the bony spinal column, as it only extends to the final thoracic vertebra. The osseous spinal column serves as a safeguard for the human spinal cord. The vertebral column is composed of osseous structures known as vertebrae. While the spinal column exhibits a degree of flexibility, certain vertebrae located in the lower regions of the spinal column undergo fusion. The spinal cord is situated within the vertebral foramen and comprises 31 segments, namely 8 cervical, 12 thoracic, 5 lumbar, 5 sacral, and 1 coccygeal. Each segment of the spinal cord gives rise to a set of two spinal nerves [26] (Spinal Cord Anatomy, n.d.).

There are distinct variations in the dimensions and morphology of the spinal cord across distinct levels. Each segment is represented by a dark gray color which signifies the presence of “gray matter.” By utilizing one’s imaginative faculties, it is possible to discern a resemblance between the structure of the gray matter and that of an H or a butterfly. The somata of neurons are situated within gray matter. The gray matter is enveloped by white matter, which exhibits a lighter color shade. This region is the location of the spinal cord's axons. Examining the proportional quantities of gray and white matter present at every segment of the spinal cord, many outcomes can be derived. The cervical segment exhibits a comparatively substantial quantity of white matter. The observed pattern can be attributed to the numerous axons ascending to the brain from various levels of the spinal cord, as well as the multitude of axons descending from the brain to distinct segments of the spinal cord. The caudal regions of the spinal cord exhibit a reduced quantity of white matter due to a decreased number of axonal pathways connecting to and from the central nervous system. Variations in gray matter are also observable. The ventral horn of the cervical segment exhibits an enlargement in its lower half. Furthermore, it can be observed that the ventral horn in the lumbar segment exhibits a significant enlargement. The aforementioned segments are characterized by the presence of motor neurons—which will be covered in more detail later—that are responsible for
regulating the movement of the upper extremities (cervical segment) and lower extremities (lumbar segment) \cite{27} (Mercadante, 2023).

The spinal cord serves as the primary conduit for neural communication between the central nervous system and the peripheral nervous system. The nerves emanating from the lumbar and sacral levels of the spinal cord are required to traverse a certain distance within the vertebral canal prior to their exit from the vertebral column. The collection of nerves situated within the vertebral canal is commonly referred to as the cauda equina, a term derived from its resemblance to the tail of a horse. The cutaneous receptors transmit sensory information to the spinal cord via the spinal nerves. The somata of these nerve fibers are situated in the ganglion of the dorsal root. The afferent nerve fibers traverse the dorsal root to enter the spinal cord. Certain fibers establish synaptic connections with adjacent neurons in the dorsal horn, whereas others proceed towards the brain. Numerous cellular bodies located in the ventral horn of the spinal cord transmit axons via the ventral root towards the muscles, thereby regulating movement.

2.1.2 Peripheral nervous system

The peripheral nervous system (PNS) refers to the network of nerves that extends from the brain and spinal cord to the rest of the body. It is responsible for transmitting sensory and motor information between the central nervous system and the limbs, organs, and tissues. Several distinctions exist between the peripheral nervous system and the central nervous system.

- In the central nervous system, agglomerations of neurons are referred to as nuclei. Within the peripheral nervous system, clusters of nerve cell bodies are referred to as ganglia.

- In the central nervous system, aggregations of axons are referred to as tracts. Within the peripheral nervous system, clusters of axons are referred to as nerves.

Within the peripheral nervous system, nerves may be classified into three distinct functional categories. The sensory (afferent) nerves are responsible for transmitting information from the sense organs to the central nervous system, while the motor (efferent) nerves are responsible for transmitting information away from the central nervous system to control muscle movement.

The cranial nerves serve to establish a connection between the brain and the peripheral nervous system, while the spinal nerves establish a connection between the spinal cord and the peripheral nervous system.

The peripheral nervous system is categorized into two principal divisions, namely the somatic nervous system and the autonomic nervous system \cite{28} (Betts, 2022b).
2.1.2.1 Somatic nervous system

The somatic nervous system is comprised of peripheral nerve fibers that transmit sensory information to the central nervous system as well as motor nerve fibers that extend to skeletal muscle. The soma is situated in either the encephalon or spinal cord and extends directly to a striated muscle. The somatic nervous system pertains to the linkage between the skin or muscle and the central nervous system, while the visceral nervous system pertains to the linkage between the internal organs and the central nervous system \cite{Libretexts2020}.

2.1.2.2 Autonomic nervous system

The autonomic nervous system governs the contraction and relaxation of smooth muscle in the viscera (internal organs), as well as the secretion of glands. The autonomic nervous system (ANS) operates involuntarily and reflexively, often rendering individuals unaware of its activity. Instances such as alterations in blood vessel diameter or an increase in heart rate often go unnoticed by individuals. The autonomic nervous system comprises three distinct components: the sympathetic nervous system, the parasympathetic nervous system, and the enteric nervous system.

The sympathetic nervous system is responsible for regulating the body's fight-or-flight response, which is triggered by danger or stress. It consists of two main components: the sympathetic preganglionic neurons, which originate from the thoracic and lumbar spinal cord, and the postganglionic neuron, which extends its projections towards the designated target organ. The somatic nervous system connects the central nervous system to the target organ through a single neuron, while the autonomic nervous system uses a two-neuron pathway. The preganglionic neuron, located in the thoracic and lumbar spinal cord, establishes synaptic connections with a post-ganglionic neuron within the ganglion. The post-ganglionic neuron then extends towards the designated target, which may be a muscle or gland. The neurotransmitter used by the synapse in the sympathetic ganglion is acetylcholine, while the post-ganglionic neuron with the target organ uses norepinephrine. Acetylcholine is used except for the post-ganglionic neuron that terminates on sweat glands \cite{Alshak2023}.

The parasympathetic system stimulates "rest-and-digest" or "feed and breed" functions including sexual desire, salivation, lacrimation (tears), urine, digestion, and feces while the body is at rest, particularly after feeding. It complements the sympathetic nervous system, which stimulates fight-or-flight responses. The central nervous system generates parasympathetic nerve fibers. Oculomotor, facial, glossopharyngeal, and vagus nerves are cranial nerves. The pelvic splanchnic nerves are parasympathetic nerves. The sympathetic nervous system has "thoracolumbar outflow," whereas the parasympathetic system has "cranosacral outflow" according to its location. The cell bodies of the parasympathetic nervous system are situated in the spinal cord's sacral region and the medulla. The medulla oblongata serves as the site where the preganglionic parasympathetic fibers of cranial nerves III, VII, IX, and X converge. The preganglionic fiber originating from either the medulla or spinal cord exhibits projection towards the ganglia in close proximity to the target organ, ultimately culminating in synaptic transmission. The synaptic transmission in question involves the
utilization of the neurotransmitter known as acetylcholine. The post-ganglionic neuron emanating from the ganglion in question employs acetylcholine at its terminal to communicate with the target organ \(^{[31]}\) (Richter & Wright, 2013).

The enteric nervous system constitutes a distinct and often overlooked autonomic nervous system component. The enteric nervous system comprises a complex network of nerve fibers that provide innervation to the viscera, including the gastrointestinal tract, pancreas, and gall bladder \(^{[32]}\) (Hibberd et al., 2022).
2.1.3 Neurons: The fundamental units of the nervous system

The human organism is comprised of numerous cells, numbering in trillions including the neurons which are specialized cells responsible for transmitting information throughout the nervous system. Neurons, also known as nerve cells, are specialized cells within the nervous system that facilitate the transmission of electrochemical signals. The estimated number of neurons in the human brain is approximately 86 billion [33] (Azevedo et al., 2009). Neurons exhibit a wide range of morphological diversity in terms of their shapes and sizes. Certain neurons exhibit cell bodies with a diameter as narrow as 4 microns. Certain neurons exhibit cell bodies that possess a width of 100 microns, rendering them among the largest neurons. It is important to note that a micron is equivalent to one-thousandth of a millimeter [34] (Verkhratsky et al., 2019).

Neurons are considered to be the most ancient and elongated cells in the human body. Throughout an individual's lifespan, the neural population remains relatively stable. While several types of cells undergo replacement, a considerable number of neurons are irreplaceable upon their demise. It is a well-established fact that the number of neurons in the brain decreases with age, resulting in a lower count in older individuals as compared to their younger counterparts. Conversely, the growth of new neurons is feasible in adult humans in a specific region of the brain, namely the hippocampus. Neurons of considerable size have been observed, with certain types, such as corticospinal neurons (which transmit signals from the motor cortex to the spinal cord) and primary afferent neurons (extending from the skin to the spinal cord and brain stem), measuring up to several feet in length.

Neurons exhibit similarities to other cellular entities within the human organism. The cellular structure of neurons is characterized by the presence of a surrounding membrane and possesses a nucleus, which harbors genetic material in the form of genes. Neurons are comprised of various organelles, including cytoplasm and mitochondria. They are responsible for executing fundamental cellular functions, including the synthesis of proteins and the generation of energy.

2.1.3.1 Neurons classification

Neurons, which are the fundamental building blocks of the nervous system, can be categorized according to various specifications. Below are several frequently employed criteria for categorizing neurons:

Structural Classification:

A method of categorizing neurons involves quantifying the number of extensions emanating from the soma, the neuron’s cell body. According to that, there are:
- Unipolar neurons which are characterized by a singular process that emanates from the cell body and subsequently divides into two branches, serving the dual functions of an axon and a dendrite.
- Bipolar neurons, which are characterized by the presence of two distinct processes emanating from the cell body, whereby one process functions as an axon and the other as a dendrite.
- Multipolar neurons, which are characterized by the presence of multiple processes emanating from the cell body, typically consisting of one axon and multiple dendrites.
- Pseudounipolar cells, such as dorsal root ganglion cells, are a type of neuron characterized by a single process that divides into two branches, giving the appearance of having two axons. In fact, it has been observed that these particular cells possess two axons as opposed to the conventional structure of an axon and dendrite. There are two axons, one of which extends centrally towards the spinal cord, while the other extends towards the skin or muscle \[^{35}\] (Queensland Brain Institute, 2022).

Functional classification:

- Sensory neurons, also known as afferent neurons, are responsible for the transmission of sensory information from sensory receptors, including those involved in touch, temperature, pain, and other sensory modalities, to the central nervous system.
- Motor neurons, also known as efferent neurons, are responsible for the transmission of signals from the central nervous system to muscles or glands. This transmission allows for the execution of movement or the secretion of substances, depending on the target organ.
- Interneurons, additionally referred to as association neurons, are a type of neuron that is found exclusively within the central nervous system. Their primary function is to facilitate communication between sensory neurons, which transmit information from sensory organs to the CNS, and motor neurons, which relay signals from the CNS to muscles and glands \[^{36}\] (Brigham Young University, n.d.).

The direction of information flow:

The direction of information flow refers to the path through which information is transmitted or exchanged. Neurons may be categorized based on the direction in which they transmit information.

- Afferent neurons, also known as sensory neurons, are responsible for transmitting information from sensory receptors located in the periphery to the central nervous system.
• Efferent neurons, also known as motor neurons, are responsible for conveying signals from the central nervous system to the peripheral regions, such as muscles or glands.
• Interneurons play a crucial role in mediating communication between afferent and efferent neurons within the central nervous system. The majority of interneurons are situated within the central nervous system [37] (Libretexts, 2023).

Location:
• Central neurons are a type of neurons that are exclusively situated within the central nervous system, encompassing the brain and spinal cord.
• Peripheral neurons are a type of neurons that are situated in the peripheral nervous system, which is distinct from the central nervous system. Their primary function is to establish connections between the central nervous system and sensory receptors, as well as effectors located throughout the body [38] (Overview of Neuron Structure and Function (Article) | Khan Academy, n.d.).

It is imperative to acknowledge that these classifications are not mutually exclusive, and a singular neuron has the potential to be categorized under multiple criteria.

2.1.3.2 Anatomy of a neuron

Neurons exhibit similarities to other cellular entities within the human organism. The cellular structure of neurons is characterized by the presence of a surrounding membrane and possesses a nucleus, which harbors genetic material in the form of genes. Neurons are comprised of various organelles, including cytoplasm and mitochondria. They are responsible for executing fundamental cellular functions, including the synthesis of proteins and the generation of energy.

2.1.3.2.1 Axons and Dendrites

Nevertheless, neurons exhibit distinct characteristics that set them apart from other types of cells in the human body. They are equipped with specialized cellular components known as dendrites and axons. Dendrites are responsible for the transmission of electrical signals toward the cell body, while axons facilitate the conveyance of information away from the cell body. In other words, dendrites serve as the primary site for receiving and integrating incoming signals, while axons function as the primary conduit for transmitting outgoing signals away from the cell body.
2.1.3.2 Dendrites

The initial two neuronal functions, namely the reception and processing of incoming information, typically occur within the dendrites and cell body. Incoming signals can either be excitatory, in which case they have a tendency to cause the neuron to fire (cause an electrical impulse to be generated), or inhibitory, in which case they tend to prevent the neuron from firing.

The dendritic trees of most neurons are subject to the reception of numerous input signals. It is possible for a solitary neuron to possess multiple sets of dendrites, thereby enabling the reception of numerous input signals, often numbering in the thousands. The firing of a neuron is contingent upon the summation of both excitatory and inhibitory signals it receives. In the event that the neuron undergoes firing, the transmission of the nerve impulse, also known as the action potential, occurs along the axon.

To acquire knowledge on the mechanism of neuronal communication, studying the phenomenon of action potential is recommended. An electrochemical mechanism facilitates neuronal communication. Neurons are comprised of distinct anatomical features, such as synapses, and biochemical components, such as neurotransmitters, so they can transmit electrical and chemical signals throughout the nervous system \(^\text{[39][40]}\) (Rollenhagen & Lübke, 2013; Boston University, n.d.).

The collective characteristics of dendrites, including their structural morphology, synaptic connectivity, expansive receptive fields, and functional interactions with ribosomes, highlight their essential role in information processing and interneuronal communication.

2.1.3.2.3 Axons

Within the realm of neuronal biology, the axon is an elongated and slender projection originating from the soma, or cell body, of a given neuron. The function of this entity involves the transmission of electrical signals, commonly referred to as action potentials, to neighboring neurons, muscles, or glands.

Due to its elongated structure, the axon is composed of microtubules and is enveloped by myelin. The axon contains microtubules organized in parallel arrays, serving as conduits for the transportation of materials to and from the soma. Specialized motor proteins traverse the microtubules, transporting substances away from the soma (anterograde transport) or towards the soma (retrograde transport). The system is capable of transporting materials along the axon at a speed of 400mm per day, as indicated in the lowest figure. Myelin is composed of distinct cells that tightly coil and envelop their membranes around the exterior of the axon. These are crucial for providing electrical insulation and enhancing the speed of action potential propagation.

Upon reaching its target, an axon divides into multiple terminations known as axon terminals. The axon terminal is specifically structured to transform the electrical signal into a chemical signal through a process known as synaptic transmission. The majority of neurons are either amitotic or undergo a loss of their capacity to undergo cell division. The rule is not
applicable to olfactory neurons (related to smell) and specific regions of the brain called hippocampal regions. Fortunately, the lifespan of amitotic neurons is approximately 100 years. However, in the event of neuronal damage or loss, the process of replacement is not readily achievable. Consequently, significant brain or spinal cord injuries typically result in limited recuperation. Presumably, the sluggish pace of recovery or absence of regeneration serves the purpose of safeguarding learned behavior and memories over the course of one's lifetime. Neurons possess remarkably elevated metabolic rates and thus necessitate substantial quantities of glucose and oxygen. The body will take extensive measures to ensure that neurons receive sufficient nourishment. In fact, if the brain detects insufficient nutrition, the body will promptly shut down, resulting in fainting \cite{41,42} \cite{Muzio,2022; Fields, 2009}.

Primary afferent axons are responsible for transmitting information regarding touch and pain to the spinal cord and brain. These nerve fibers are connected to several types of receptors located in the skin, muscle, and internal organs. The primary afferent axons exhibit variations in their diameters and can be classified into distinct categories on the basis of their dimensions. The various nerve fiber groups, namely A-alpha, A-beta, A-delta, and C-nerve fibers, are listed in descending order of size. The nerve fibers A-alpha, A-beta, and A-delta are characterized by the presence of myelin insulation. C-fibers lack myelin sheaths. There exists a positive correlation between the thickness of a nerve fiber and the velocity of information transmission therein; specifically, a greater thickness of the nerve fiber corresponds to a higher speed of information propagation. Further details regarding the distinct primary afferent axons:

A-alpha nerve fibers transmit proprioceptive information pertaining to the sense of muscle position and movement.

A-beta nerve fibers are responsible for transmitting sensory information associated with the sense of touch.

A-delta nerve fibers are responsible for transmitting sensory information pertaining to temperature and pain.

C-fibers are responsible for transmitting sensory information pertaining to pain, temperature, and itch.

To comprehend the functioning of diverse nerve fibers, contemplate the following scenario when you accidentally hit your toe against a hard object. Initially, the individual will experience the tactile perception of their toe making contact with the surface. The prompt elucidates that the expeditious transmission of data regarding the contact of one's toe with the ground is facilitated by the A-beta nerve fibers, which are known for their significant diameter and velocity. Consequently, this information is relayed to the brain in a prompt manner. fibers, which means it takes longer for the pain signals to reach your brain. A-delta and C-nerve fibers are two types of nerve fibers that transmit sensory information from the body to the central nervous system.

The velocity of electrical impulses in the nervous system is enhanced in axons that are encased by a myelin sheath, which serves as a protective covering. The process of myelination involves the production of myelin by specific glial cells, which subsequently envelop the axons, thereby promoting the rapid conduction of electrical impulses along the length of the axon.
It is noteworthy that myelin does not uniformly envelop the entire axon; rather, it displays periodic interruptions that are referred to as nodes of Ranvier. The aforementioned nodes refer to interruptions in the myelin sheath, with inter-node intervals varying from 0.2 to 2 mm. As the action potentials propagate along the axon, they demonstrate a phenomenon known as "saltatory conduction" whereby they leap from one node of Ranvier to the next. The method by which signals are transmitted is commonly known as saltatory conduction, which is derived from the Latin word "saltare," signifying "to leap." The phenomenon of saltatory conduction facilitates the rapid propagation of electrical signals along axons that are enveloped by myelin sheaths, as opposed to those that lack such sheaths.

Saltatory conduction is a mechanism that enhances the efficiency of signal propagation by restricting the depolarization and repolarization events linked with action potentials to the nodes of Ranvier. The aforementioned process serves to reduce the amount of energy required to restore the electrical state at every point along the axon, thus facilitating the swift transmission of information throughout the nervous system. The existence of myelin and the process of saltatory conduction are important adaptations that improve the speed and effectiveness of electrical signal transmission in neural networks (Fields, 2009; Raphael & Talbot, 2011).

2.1.3.2.4 Axons and Dendrites Differences

Axons and dendrites display distinct structural and functional characteristics that are worthy of note. Axons are mainly responsible for transmitting information away from the cell body, whereas dendrites are specialized in facilitating the transmission of information toward the cell body. Axons are typically characterized by their smooth surface that lacks any roughness or irregularities, thereby setting them apart from dendrites. Typically, a solitary axon is observed per cell, and ribosomes, the intracellular organelles responsible for protein synthesis, are absent.

In contrast to axons, dendrites exhibit a unique rough texture that is further emphasized by the existence of dendritic spines. The dendritic spines play a crucial role in augmenting the surface area of dendrites, thereby enabling a higher count of synaptic connections with adjacent neurons. The potential for synaptic plasticity in neuronal circuits is influenced by the structural characteristics of dendritic spines. This enables the establishment and modification of synaptic connections, which is a fundamental mechanism underlying learning and memory.

Dendrites are further distinguished by considerable branching, which results in the existence of multiple dendrites per cell. The dendritic arborization facilitates the reception and integration of signals from a wide array of sources, thereby augmenting the neural processing capability of the neuron. Ribosomes, which are located in dendrites, have a crucial function in protein synthesis in the neuronal cytoplasm, thereby facilitating the maintenance and function of dendritic processes.
In contrast to axons, dendrites do not possess myelin insulation, which makes them more vulnerable to the weakening of electrical signals. Myelin, the insulating layer generated by oligodendrocytes in the central nervous system and Schwann cells in the peripheral nervous system, is essential in augmenting the acceleration and efficiency of electrical impulse propagation along axons. The process of myelination aids in the effective propagation of electrical signals by providing insulation, which allows axons to extend and branch over longer distances from the cell body. It is noteworthy that the occurrence of myelin-enhanced conduction remains intact despite the existence of dendrites, thereby guaranteeing prompt and dependable transmission of information to the neuronal cell soma. However, dendrites are strategically located in close proximity to the cell body, thereby enabling swift and effective transmission and integration of signals within the neuron \(^{[45],[46]}\) (Mihailoff & Haines, 2018; Simple Study on the Difference Between Axon and Dendrite, 2022).

2.1.3.3 Synapses

Connections between neurons are created by attaching one neuron's dendrites to the cell bodies and cell processes of another neuron. The synapses, which are referred to as connections, serve as the locations where information is transmitted from the presynaptic neuron to the postsynaptic neuron. The anatomical connections linking neurons and skeletal muscle cells are commonly referred to as neuromuscular junctions, while the connections between neurons and smooth muscle cells or glands are commonly referred to as neuroeffector junctions. The categorization of synapses into distinct types is determined by their precise anatomical locations at which they are formed between neurons. An example of a synapse is the axodendritic synapse, which takes place when the axon terminal of a neuron connects with the dendrites of another neuron. Integration and processing of signals need this sort of synapse, which transmits information from one neuron to another via the dendritic tree. An additional example of the synapse is the axosomatic synapse, characterized by the connection between the axon terminal of one neuron and the cell body (soma) of another neuron. Axosomatic synapses are essential in the modulation of neuronal activity and firing patterns. The axoaxonic synapse pertains to the interconnection established between the axon terminal of one neuron and the axon of another neuron \(^{[47]}\) (Caire, 2023). The aforementioned synapses play a role in the modulation of neurotransmitter release, thereby exerting an influence on inter-neuronal communication. The intricate neural circuitry and precise control over information flow in the nervous system are made possible by the diversity of synapse types.

2.1.3.4 Neurotransmitters

Neurotransmitters and neuroactive peptides are crucial molecules involved in the communication between neurons in the nervous system. Neurotransmitters, which are chemical messengers, are typically responsible for transmitting information at most synapses and junctions. When an action potential propagates along an axon and arrives at the terminal region of the axon, it initiates the exocytosis of neurotransmitter molecules from the presynaptic neuron. Neurotransmitter molecules traverse the synaptic cleft and attach to membrane receptors located on the postsynaptic cell, transmitting either an excitatory or inhibitory signal. Based on the role of neurotransmitters in neural communication there are two types of neurons.
The excitatory neurons are responsible for the release of excitatory neurotransmitters, such as glutamate, which serve to enhance the probability of action potential generation in the postsynaptic neurons. The inhibitory neurons are a type of neuronal cell that are responsible for the release of inhibitory neurotransmitters, such as gamma-aminobutyric acid (GABA). The primary function of these neurotransmitters is to reduce the probability of action potential generation in the postsynaptic neurons \(^{[48][49]}\) (Sheffler, 2023; Cleveland Clinic, n.d.).

Hence, the third fundamental neuronal function, which involves transmitting information to target cells, is executed by the axon and its corresponding axon terminals. Similar to the manner in which a solitary neuron can receive inputs from multiple presynaptic neurons, it is also capable of establishing synaptic connections with numerous postsynaptic neurons through distinct axon terminals.

The process of interneuronal communication is dependent on the complex transportation of chemical substances through a specialized intercellular connection, the synapse. In this particular context, the chemical substances known as neurotransmitters are discharged from the presynaptic nerve ending of a neuron and cross the synaptic cleft, with the possibility of binding to particular receptors located on the postsynaptic neuron. Stimulation of receptor sites can elicit discrete physiological reactions, including depolarization that induces excitatory postsynaptic potentials, or hyperpolarization that leads to inhibitory postsynaptic potentials. Action potential production is more likely when membrane potential is depolarized, and less likely when membrane potential is hyperpolarized.

Otto Loewi's discovery of the first neurotransmitter, acetylcholine, in 1921 was achieved through an experiment that involved the stimulation of frog hearts. The discovery in question was of great importance as it brought to light the fact that the application of electrical stimulation to the vagus nerve resulted in the release of a chemical substance, subsequently identified as acetylcholine, which had notable physiological impacts on neighboring organs. Following this, a set of standards were developed to determine the categorization of a substance as a neurotransmitter. These standards include aspects such as its synthesis and localization within neurons, discharge upon neuronal activation, impact on postsynaptic receptors, subsequent deactivation mechanisms, and the capacity to reproduce its effects when externally administered \(^{[50]}\) (Finger, 2005).

Numerous chemicals have been recognized as neurotransmitters, including small-molecule neurotransmitters like amino acids, neuroactive peptides, and soluble gases. Amino acids function as neurotransmitters in the central nervous system. Neuroactive peptides, which are distinguished by their comparatively greater size and intricacy, also serve as neurotransmitters. Soluble gases, such as nitric oxide (NO), function as unconventional neurotransmitters by diffusing out of neurons shortly after their synthesis to activate enzymes that participate in the generation of secondary messengers.

The process of synthesizing neurotransmitters involves intricate enzymatic mechanisms. The synthesis of acetylcholine involves the enzymatic reaction catalyzed by choline acetyltransferase, which combines choline and acetyl coenzyme A (CoA). The production of catecholamines, namely dopamine, norepinephrine, and epinephrine, involves a series of enzymatic transformations \(^{[51][52]}\) (Corbière, 2019; Khan Academy, n.d.).
The recognition of a chemical compound as a neurotransmitter necessitates conformity to precise standards that have been established by experts in the field of neuroscience. The criteria below function as a set of directives for differentiating authentic neurotransmitters from other molecules in the neuronal milieu.

Initially, a neurotransmitter must be synthesized within a neuron, thereby establishing its inherent connection with neuronal activity. Furthermore, the chemical must be recognized within neural structures, confirming its existence within the neurons themselves.

Furthermore, following neuronal stimulation and consequent depolarization, the neurotransmitter needs to be discharged from the presynaptic neuron. The liberation of the neurotransmitter into the synaptic cleft is expected to take place as a reaction to the activation of the presynaptic neuron. Moreover, upon its release, the aforementioned chemical is expected to interact with postsynaptic receptors by binding to particular sites, thereby triggering a biological response in the recipient neuron. The aforementioned phenomenon can exhibit itself in the form of either a stimulatory or suppressive reaction, thereby exerting an impact on the electrical condition of the neuron located downstream.

After its release and subsequent binding to postsynaptic receptors, the neurotransmitter must undergo a process of inactivation to cease its activity. The mechanisms of inactivation comprise reuptake, which involves the active transportation of the neurotransmitter back into the presynaptic neuron, and enzymatic degradation, wherein particular enzymes alter the chemical composition of the neurotransmitter, leading to its inactivation. The temporal regulation of neurotransmitter signaling and prevention of excessive or prolonged stimulation of postsynaptic receptors is ensured through effective inactivation.

Ultimately, the neurotransmitter ought to evoke an identical biological response upon direct application to the postsynaptic site.

The transportation of neurotransmitters takes place from the soma to the presynaptic terminal, where they are sequestered in vesicles. Following neuronal depolarization, synaptic vesicles merge with the axon terminal membrane, resulting in the discharge of neurotransmitters into the synaptic cleft. It is noteworthy that nitric oxide (NO) exhibits a distinct characteristic from other neurotransmitters in that it is not sequestered in vesicles, but rather, it is promptly discharged and diffuses out of the neuron to stimulate enzymes in adjacent cells.

Neurotransmitters exhibit selectivity in their binding to particular receptors located on the postsynaptic membrane, which are equipped with recognition sites that are receptive to these chemical messengers. The process of neurotransmitters binding to their respective receptors triggers a series of biochemical reactions that facilitate the postsynaptic reaction.

The function of inactivation mechanisms is to bring an end to the activity of neurotransmitters. The process of diffusion facilitates the dispersion of neurotransmitters from the synaptic cleft, thereby impeding their ability to interact with receptors. Enzymatic degradation is a biochemical process that entails the alteration of neurotransmitter structure by specific enzymes, resulting in the loss of their ability to bind to receptors. Furthermore, glial
cells, specifically astrocytes, play a role in eliminating neurotransmitters from the synaptic cleft. Reuptake is a frequently observed mechanism in which neurotransmitters are reabsorbed into the presynaptic axon terminal, thus preventing their binding to receptors. The process of reuptake plays a crucial role in the cessation of the activity of neurotransmitters, including but not limited to norepinephrine, dopamine, and serotonin [53], [54], [55] (Inoue, 2008; Learning Ink, n.d.; Purves, 2001).

To summarize, the communication between neurons is significantly influenced by neurotransmitters and neuroactive peptides. The neural signaling within the complex network of the nervous system is dynamically orchestrated by the collective mechanisms of synthesis, transport, release, receptor binding, and subsequent inactivation. Comprehending these basic mechanisms is crucial in deciphering the intricacies of neural operation and maloperation.

2.1.3.5 Neuronal communication

Upon the arrival of an electrical impulse at the axon terminals, a cascade of events is initiated, leading to the liberation of neurotransmitters into the synapse. These chemical messengers play a crucial role in facilitating the transmission of the signal to the subsequent neuron or target cell.

So, the synaptic cleft is a narrow gap that separates adjacent neurons which is comprised of the presynaptic terminal including various cell organelles, including neurotransmitters and mitochondria and the postsynaptic ending is comprised of receptor sites that are receptive to neurotransmitters. Additionally, a synaptic cleft or gap separates the presynaptic and postsynaptic endings. In order to facilitate inter-neuronal communication, it is imperative that an electrical signal propagate along the axon and reach the synaptic terminal [56] (Südhof, 2021).

2.1.3.5.1 The process of mobilizing and releasing neurotransmitters

Upon reaching the synaptic terminal, the presynaptic ending, the occurrence of an electrical impulse will initiate the movement of vesicles that house neurotransmitters, towards the presynaptic membrane. Upon fusion of the vesicle membrane with the presynaptic membrane, the neurotransmitters are released into the synaptic cleft. Prior to recent times, the prevailing belief was that a neuron was responsible for the production and release of a singular type of neurotransmitter. The aforementioned principle was denoted as "Dale's Law." Recent findings suggest that neurons have the capacity to store and secrete multiple types of neurotransmitters [57] (Mosier, 2010).

The process of neurotransmitter diffusion across the synaptic cleft is a fundamental mechanism in the communication between neurons. Subsequent to their release, the neurotransmitter molecules undergo diffusion across the synaptic cleft, thereby enabling them to interact with receptor sites located on the postsynaptic ending. This interaction subsequently exerts an influence on the electrical response of the postsynaptic neuron. The dendrite serves as the postsynaptic ending in the axodendritic synapse, while the axoaxonic synapse and
Axosomatic synapse are characterized by synapses that occur on axons and cell bodies, respectively.

The binding of a neurotransmitter to a receptor located on the postsynaptic membrane of the synapse results in a modification of the excitability of the postsynaptic cell, which can either increase or decrease the likelihood of the cell generating an action potential. When the quantity of excitatory postsynaptic events reaches a certain threshold, they can collectively trigger an action potential in the postsynaptic cell, thereby facilitating the propagation of the neural signal. Numerous psychoactive substances and neurotoxic agents have the capacity to alter the characteristics of neurotransmitter release, reuptake of neurotransmitters, and the accessibility of receptor binding sites.

2.1.3.6 The membrane potential

Neurons transmit information through electrochemical signaling. This implies that the interaction of chemicals results in the generation of an electrical impulse. Ions are formed when chemicals within the body acquire an electrical charge. The crucial ions in the nervous system include sodium and potassium, which possess a single positive charge, as well as calcium, which bears two positive charges. Additionally, chloride is a negatively charged ion that plays a significant role in the nervous system. Additionally, there exist protein molecules that carry a negative charge. It is imperative to bear in mind that nerve cells are enveloped by a selectively permeable membrane that facilitates the diffusion of certain ions while impeding the movement of others. The membrane in question is referred to as semi-permeable.

The resting membrane potential is a term used in physiology to describe the electrical potential difference across the plasma membrane of a cell when it is in a state of rest.

The state of a neuron in which it is not transmitting an electrical impulse is referred to as the resting state. At present, the intracellular environment of the neuron exhibits a negative charge in comparison to the extracellular milieu. Despite the equilibrium sought by the ion concentrations on either side of the membrane, the selective permeability of the cell membrane through ion channels restricts the passage of certain ions. Potassium ions (K+) exhibit high permeability across the membrane while in a state of rest. In a state of rest, the transmembrane movement of chloride ions (Cl-) and sodium ions (Na+) is comparatively restricted. The membrane impeded the intracellular anionic protein entities (A-) from traversing to the extracellular space. Apart from the aforementioned selective ion channels, there exists a pump that expends energy to extrude three sodium ions from the neuron while simultaneously importing two potassium ions. Upon achieving equilibrium, the resting potential is attained by measuring the voltage differential between the interior and exterior of the neuron. The resting membrane potential of a neuron is approximately -70 mV, signifying that the intracellular environment of the neuron is 70 mV less than the extracellular milieu. In a state of quiescence, there exists a comparatively higher concentration of sodium ions extracellularly and a greater abundance of potassium ions intracellularly within the neuron [58], [59] (Ramahi, 2004; Libretexts, 2003).

The action potential is a rapid and transient change in the electrical potential of a cell membrane, which occurs in response to a stimulus. This phenomenon is a crucial mechanism
for the transmission of information in the nervous system and is characterized by a sequence of depolarization and repolarization events.

The resting potential pertains to the state of a neuron when it is not actively transmitting signals. The phenomenon of action potential takes place when a neuron transmits information along its axon, in a direction that is away from the soma. Alternative terminologies, such as "spike" or "impulse," are employed by neuroscientists to refer to the action potential. The phenomenon known as the action potential is characterized by a sudden surge of electrical activity that arises from the influx of depolarizing current. This implies that a particular occurrence (a stimulus) elicits a depolarization of the resting membrane potential towards 0 mV. Once the depolarization of a neuron reaches approximately -55 mV, it will initiate an action potential. This represents the point of entry, or the minimum level required. In the absence of attaining the critical threshold level, the neuron will not initiate an action potential. Upon reaching the threshold level, a constant amplitude action potential is triggered, regardless of the neuron in question, as the size of the action potential remains uniform. In a single nerve cell, all action potentials are uniform in magnitude, regardless of their amplitude. Consequently, the neuron will either fail to attain the threshold or generate a complete action potential, adhering to the "ALL OR NONE" principle (Chrysafides, 2023).

The generation of action potentials is attributed to the transmembrane movement of distinct ions. The initial event is the activation of sodium channels. The influx of sodium ions into the neuron is due to the concentration gradient, where the extracellular environment contains a higher concentration of sodium ions compared to the intracellular environment. This results in a net positive charge on the extracellular side of the membrane, leading to an electrical potential difference across the membrane. As a consequence, sodium ions move down their electrochemical gradient and enter the neuron, causing depolarization. It is important to note that sodium ions carry a positive charge, thus resulting in an increase in the positive charge of the neuron and subsequent depolarization. The opening of potassium channels is characterized by a longer duration. Upon opening, the efflux of potassium ions from the cell results in the reversal of depolarization. Around this juncture, the closure of sodium channels commences. As a result, the action potential undergoes repolarization and returns towards the resting membrane potential of -70 mV. The hyperpolarization phase of the action potential is prolonged due to the prolonged opening of potassium channels, causing the membrane potential to dip below the resting potential of -70 mV. Over time, the ion concentrations undergo a gradual restoration process, leading to the restoration of the cell's resting potential of -70 mV (Ramahi, 2014).

2.1.4 Glial cells

The brain is a highly intricate organ that comprises a diverse assemblage of cells, extending beyond the neuronal population, encompassing glial cells. The brain is known to contain approximately 86 billion neurons, and a similar number of glial cells are estimated to be present. Unfortunately, glial cells are frequently overlooked in scientific research, as the emphasis is typically placed on neurons. Despite not participating in the transmission of nerve impulses or action potentials, glial cells perform essential roles that are imperative for the appropriate operation of neurons.
2.1.4.1 The Different Types of Glia and Their Functions

Glia can be classified into discrete subtypes, each of which is distinguished by particular functional roles. Astrocytes, characterized by their distinctive star-shaped appearance, offer both physical and nutritional assistance to neurons. The diverse range of functions performed by these cells includes the removal of waste material from the brain, the transportation of nutrients to neurons, the preservation of neuronal positioning, the breakdown of residual matter from expired neurons, and the control of the extracellular environment.

Similarly, microglia, like astrocytes, are involved in the process of phagocytosis of cellular waste produced by dead neurons. In contrast, oligodendroglia play a role in the insulation of neurons in the central nervous system by producing myelin sheaths. Satellite cells offer structural assistance to neurons located in the peripheral nervous system, whereas Schwann cells are responsible for providing myelin sheaths to neurons in the same system.

The oligodendrocytes found in the central nervous system and the Schwann cells present in the peripheral nervous system exhibit a comparable physiological role. Both of these categories of glial cells are responsible for the production of myelin, which is the insulating material that envelops the axons of numerous neurons. Myelin significantly enhances the velocity at which an action potential propagates along the axon, thereby exerting a pivotal influence on the functioning of the nervous system.

Along with the three primary categories, glia also contain satellite glial cells and ependymal cells.

Satellite glial cells envelop the cell bodies of neurons located within the ganglia of the peripheral nervous system. Satellite glial cells are hypothesized to provide support to neurons and potentially serve as a protective barrier; however, their precise function remains inadequately comprehended.

Ependymal cells are specialized epithelial cells that form a lining along the ventricles of the brain and the central canal of the spinal cord. These cells possess cilia, which are hair-like structures that exhibit rhythmic beating. The primary function of these cilia is to facilitate the circulation of cerebrospinal fluid within the ventricles and spinal canal.\[62],[63],[64] (Purves, 2001; Jakel, 2017; Ludwig, 2023)

Multiple differentiations can be observed between glial cells and neurons. Neurons are characterized by the presence of two distinct processes, namely axons, and dendrites, while glial cells possess a singular process. Neurons exhibit the capability to produce action potentials, while glial cells do not possess this capacity. Despite this, glial cells are able to maintain a state of electrical potential at rest. Furthermore, neurons participate in synaptic connections utilizing neurotransmitters, a feature that is absent in glial cells that do not possess chemical synapses.

In summary, glial cells play crucial roles in the appropriate operation of the brain, despite frequently being overlooked due to the focus on neurons. The varied forms and roles of glial cells play a crucial role in maintaining the well-being, structural integrity, and
homeostasis of neurons, highlighting their essentiality in the complex milieu of the nervous system.
Mirror Neurons (MNs) are a unique group of neurons that convert sensory information into a motor format. They were initially identified in monkeys and have since been found in humans as well. Mirror neurons are involved in various cognitive processes such as action comprehension, imitation, speech, and emotional perception. They are located in the premotor and parietal cortex, and their activation is influenced by an individual's motor experience. The mirror system in humans is similar to that found in monkeys and plays a role in understanding the purpose and intention behind observed motor actions. It can also distinguish between intended and unintended actions. Additionally, mirror neurons are activated not only when individuals perform a motor action but also when they observe someone else performing a similar action. This ability to imitate and understand the actions of others is facilitated by the mirror system.

Mirror neurons exhibit a significant level of generalization, with responses remaining consistent regardless of whether the action is performed in close proximity or at a distance from the subject that is observed. They have been classified into two categories: "strictly congruent" and "broadly congruent," based on the type of congruence they demonstrate. The initial investigations of mirror neurons primarily focused on the upper region of F5, which predominantly represents hand movements. A recent study found that approximately 25% of the examined neurons exhibited mirror properties. The mirror-neuron circuit refers to a neural pathway involved in mirroring and imitating the actions and emotions of others. Neurons that react to the observation of actions performed by others are not limited to area F5. Area 7b, also known as PF of Von Economo, contains neurons that are activated when observing actions performed by other individuals [65] (Rajmohan & Mohandas, 2007).

Neurons in the PF region that react to sensory stimuli are categorized into three groups: "somatosensory neurons" (33%), "visual neurons" (11%), and "bimodal neurons" (56%). Approximately 40% of the neurons that respond to visual stimuli are specifically activated by observing actions, and about two-thirds exhibit mirror properties [66] (Rizzolatti & Craighero, 2004).

Mirror neurons were first identified in 1992 as a group of premotor cells in monkeys that activate both during the execution of an action and the observation of that action. Recent studies in various species, ranging from birds to humans, have uncovered a diverse range of cell types present in multiple motor, sensory, and emotional brain regions. These cells collectively form a mirror mechanism that is more intricate and adaptable than previously believed. This mirror mechanism serves a crucial role in social interaction and has been conserved throughout evolution.

The human parieto-frontal mirror system performs the same functions as the corresponding mirror system in monkeys, which involves comprehending the purpose of actions performed by others and discerning their underlying intentions. Multiple brain imaging studies have demonstrated that the primary components of the human mirror system are the inferior parietal lobule (IPL), the ventral premotor cortex (PMv), and the caudal portion of the inferior frontal gyrus (IFG) [67] (Acharya & Shukla, 2012). The mirror system is strongly
activated by motor acts well-represented in the observer's motor repertoire. Recent brain imaging studies have demonstrated mirror activations in individuals skilled in specific motor skills, with a stronger activation observed in those with different motor experiences.

Recent research has shown that the human mirror system, similar to that found in monkeys, plays a crucial role in comprehending both the purpose of observed motor actions and the underlying intention behind them. This was demonstrated through an fMRI study where participants were tasked with deducing the intentions of agents by observing their execution of a physical action. The findings indicated that the mirror system was activated in both the action and intention conditions, with comprehension of the doer's intention leading to a substantial enhancement in the activity of the mirror system.

Unlike mirror neurons in monkeys, mirror neurons in humans are activated even when observing nonsensical (intransitive) movements. When transitive actions are observed, both the frontal and temporal regions of the MNS are activated, whereas only the frontal node is activated when observing intransitive actions (Iacoboni et al., 2001). Another fMRI study examined the neural mechanisms underlying humans' ability to distinguish between actions that reflect the intention of the agent (intended actions) and actions that do not (non-intended actions). The ability to identify unintended actions relies on the activation of regions that indicate unexpected events in both space and time, as well as the functioning of the mirror system. The activation of the right temporo-parietal junction is interpreted as an attentional mechanism, aligning with introspection indicating that an unintended action does not lead to attempts to attribute intention to the agent (Fabbri-Destro & Rizzolatti, 2008).

The discovery of MNs quickly gained significant attention in the scientific community, with some researchers asserting it would have a transformative impact on psychology, comparable to the influence of DNA on biology. However, others characterized MNs as an overhyped concept in neuroscience. Most of the research stemming from the identification of monkey MNs pertained to human subjects, focusing on social and nonsocial cognition, language, perception, motor action, and emotion.

Human studies have investigated the translational significance of MNs. The majority of studies resulting from the MN discovery have focused on human subjects, but only one study has documented the activity of individual neurons while patients performed or observed hand-grasping actions and facial emotional expressions (Bonini et al., 2022). Both human and monkey fMRI studies have demonstrated that the identical network of sensorimotor cortical areas is activated during both action execution and action observation in both species.

Emotional expressions of others seem to be handled using a similar mechanism, as they are visible, can be caused by living and non-living things, vary depending on the situation, and involve a physiological response linked to subjective arousal and emotional experience. A group of deep brain regions partially interact with the somatomotor cortical circuit, responsible for both expressing and perceiving emotions in various animal species and enabling humans to synchronize their emotional responses and social behaviors with those of others. A comprehensive framework for understanding the fundamental somatomotor and emotional MN mechanisms in humans and other animals is presented, focusing on a wide-ranging mapping from others' bodily actions and emotional displays to the observer's motor and visceromotor structures (Baars & Gage, 2010).
The human brain plays a crucial role in perceiving and predicting the actions of others, as evidenced by studies on lesions in the left inferior frontal, inferior parietal, and middle-superior temporal cortex. The motor system's perceptual and predictive functions are strongly associated with its evolutionarily conserved role in planning and coordinating behavioral responses to others' actions. When individuals observe someone else's action, they can choose from several options that engage the central nodes of the human mirror neuron network: faithfully imitating or emulating the observed action, refraining from doing so, or performing a complementary or alternative action. Environmental circumstances and internal conditions greatly influence how they interpret and replicate an observed action using their own motor system. Transcranial magnetic stimulation (TMS) was used to induce neural activity during the observation of actions, showing an initial, sensory-driven, and non-specific motor response to occur approximately 150 ms after the start of the observed action. A later motor response occurred around 300 ms after the start of the stimulus, indicating flexibility and suggesting that previous training may allow for a voluntary response to the observed action.

Recent studies using ultra-high-field fMRI showed that watching complex everyday action sequences in their natural order leads to enhanced information transmission from frontal premotor output layers to parietal input layers. This discovery offers anatomofunctional evidence supporting the hypothesis that frontal regions transmit anticipated perceptual results of others' actions to parietal regions, which integrate incoming sensory signals regarding the ongoing observed action as a prediction error.

Advancements in hyperscanning techniques are enabling researchers to study real-time reciprocal interactions among a pair or even a group of subjects as a unified system. Interbrain synchronies facilitate social interaction through the neural machinery underlying it, with self-related neurons in Subject 1 controlling behavior and other-selective neurons in Subject 2 activating their own self-related neurons. Recent studies have revealed the importance of agent-based representations in facilitating bidirectional interbrain correlations, even for complex social behaviors like spontaneous communicative interactions. Interbrain synchronies are known to play a crucial role in facilitating social interaction through the underlying neural machinery.
2.3 Electroencephalogram (EEG)

An electroencephalogram (EEG) is a test used to evaluate the electrical activity in the brain. It can help detect potential problems with brain cell communication. An EEG tracks and records brain wave patterns. Small flat metal discs called electrodes are attached to the scalp with wires. The electrodes analyze the electrical impulses in your brain and send signals to a computer that records the results. The electrical impulses in an EEG recording look like wavy lines with peaks and valleys. Irregularities may be a sign of seizures or other brain disorders.

2.3.1 History of EEG

The electrical properties of the brain were first observed by the English scientist Richard Caton in 1875, who used a sensitive galvanometer to record electrical activity from the brains of animals, observing changes in activity during sleep and a complete lack of activity after death. Hans Berger, a German psychiatrist, documented the inaugural human electroencephalograms (EEGs) in 1924. Fisher and Lowenback were the first to showcase epileptiform spikes in 1934. Gibbs, Davis, and Lennox provided a description of interictal epileptiform discharges and 3-Hz spike-wave patterns observed during clinical seizures in 1935. The following year, Gibbs and Jasper will document the characteristics of focal interictal spikes. The 1930s and 1940s saw the establishment of the first clinical electroencephalogram (EEG) laboratories in the United States. An organization that would later become known as the American Clinical Neurophysiology Society was established in 1947 as the American EEG Society [72], [73] (St Louis, 2016; Historical Overview of Electroencephalography: From Antiquity to the Beginning of the 21st Century, n.d.). Today, electroencephalography (EEG) is the gold standard for defining neurological disorders and has solidified its place in the diagnosis and treatment of neurological disorders.

2.3.2 Function of EEG

Electroencephalography (EEG) is a technique used to capture an electrogram of the inherent electrical activity of the brain. EEG has demonstrated the ability to capture biosignals that correspond to the postsynaptic potentials of pyramidal neurons in both the neocortex and allocortex. The procedure is generally non-invasive, involving the placement of EEG electrodes on the scalp, commonly referred to as "scalp EEG," using the International 10–20 system or its variations. Electrocorticography, which requires the surgical implantation of electrodes, is also known as "intracranial EEG". The clinical interpretation of EEG recordings
is typically conducted through the visual examination of the tracing or the analysis of quantitative EEG data. Voltage fluctuations measured by the EEG bioamplifier, and electrodes allow the evaluation of normal brain activity. A healthy human EEG shows patterns of activity that correlate with how awake a person is. EEG can detect abnormal electrical discharges, such as sharp waves, spikes, or spike-and-wave complexes, as seen in people with epilepsy. It is often used to inform medical diagnosis, detect the onset and spatio-temporal evolution of seizures, and the presence of status epilepticus. EEG is one of the few mobile techniques available and offers millisecond-range temporal resolution, which is not possible with the other brain imaging techniques (namely CT, PET, or MRI) (Rayi, 2022; Sun et al., 2020).

EEG derivatives encompass evoked potentials (EP), which entail the computation of the average EEG activity synchronized with the introduction of a stimulus, be it visual, somatosensory, or auditory. Event-related potentials (ERPs) are EEG responses that are averaged and synchronized with the timing of more intricate stimulus processing. This method is employed in the fields of cognitive science, cognitive psychology, and psychophysiological research (Event-Related Potentials (ERPs) — Neural Data Science in Python, n.d.).

2.3.3 EEG configurations

Conventional EEG configurations record electrical brain activity from various locations on the scalp. The placement of electrodes typically follows the international 10–20 system for approximately 21 channel recordings, the 10–10 system for between 64 and 85 channels, or the 10–5 system for high-density caps with more than 300 channels (Oostenveld & Praamstra, 2001). These values represent the electrode distances relative to the overall size of the cap, specifically 20% of the distance between the inion to the nasion. Their purpose is to ensure consistency in experiments. Anatomical landmarks, including the inion, nasion, and left and right pre-auricular points, are used to guide the placement of electrodes on the head of the participant. The electrodes are positioned in such a way that the central electrode namely Cz is substantially aligned with the vertex. Researchers make the assumption that participants’ electrode placements will be approximately consistent due to the meticulous positioning of the electrode cap during the experimental setup. Moreover, in the process of choosing a subset of electrodes for EEG analysis, it is presumed that the electrodes are positioned similarly among participants and that the activation being compared originates from relevant brain regions (Scrivener & Reader, 2022).
The EEG bioamplifier and electrodes enable the assessment of normal brain activity by measuring voltage fluctuations. The electrical activity detected by EEG is generated by neurons in the brain tissue beneath the scalp. The recordings obtained from the electrodes on the scalp are influenced by the orientation and proximity of the electrodes to the source of the activity. Moreover, the measured value is altered by intermediate tissues and bones, which function similarly to resistors and capacitors in an electrical circuit. Consequently, the EEG signal primarily reflects the activity of cortical neurons located in close proximity to the electrodes on the scalp, rather than all neurons uniformly. The EEG does not directly capture activity from deep structures in the brain that are located further away from the electrodes. These structures include the base of the cortical gyrus, mesial walls of the major lobes, hippocampus, thalamus, and brain stem \cite{79,80} (Electroencephalogram (EEG), 2021; St Louis, 2016).

An individual with a healthy electroencephalogram (EEG) will exhibit specific activity patterns that are associated with their level of wakefulness. The observed frequencies range from 1 to 30 Hz, while the amplitudes will vary between 20 and 100 μV. The recorded frequencies are categorized into different bands:

- alpha (8–13 Hz)
- beta (13–30 Hz)
- delta (0.5–4 Hz)
- theta (4–7 Hz)

Alpha waves are detected during a state of relaxed wakefulness and are most noticeable over the parietal and occipital regions. During periods of heightened cognitive activity, beta waves exhibit greater prominence in the frontal cortex and other brain regions. When a calm individual is instructed to open their eyes, one can observe a decrease in alpha brainwave activity and an increase in beta brainwave activity. Theta and delta waves are absent during wakefulness, and their presence may indicate a malfunction in the brain \cite{81} (Mari-Acevedo et al., 2019).

EEG is capable of identifying anomalous electrical discharges, such as sharp waves, spikes, or spike-and-wave complexes, which are commonly observed in individuals with epilepsy. Consequently, it is frequently employed to aid in medical diagnosis. EEG is capable of identifying the initiation and spatiotemporal progression of seizures, as well as the occurrence of status epilepticus. Additionally, it is employed for the purpose of diagnosing sleep disorders, determining the level of anesthesia, assessing coma, detecting
encephalopathies, evaluating cerebral hypoxia following cardiac arrest, and confirming brain
death. Previously, EEG was commonly used as the initial diagnostic method for tumors, stroke,
and other specific brain disorders \(^{[82]}\) \(\text{(Neurological Diagnostic Tests and Procedures, n.d.)}\).
However, its usage has declined due to the introduction of advanced imaging techniques like
magnetic resonance imaging (MRI) and computed tomography (CT), which provide more
detailed anatomical information. Although EEG has a restricted spatial resolution, it remains a
valuable instrument for research and diagnosis. It is a rare mobile technique that provides
temporal resolution in the millisecond range, a capability not achievable with CT or MRI \(^{[83]}\)
(Peters, 2023).

2.3.4 Other Brain imaging methods

Neuroimaging, also known as brain imaging, is a field that uses a variety of methods to
provide pictures of the neurological system's anatomy, physiology, and pharmacology. Various
brain imaging techniques are employed in the fields of neuroscience and clinical practice to
examine the anatomy and activity of the brain \(^{[84]}\) (Song et al., 2021). Below is a concise
summary and a comparison of several prevalent brain imaging techniques:

2.3.4.1 Imaging the structure of an object or system

Magnetic Resonance Imaging (MRI): is a technique that produces detailed and clear
images of the brain's structure with high precision. This procedure is non-invasive and does
not utilize ionizing radiation. Aspects of the brain's anatomy can be highlighted by diverse
types of magnetic resonance imaging (MRI), including T1- and T2-weighted imaging showing
normal soft-tissue anatomy and fat as well as fluid and abnormalities, respectively.

Computed Tomography (CT): employs X-rays to generate axial images of the brain.
Although it offers high spatial resolution, this imaging technique poses a risk of ionizing
radiation to the patient, making it less desirable for multiple scans.

2.3.4.2 Functional Imaging

Functional Magnetic Resonance Imaging (fMRI): is a technique that quantifies cerebral
blood flow and oxygenation in order to identify and analyze brain activity. Functional
connectivity is extensively employed to investigate and identify brain regions engaged in
diverse tasks. It possesses a significant level of spatial resolution, but its temporal resolution is comparatively low.

Positron Emission Tomography (PET): is a medical imaging technique that entails the introduction of a radioactive tracer into the body, which emits positrons. The gamma rays that are released are detected, and the collected data is utilized to generate images depicting the regional blood flow, metabolic activity, or density of neurotransmitter receptors in the brain.

Near-Infrared Spectroscopy (NIRS): detects near-infrared light absorption to determine changes in blood oxygenation and hemodynamics. Functional brain imaging studies frequently employ this technique, particularly in pediatric populations, due to its excellent temporal resolution.

Electroencephalography (EEG): is a method used to detect and record the electrical activity in the brain by placing electrodes on the scalp as already mentioned. Its temporal resolution is exceptional, making it ideal for investigating neural oscillations and event-related potentials.

Magnetoencephalography (MEG): is a technique used to detect and measure the magnetic fields produced by the activity of neurons. Functional magnetic resonance imaging (fMRI) offers superior temporal and spatial resolution in comparison to electroencephalography (EEG), rendering it valuable for investigating brain dynamics.

2.3.4.3 Diffusion imaging

Diffusion Tensor Imaging (DTI): is a magnetic resonance imaging (MRI) technique used to quantify the movement of water molecules within brain tissue. It is frequently employed to investigate the structure and connectivity of white matter tracts in the brain.

2.3.4.4 Molecular imaging

Single-Photon Emission Computed Tomography (SPECT): is a medical imaging technique that utilizes gamma-ray-emitting tracers to visualize and study blood flow, metabolism, and receptor density in the brain.

Functional PET imaging: encompasses the examination of distinct molecular targets within the brain, including protein aggregates or neurotransmitter receptors that are linked to neurodegenerative disorders, in addition to structural information.
The selection of imaging modality is contingent upon the particular research or clinical inquiry, the preferred spatial and temporal precision, invasiveness, and additional considerations. Researchers frequently employ a blend of these methodologies to acquire a thorough comprehension of the structure and function of the brain. Every method possesses unique advantages and constraints, and the selection is contingent upon the specific demands of the investigation or diagnosis \cite{85, 86, 87, 88} (Technology Networks, 2022; Xue et al., 2010; Kim et al., 2021; Lovering, 2021).

Brain imaging techniques are essential instruments in the field of neuroscience for investigating the anatomy and activity of the brain. Multiple imaging techniques exist, each possessing distinct advantages and disadvantages. Below is a comparative table (table 2) of several prevalent brain imaging techniques:

Table 2. Comparative table summarizing the advantages and limitations of various structural and functional imaging techniques

<table>
<thead>
<tr>
<th>IMAGING TECHNIQUE</th>
<th>ADVANTAGES</th>
<th>CONSTRAINTS</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Structural Imaging</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Magnetic Resonance Imaging</td>
<td>- Offers high-resolution, intricate visuals of cerebral structures.</td>
<td>- Costly equipment and may not be appropriate for specific patient demographics.</td>
</tr>
<tr>
<td>(MRI)</td>
<td>- This procedure is non-invasive and does not utilize ionizing radiation.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>- Both white and gray matter can be visually represented.</td>
<td></td>
</tr>
<tr>
<td>CT scan</td>
<td>- Offers comprehensive visual representations of cerebral anatomical features.</td>
<td>- Entails the utilization of ionizing radiation.</td>
</tr>
<tr>
<td></td>
<td>- Readily accessible and more expedient than magnetic resonance imaging (MRI).</td>
<td>- MRI exhibits higher soft tissue contrast in comparison to other imaging techniques.</td>
</tr>
</tbody>
</table>
- Valuable for identifying sudden and severe conditions such as hemorrhages.

### Functional Imaging

<table>
<thead>
<tr>
<th>fMRI (Functional Magnetic Resonance Imaging)</th>
<th>PET (Positron Emission Tomography)</th>
<th>SPECT (Single-Photon Emission Computed Tomography)</th>
<th>Diffusion Imaging</th>
</tr>
</thead>
<tbody>
<tr>
<td>- It assesses alterations in blood flow, providing indirect information about neural function.</td>
<td>- Utilizes radiotracers to quantify metabolic activity.</td>
<td>- Assesses the flow of blood in the brain and its metabolic activity.</td>
<td>- Utilizes mapping techniques to track the spread of water molecules and identify white matter pathways.</td>
</tr>
<tr>
<td>- Superior level of detail in terms of spatial resolution.</td>
<td>- It can provide information regarding the activity of neurotransmitters.</td>
<td>- Ubiquitous and more affordable than PET.</td>
<td>- Restricted in effectively resolving intricate fiber crossings.</td>
</tr>
<tr>
<td>- Not requiring any penetration or incision.</td>
<td>- The temporal resolution is comparatively lower in comparison to certain other techniques.</td>
<td>- Spatial resolution is inferior when compared to fMRI and PET.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>- Measures changes in blood flow and related physiological responses instead of directly monitoring neural activity.</td>
<td>- Includes the use of ionizing radiation.</td>
<td></td>
</tr>
</tbody>
</table>
- Beneficial for examining the interconnectedness of structures.
- Prone to being affected by motion artifacts.

**Electroencephalography (EEG) and Magnetoencephalography (MEG)**

<table>
<thead>
<tr>
<th>EEG and MEG</th>
<th>Offer exceptional temporal resolution.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Examination of neural activity in its direct form.</td>
</tr>
</tbody>
</table>
|             | Appropriate for the examination of dynamic phenomena such as event-related potentials (ERP).
|             | The spatial resolution is limited in comparison to structural imaging. |
|             | Prone to interference from electrical artifacts and noise. |
|             | The EEG is affected by the structure of the skull and the outer layer of the scalp. |

The selection of the suitable imaging technique relies on the particular research inquiry, the necessary spatial and temporal precision, and practical factors such as expense and availability. Researchers frequently employ a blend of methodologies to acquire a more holistic comprehension of brain structure and function.

2.3.5 Characteristics of EEG

Electroencephalography is a fundamental tool in the field of neuroimaging, providing a valuable understanding of the complex functioning of the human brain. EEG is a versatile tool for studying brain function because it can capture real-time electrical activity. Below are presented the advantages and drawbacks of EEG, providing insights into its impressive capabilities and inherent limitations.

Benefits of EEG:

- They are an efficient, cost-effective, and secure method for assessing the functionality of various brain regions.
- Accurate time measurements with a high level of precision
- Today's EEG technology has the capability to precisely detect brain activity with a resolution of one millisecond.
• EEG electrodes are adhered to the scalp. Consequently, it is a procedure that does not require any incisions or invasive techniques.
• EEG equipment is relatively affordable in comparison to other devices and is straightforward to operate.

Limitations of EEG:

• EEG recording is primarily limited by its inadequate spatial resolution.
• The EEG signal is not effective in precisely identifying the specific origin of activity. Put simply, they lack precision.
• EEG waveform does not enable researchers to differentiate between activities originating in different yet closely neighboring locations \([89], [90]\) \(\text{(Beres, 2017; Advantages and Disadvantages of EEG Advantages \textbullet It Has No Ability To. . ., n.d.)}\).
2.4 Event-related potentials

Event-related potentials (ERPs) are obtained by analyzing the neural activity recorded through electroencephalographic (EEG) measurements. Brain voltage changes in response to certain sensory inputs (sight, sound, touch, smell, taste, touch, etc.), as well as signals for motor planning, motor execution, or hidden mental processes (such as imagining), can be measured with an ERP. The ERP is derived by extracting and subsequently averaging several temporal segments from the ongoing EEG that specifically represent the event of interest. Positive and negative deflections are analyzed for their amplitude, latency, and topography to determine the underlying mental operations. ERPs shed light on innumerable cognitive processes, including those involving perception, focus, emotion, behavior, memory, and more. The event-related field (ERF) is the magnetoencephalography (MEG) equivalent of the event-related potential (ERP). Evoked potentials and induced potentials are specific categories of event-related potentials [91], [92] (Bradley et al., 2012; Luck, 2005).
2.5 EEG analysis

EEG analysis is a method that uses mathematical signal analysis techniques and computer technology to extract information from electroencephalography (EEG) signals. The objectives of EEG analysis are to enhance researchers' understanding of the brain. EEG analysis methods can be classified into four distinct categories: time domain, frequency domain, time-frequency domain, and nonlinear methods.

Frequency domain analysis, also known as spectral analysis, is a widely used method for analyzing EEG data using statistical and Fourier Transform techniques. It provides an understanding of the information in the frequency domain of EEG waveforms. Power spectral analysis is the most commonly used method as it accurately represents the "frequency content" of the signal. This method can examine alterations in energy levels of various frequency components in EEG signals during analysis, making it suitable for investigating neurological disorders and neuroscience, as these conditions can induce alterations in EEG energy during transitions in states like sleep phases, seizures, and emotional states.

Time domain methods for EEG analysis provide a reliable and efficient way to analyze non-stationary signals in real time using time-based calculations. Linear Prediction and Component Analysis are two crucial techniques used in the time domain for EEG analysis where Linear Prediction estimates values by combining past output and input values linearly while Principal Component Analysis (PCA) maps a dataset to features. Time domain methods also allow real-time measurement of fundamental signal properties using time-based calculations, requiring less sophisticated equipment compared to traditional frequency analysis. They rely on time-based parameters and statistical moments of the power spectrum as they establish a connection between physical time interpretation and conventional spectral analysis.

Time-frequency domain techniques can also be used to study brain activity fluctuations over time and frequency domains. These methods provide a more comprehensive understanding of brain dynamics than traditional time-domain or frequency-domain analyses. They capture the evolution of spectral characteristics of neural signals over time, making them valuable for studying temporary phenomena like oscillatory activity fluctuations or neural rhythm adjustments during cognitive tasks. Common techniques for time-frequency analysis include the Short-Time Fourier Transform (STFT), which partitions EEG signals into short-time windows and calculates the Fourier transform within each window, and the Wavelet Transform or the Hilbert-Huang Transform (HHT), which breaks down EEG signals into distinct frequency components using wavelet functions of different scales. Also, a spectrogram can display the changing power spectrum of EEG signals over time. These techniques are useful for investigating cognitive processes like attention, memory, and perception, as they enable researchers to monitor the changing patterns of neural oscillations linked to these functions.

EEG signals, like many natural phenomena, exhibit nonlinearity and non-stationarity, making their analysis more complex. Since 1985, the theory of nonlinear dynamic systems, known as 'chaos theory', has been widely used in nonlinear EEG analysis. Researchers have
incorporated nonlinear parameters like Lyapunov Exponent, Correlation Dimension, and entropies like Approximate Entropy and Sample Entropy to perform nonlinear EEG analysis.

The use of Artificial Neural Networks (ANN) for classifying electroencephalogram (EEG) signals is another method. EEG data undergoes wavelet transform preprocessing before being inputted into ANN. Recurrent neural networks (RNNs) were previously used in EEG analysis. The CNN method, which uses deep learning techniques, has gained popularity in recent studies. By providing limited training, CNN achieves impressive accuracy levels and superior decoding performance. However, large EEG data requires secure storage and computational resources for real-time processing. A cloud-based deep learning approach is proposed for real-time EEG data examination [93,94] (Zhang et al., 2023; Mike X Cohen, 2017).

2.5.1 Time domain methods

EEG is a complex technique that uses data from numerous trials to understand the consistent responses to stimuli. The signal-to-noise ratio of ERP data is directly proportional to the square root of the number of trials contributing to it. To ensure a reliable ERP, experiments may present varying numbers of stimuli from each experimental condition, ranging from 30 to 100 or even 1000. The quantity of stimuli depends on the magnitude of the anticipated ERP signal and practical limitations.

In an ERP experiment, multiple trials are presented in two or more experimental conditions, and the results are analyzed collectively across all trials in each condition. The impact of interest can develop either prior to or subsequent to the specific event to which the ERPs are synchronized. The analysis typically focuses on event-related potentials (ERPs) that occur after the stimulus is presented. If the focus is on motor response, the analysis may focus on brain activity preceding the initiation of the response, such as in response preparation. Alternatively, it may focus on brain activity following the response, particularly in relation to how individuals interpret their responses.

To analyze ERP data effectively, it is necessary to divide the EEG data into brief time intervals centered around the events of experimental significance. These segments, also known as epochs, can range from a few hundred milliseconds to several seconds, depending on the timing of the anticipated effects. When multiple EEG epochs are combined, an average ERP waveform can be discerned. ERP research focuses on the various constituents of an ERP waveform, which are defined by consistent timing, scalp distribution, polarity, and relationship with a specific experimental context.

ERP waveforms are observed on the scalp as a sequence of positive and negative peaks with variations in polarity, amplitude, and duration over time. While peaks are visually prominent, there is no inherent justification to assume each corresponds to a specific brain process. Early ERP research scholars commonly assumed that each peak corresponds to a specific brain process, which significantly impacted the terminology and analytical methods used in ERP studies. Experienced ERP researchers recognize that peaks are somewhat arbitrary and differentiate between peaks (local voltage maxima) and components (distinct intracranial sources of voltage reflecting specific neurocognitive processes).
The study of ERP waveforms involves understanding the correlation between peaks and components. The observed ERP waveform represents variations in recorded voltage over time, reflecting sensory, cognitive, affective, and motor processes triggered by a stimulus. ERP peaks are consistent local maximums in the observed ERP waveform, either positive or negative, excluding local maxima caused by high-frequency noise. The term ERP component is difficult to articulate, often used in the literature but seldom defined or conceptualized beyond the peaks in the observed ERP waveform. ERP researchers often differ in their definition and application of the term "component," making it difficult to find a universally acknowledged definition.

Broadly ERP components can be defined as scalp-recorded voltage changes that reflect specific neural or psychological processes. While terms like "reflect" and "process" lack precise definitions, they provide a reasonably accurate representation of how ERP components are typically employed by ERP researchers.

To understand the complex consolidation of signals captured on the outer layer of the head, it is essential to grasp the specific locations and neural mechanisms from which these signals originate. The scalp-recorded voltage changes that produce the ERP waveform result from the combination of postsynaptic potentials (PSPs) that occur simultaneously in numerous cortical pyramidal cells that are oriented in a similar manner relative to the scalp. These PSPs arise from alterations in electrical potential caused by the opening or closing of ion channels in response to the binding of neurotransmitters to receptors on the postsynaptic cell membrane.

The specific distribution of positive and negative voltages recorded on the scalp is determined by the position and orientation of the equivalent current dipole or neural generator source in the head. The choice of reference electrode can also influence the voltage distribution. The voltage reversal on the opposite side of the equivalent current dipole is typically inconspicuous due to the electrodes not being positioned across the entire head. The polarity of an ERP component at a specific electrode site is determined by numerous factors, including the orientation of the equivalent current dipole in relation to the electrode. It is generally not possible to associate polarity with a specific type of neural processing, such as inhibition or excitation.

ERP waveforms reflect synaptic activity at a specific moment, but they do not solely reflect the neural activity initiated at that moment. Potential synaptic potentials (PSPs) that generate event-related potentials (ERPs) have a duration of tens to hundreds of milliseconds, and as new cognitive processes develop, previous neural activations endure. Multiple current dipoles of equal strength are active at the same time, with up to 10 distinct equivalent current dipoles being simultaneously active. ERP components are defined as distinct neural processes, and each equivalent current dipole can be considered as an individual ERP component.

Neurons involved in a particular mental process can sometimes be spread out across different regions of the brain, resulting in two identical current dipoles. Classifying these two dipoles as distinct ERP components or a unified ERP component is a minor aspect of the definition of ERP components and requires a thorough description of the concept of mental process in relation to the conduct of neurons.

The superposition problem arises when multiple ERP components are combined on the scalp. The scalp-recorded voltage is determined by the cumulative sum of the voltages
generated by each individual active ERP component. This is a straightforward additive process, but the precise waveform of each component remains unknown in actual recordings. Gaining knowledge about how the voltage measured at a specific electrode location represents the different internal generator sources through simulated data can help understand the characteristics and complexities of ERP signals.

The transmission of voltage from a single generator location to a specific electrode location is influenced by the position and alignment of the ERP generator source in relation to the electrode, as well as the conductivity of the brain, skull, and scalp. The set of weighting values between each source and each electrode site collectively forms a mixing matrix, which determines how the different components are combined at each site.

The ERP waveform observed at a specific electrode site is difficult to correlate with the neural tissue directly beneath it due to the characteristics of the head. The skull and scalp have conductivity enough to allow electrical activity produced in the brain to be visible on the surface, but their high resistance causes voltage to spread sideways, resulting in additional distortion of the correlation between the voltage at a specific electrode location and the cortex directly beneath it. Variations in the shape and magnitude of the ERP waveform occur across electrode sites, and the combined signals are not the same at every site.

Each component is characterized by a waveform and a generator location, with the impact of each individual waveform component on the recorded waveform at a specific electrode location determined by a weighting factor. The presence of interference at the head hinders the ability to accurately identify the specific locations of generator sources based solely on the observed waveforms.

The ERP waveform represents continuous synaptic activity associated with cognitive processing, occurring in a precise time frame of milliseconds. However, scalp-recorded signals can only capture a fraction of neural activity that arises in response to a stimulus, as they rely on the concurrent activation of extensive clusters of neurons with similar spatial orientation. Additionally, the ERP waveform recorded at a specific electrode site represents the combined activity of multiple ERP components that occur simultaneously and overlap in time [95] (Cognitive Neuroscience Compendium, 2019)

2.5.1.1 Applications Of ERP Components

It is crucial to examine the definition of an ERP component and its application in various brain processes. Four different approaches are used to define components: source localization, principal component analysis (PCA), independent component analysis (ICA), and time-frequency analysis. Source localization techniques define a component based on its scalp distribution, assuming it remains stable throughout a single experimental session. These methods yield a separation matrix representing the estimated distribution of each component on the scalp, which is then calculated by applying this matrix to the observed waveforms.

Source localization techniques consider a component as a neural generator source, using biophysical assumptions about the flow of current through the conductive tissues of the head to determine the scalp distribution of each component. They also depend on supplementary assumptions, such as a specific quantity of distinct dipoles or maximum evenness in the dispersion of electrical current across the cortical surface.
Principal component analysis (PCA) and independent component analysis (ICA) do not rely on biophysical assumptions but use statistical properties of the data to determine the scalp distributions of the components. Principal component analysis aims to identify an unmixing matrix that consists of a limited number of components, each having its scalp distribution. This simplifies a vast collection of observed scalp distributions into a limited number of component scalp distributions.

Independent Component Analysis (ICA) aims to optimize the independence of each component, ensuring that each individual component captures the maximum amount of information. The scalp distributions of the components in ICA may exhibit correlation, which is expected for two independent but nearby neural sources. However, the activation strength of each component varies independently of the strength of other components across time points and conditions.

Spatial PCA alone is unlikely to generate components specifically associated with individual neural and psychological processes. Independent Component Analysis (ICA) aligns with a logical conjecture regarding these processes, as it requires a unique process to be distinguishable from other processes. ICA uses a mathematical methodology instead of hypothesis-testing to determine components, aligning closely with the definition of ERP components.

However, connecting ICA components to ERP components can be challenging due to practical issues such as establishing relationships between ICA components obtained for different subjects and comparing components across experiments. The computational approach also requires that the quantity of ICA components always matches the number of electrodes, which can result in merging multiple genuine components into a single ICA component or dispersion of a single genuine component across multiple ICA components.

The time-frequency approach differs significantly from source localization, ICA, and PCA approaches. It breaks down EEG into a collection of oscillations, and the power in each frequency range is calculated at each specific moment in time. The outcomes of this method can be associated with traditional ERP elements in two primary ways: random variations in phase across different trials, which typically vanished when individual EEG epochs are averaged, and a stimulus disrupting the phase of a continuous oscillation, resulting in a consistent phase across multiple trials, which can persist during the process of averaging.

ERP components offer a unique perspective on cognitive processes in the brain, providing valuable insights that cannot be obtained solely through behavioral measures. The high temporal resolution of ERPs is what makes them extremely useful as a measure of brain processing. ERPs are highly desirable for measuring brain processing, as they allow us to observe cognitive processing before, during, and after behavioral responses. However, ERPs are only suitable for addressing specific categories of inquiries, and understanding the categories of questions that can be easily addressed using ERPs is crucial for effective utilization.

The four domains that EEG Analysis includes are identifying cognitive or neural processes that vary between different conditions or groups, determining the completion of a specific set of processes by the brain and the timing of this completion, discovering new mental processes, and dividing known processes into smaller components, and secretly monitoring the
processing of information in situations where it is difficult to measure or interpret overt behavior. ERPs have been utilized to achieve scientific advancements in various areas, such as identifying cognitive or neural processes that vary between different conditions or groups, determining the completion of a specific set of processes by the brain, discovering new mental processes, and secretly monitoring the processing of information in situations where it is difficult to measure or interpret overt behavior.

To effectively utilize ERPs, researchers must have a clear understanding of the specific neural or psychological process being measured by a component and be effectively separated from its surrounding elements. To use ERP components as indexes of specific processes, it is crucial to successfully isolate the component of interest from surrounding ERP components. Strategies include focusing on large ERP components, focusing on task design with only one or two ERP components across conditions, or subtracting overlapping components by creating difference waves between conditions or electrode sites. These methods depend on the specific task, ERP component, and question of interest. By implementing these strategies, researchers can better understand and measure specific ERP components.

2.5.1.1.1 Methods for isolating an ERP component

The subtraction process effectively isolates response selection activity, excluding other processes that do not differ between the contralateral and ipsilateral hemispheres. Any brain activity that differs between electrode sites relative to the hand that responds must be generated during or after the process that determines which hand should respond. However, difference waveforms are not a panacea as they are effective only when all or most other components do not vary across the two conditions used in the subtraction.

Differentiating ERP components can be challenging when a wave's amplitude varies across groups or conditions. Activity in a different wave could also affect latency differences between the two original waveforms. Strategies like scalp distribution information can isolate components, such as measuring a component at a large electrode site or using vector filters. Event-related potential source localization techniques provide source waveforms for each estimated generator site. Understanding these limitations is crucial for the successful use of ERP techniques.

Before using source localization, ICA, or simple difference waves, it is crucial to understand the technique's workings and potential failures. ERP components are often measured using amplitude and latency assessments to compare them across conditions or groups. Peak amplitude and latency measures are used to quantify ERP results, as they represent the magnitude and timing of the component. Historically, peak measures were used due to their simplicity, but modern computers can perform advanced algorithms, making these techniques more advanced.

2.5.1.1.2 Methods for measuring an ERP component

It is necessary to conduct a quantitative evaluation of the isolated component after its overlapping activity has been successfully removed in order to compare it across conditions or subject groups. The amplitude and timing of peaks in an observed waveform can differ significantly from the underlying components that produce the waveform. Factors like latency
variability can significantly influence peak amplitude. It is unrealistic to assume that a process over hundreds of milliseconds can be quantified by a single time point. Peak measurements have other shortcomings, and there is a clear trend away from them among sophisticated ERP researchers. To better quantify the magnitude and timing of an ERP component, it is essential to consider other methods.

To isolate a component in an ERP waveform, compute a difference wave that subtracts away most other components. This method works well only if other components are equivalent across the two waveforms used for the subtraction.

Peak amplitude measures can be useful for quantifying the amplitude of a component in difference, but they do not necessarily reflect the magnitude of the underlying process. The area under the curve or mean voltage over the duration of a component is more appropriate. Peak latency is a poor measure, as it is not a particularly interesting time point. The 50% area latency measure, closely related to median RT, can be used to quantify the midpoint of a component. Cognitive process theories often predict the onset or duration of a process.

2.5.1.1.3 Assessing the Time Course of Processing

ERPs are a highly effective instrument for ascertaining the temporal progression of neural or psychological processes. An uncomplicated approach to accomplish this task is to assess the latency of a specific peak under two distinct conditions or groups, utilizing it as a metric for the duration of the process in each condition or group. Nevertheless, this method is typically lacking in effectiveness as it fails to isolate a particular element and relies on the peak as a timing indicator. A more robust method involves comparing the waveforms of two conditions or two groups of subjects to determine the exact moment when the waveforms start to deviate.

ERPs have been employed in the field of emotion research to ascertain the point at which, following the initiation of a stimulus, there is a divergence in processing between stimuli that elicit emotions and those that are neutral. The utilization of ERPs in this manner presents both benefits and constraints, which will be examined through various illustrations. For instance, in the context of emotions, we seek to determine the specific moment at which the processing of the emotional aspects of a stimulus initiates. To address this inquiry, we can analyze the ERP waveforms generated in response to neutral stimuli, such as a picture of a landscape, and stimuli that evoke emotions, such as a picture of a mutilation. The point in time at which the waveforms start to diverge is used as an indicator of when the brain has differentiated between the neutral and emotional stimuli. This distinction is made regardless of which component was responsible for this divergence.

Emotional processing is an intricate procedure that can be impacted by multiple factors, such as attention, sensory processing, and the locus of selection. Event-related potentials (ERPs), which are neural oscillations that deviate at specific time intervals, offer empirical support for the occurrence of an effect at an early stage in the cognitive processing pathway.
Nevertheless, it is incapable of substantiating the absence of an effect until the later stages of the processing stream.

ERPs have played a crucial role in addressing significant inquiries regarding cognitive and neural processing. They have resolved a longstanding controversy in the attention literature regarding the temporal stage at which attention operates, whether it be early or late in the processing. ERPs offer a consistent measurement of cognitive processing from the presentation of a stimulus to the generation of a response, enabling the evaluation of the specific point of attentional focus. Studies employing this methodology have demonstrated that attention exerts an impact on sensory processing within the initial 50 ms following the initiation of auditory stimuli and within the initial 100 ms following the initiation of visual stimuli.

The time-based approach is frequently integrated with the process-specific approach, wherein the impacts are associated with particular components. Researchers contend that the initial attention effects in event-related potentials (ERPs) involve alterations in particular sensory-evoked ERP components. Establishing this with absolute certainty has been challenging due to the complexities involved in identifying precise components. Nevertheless, the converging evidence approach has offered significant backing for the hypothesis that attention has an impact on distinct ERP components.

2.5.1.1.4 Measuring processes that occur prior to a component

An alternative method involves utilizing an ERP component to evaluate the preceding processes that are necessary for the functioning of the ERP component. This methodology does not necessitate a concrete connection between an ERP component and a particular process, but instead relies on basic assumptions about the processes that must have taken place prior to the ERP component in order to make deductions about these processes.

Event-related potentials have proven valuable in detecting novel mental processes and further categorizing established processes into distinct subprocesses. Event-related potentials offer a continuous assessment of cognitive processing that occurs before, during, and after the execution of a behavior. This enables the identification of previously unidentified cognitive processes. For instance, error-related negativity (ERN) arises following the completion of a response, thus indicating a process that cannot be directly assessed by behavioral measures.

ERPs have been employed to investigate the human brain, specifically in relation to error detection and monitoring of response conflicts. The error-related negativity has directed research toward investigating processes that occur within a time frame of 100 milliseconds following an error response. This has resulted in a significant number of studies exploring error detection and response-conflict monitoring. ERPs can also be utilized to ascertain whether a specific behavioral effect arises from a modification in a singular process or from various distinct subprocesses.

The initial experiments that elicit a behavioral response result in variations in several ERP components, suggesting that the behavioral effect is influenced by alterations in multiple processes. For instance, research has demonstrated that manipulating attention can impact various event-related potential (ERP) components. This indicates that different attention
mechanisms are at play, resulting in different behavioral effects depending on the specific conditions. The capacity to observe and track numerous processes using ERPs enables the collection of empirical data that refutes oversimplified explanations of behavior that rely on a singular mechanism.

2.5.1.2 **Different ERP waveforms**

As was already mentioned event-related potentials (ERPs) are unique waveforms in the brain's electrical activity that arise as a result of particular events or stimuli. These event-related potentials (ERPs) can offer valuable insights into diverse cognitive processes. Presented below are several prevalent ERP waveforms along with their corresponding interpretations:

- The N170 component is commonly observed when individuals look at faces. It mirrors the cognitive processing of facial characteristics and plays a crucial role in the identification of faces.

- The N400 and P600 components are associated with the processing of language. The N400 is correlated with the cognitive processing of meaning, whereas the P600 is associated with the cognitive processing of sentence structure. They facilitate the comprehension of language by the brain.

- The N200 event-related potential (ERP) is detected when individuals inhibit a specific response, such as abstaining from pressing a button. This phenomenon demonstrates the ability to suppress or restrain certain actions and is crucial for investigating cognitive processes related to control.

- The N1 and P1 components can arise from either the visual cortex or the auditory cortex, depending on the sensory modality. Within the visual cortex, they represent fundamental visual processing, whereas, within the auditory cortex, they signify fundamental auditory processing.

- Mismatch Negativity (MMN) which occurs when there is a disparity between an anticipated stimulus and an actual stimulus. It represents the cognitive capacity of the brain to perceive alterations in the surroundings and is linked to focus and anticipation.

- The P300 component is frequently linked to cognitive processes involving attention and memory. It is triggered by stimuli that are noticeable or surprising, indicating the distribution of cognitive resources.

ERPs are highly valuable instruments in the field of neuroscience research and clinical studies. This type of waveform analysis allows scientists to learn more about the brain and its many functions, as well as identify anomalies linked to neurological and mental diseases [96] (Sur & Vk, 2009).
3 Experiment and Methods

Participants: The study recruited sixteen normal healthy adult participants. The study was carried out in accordance with the principles delineated by the Italian Institute of Technology.

Experimental Paradigm: Participants were exposed to two distinct actions: a purposeful grasp action and a touch action. The actions were visually represented through the use of two images: "grasp.jpg" and "mimic.jpg". Every participant executed these actions while EEG data were simultaneously recorded.

Data Collection: EEG data were acquired. To precisely record participants' movements as they carried out actions, the EEG system was synchronized with a motion capture system. In addition, figures that showed the trajectories of the markers for all 40 trials in the Epochs data structure were included.

Data Analysis: The EEG epochs were synchronized with the start of movement initiation, specifically when the hand started moving from its initial resting position. Nevertheless, the alignment could have been modified to correspond with other pertinent occurrences, such as the contact with the object. The preprocessing steps encompassed various procedures such as artifact removal, filtering, and other relevant techniques. The EEG epochs were further examined to explore the neural correlates linked to goal-directed grasp actions in comparison to mimic touch actions.

Statistical Analysis: To identify significant differences in EEG activity between the two action conditions, we conducted statistical comparisons using appropriate methods such as t-tests, and machine learning. The threshold for statistical significance was established at p < 0.05.

Conclusion: The experimental design and methodology described above seek to examine the neural mechanisms that underlie goal-directed grasp actions in comparison to non-manipulative touch actions using EEG analysis. The results obtained from this study will enhance the comprehension of motor control and the perception of actions.
4 EEG Analysis Workflow

The analysis of time series data, such as EEG or MEG data, follows a standard procedure. Below is a comprehensive workflow:

1. **Preprocessing of data:**
   a. **Data Import:** The raw EEG or MEG data should be loaded into the analysis environment, such as MNE-Python.
   b. **Filtering:** To eliminate background noise and focus on specific frequency ranges the application of suitable filters is involved. Commonly used filters encompass high-pass, low-pass, and band-pass filters.
   c. **Epoching:** This process involves partitioning the data into smaller, more manageable segments to facilitate analysis. It involves the process of dividing continuous time series data into epochs or trials, which are determined by event markers or conditions that are of interest.
   d. **Artifact Rejection and Correction:** The objective of the process of rejecting and correcting artifacts is to detect and rectify any artifacts present in the data, including but not limited to eye blinks, muscle activity, or environmental interference. Methods such as Independent Component Analysis (ICA) can be employed to facilitate the elimination of artifacts.
e. **Baseline correction**: Optionally, a consistent baseline for the epochs can be established by focusing on event-related changes in the data.

2. **Features Extraction**:
   a. **Time-Domain Features**: Calculation of time-domain characteristics such as average amplitude, maximum amplitude, or slope within designated time intervals is performed.
   b. **Frequency-Domain Features**: Methodologies such as Fourier analysis, wavelet transforms, or power spectral density estimation to compute features in the frequency domain are employed.
   c. **Connectivity analysis**: The examination of functional connectivity between EEG/MEG sensors through the utilization of various measures such as coherence, phase-locking, or cross-correlation is performed.

3. **Statistical Analysis**:
   a. **Hypothesis Testing**: By conducting statistical methodologies, such as t-tests, ANOVA, or non-parametric tests, the assessment and comparison of the conditions or groups under investigation is achieved. Notable disparities or recurring trends within the dataset can be identified.
   b. **Comparative Analysis**: To account for the potential influence of family-wise error rate, it is recommended to employ corrections such as the Bonferroni correction or False Discovery Rate correction when conducting multiple tests or comparisons.

4. **Visualization**
   a. The creation of diverse plots and visual representations to effectively explore and present the obtained results is performed. The visual representations encompass time series plots, topographic maps, spectrograms, and statistical plots.

5. **Interpretation**
   a. The objective is to analyze the results within the framework of the research inquiry and recognize the physiological or cognitive aspects associated with the observed patterns.

6. **Additional Analyses**:
   a. Following the research inquiry, it is possible to conduct more sophisticated analysis techniques, such as source localization for the purpose of estimating the neural generators of EEG/MEG signals, or time-frequency analysis to investigate oscillatory dynamics.

In order to ensure reproducibility, it is essential to thoroughly document the analysis steps, results, and any preprocessing details.

7. **Reporting and Documentation**:
a. The presentation of the results of the investigation in a scholarly article or report, incorporating numerical data and statistical analysis is of great importance.

8. **Additional Steps**
   a. In accordance with the particular research objectives, it may be necessary to conduct supplementary analysis, such as machine learning classification, event-related potential (ERP) analysis, or source reconstruction.

The presented workflow offers a systematic methodology for the analysis of time series EEG or MEG data, encompassing various stages such as data preprocessing, interpretation, and reporting. The specific procedures and methodologies employed may differ based on the research inquiry and the attributes of the data.
4.1 Results

EEG data were recorded while the subject examined the actions shown in the figures grasp.jpg and mimic.jpg. The data are from a single subject. A total of 20 trials were conducted for the grasp and mimic tasks, respectively.

Figure 2. Subject performing a grasping motion during the experiment. The subject's hand moves from its resting position to the object, and the picture catches the instant it completes the movement, grasping it.

Figure 3. Subject performing a mimic of grasping motion during the experiment. The subject's hand moves from its resting position to the object, and the picture catches the instant it completes the movement, touching it.
While this particular alignment of EEG epochs occurred at the beginning of the movement (when the hand began to move from its resting position), other relevant events, such as the object's touch, could also be used. In EEG or MEG research, various categories of events are often encountered, such as stimulus presentations, responses, and other experimental occurrences. Usually, these events are given names that describe them (e.g., "stimulus_onset", "response"), but for data analysis, it is better to assign unique numerical codes to these categories. Using event codes helps to efficiently categorize and compare trials that are of specific interest. This ability is particularly valuable when analyzing event-related potentials (ERPs). This technique helps focusing the analysis on specific aspects of the experimental data.

To begin this analysis, it is essential to import the dataset, comprising EEG data from a single subject who participated in this visual experiment. The process starts with accessing a particular compact binary format (pickle) file, that holds EEG data and related motion capture information. The data is subsequently loaded into memory utilizing the pickle module. The load() function extracts three main objects: epochs, mocap_data, and marker_names. The epochs indicate divided EEG data and specific time intervals of EEG signals synchronized with particular events or stimuli. The mocap_data includes details of the physical movements or gestures made during the EEG recording, which can be aligned with EEG data to investigate the neural connections of the subject’s response. The marker_names serve as labels or identifiers for particular events or conditions in the EEG data, assisting in the interpretation and analysis of experimental outcomes. Important metadata about the EEG recording setup can be retrieved by accessing the info attribute of the epochs object. This includes channel configurations, sampling frequency, and any preprocessing steps that were applied to the data.

```python
f_name = open("PATH", "rb")
[epochs, mocap_data, marker_names] = pickle.load(f_name)
epochs.info
```

The output provides crucial information about the attributes and preparation of EEG data. It provides essential details about the EEG dataset, including the spatial arrangement of electrodes, sampling frequency, high-pass and low-pass filter cutoff frequencies, and the timestamp. More specifically, it identifies specific brain regions under investigation using 58 EEG channels, as well as their EEG channel names too, such as "Fz", "F3", and "F7". There are no significant bad channels in the dataset, indicating that the data is quite clean and can be relied upon for analysis. The sampling frequency of 500.0 Hz ensures high temporal resolution, to accurately capture neural activity. The low-pass filter at 100.0 Hz removes high-frequency noise, while the high-pass filter at 0.3 Hz retains low-frequency components for slow neural oscillations.

4.1.1 Data Acquisition - Event Extraction

Event handling and visualization are crucial in EEG analysis, enabling researchers and clinicians to identify specific events during complex and vast data-filled recordings, making it challenging to identify events of interest without proper techniques. By marking events like EEG spikes, researchers can better understand brain activity. Visualization techniques also aid in interpreting EEG data by providing a clear representation and highlighting important patterns and trends.
The assignment of distinct event IDs to particular event types is specified by the command `epochs.event_id`. In this case, the 'grasp_start' events are identified with the ID 11, and the 'mimic_start' events are assigned the ID 21. These event IDs function as markers in the EEG data, allowing for the identification and analysis of various stimuli or experimental conditions. The following lines include plotting these events for visualization. The `epochs.plot()` function creates a plot of the EEG data divided into epochs, with event markers displayed based on the specified event IDs. The `mne.viz.plot_events()` function generates a plot designed to display the event markers and their temporal distribution in the EEG data.

The use of a graphical representation that depicts the occurrence of events by the placement of markers along a temporal axis, as shown in the plot on the left, is really useful. On the time axis, each event is commonly depicted as a point or a vertical line. The event markers are assigned labels and color-coded according to the event_id mapping, simplifying the identification and differentiation of various event categories. The utilization of this visualization tool proves to be favorable in the examination of the temporal aspects and spatial patterns of events within EEG data. This is crucial for comprehending the experimental framework and easing the development of the following research, such as event-related potential (ERP) or event-related spectral analysis.

The plot on the right illustrates the brain activity of the individual while performing grasp and mimic actions, as shown in the "grasp" and "mimic" images. The EEG data were recorded while actions were being performed and synchronized with the start of hand movement. Some notable disparities in brain activity between these two conditions are observed. Initially, there is a surge of increased positivity in the grasp condition when compared to the mimic start. This may indicate increased activity in brain areas such as the premotor cortex and posterior parietal cortex, which are involved in planning and preparing the movement to grasp objects. Further, there is an alteration, with the grasp condition showing...
more noticeable negativity. This probably indicates the activation of motor execution regions such as the primary motor cortex and supplementary motor area, which are specifically responsible for performing an action.

In the context of a z-score plot or a figure utilizing blue and red colors, the utilization of color-coding, specifically red and blue, is employed to emphasize areas of relevance or regions of interest from a statistical standpoint. It facilitates the rapid identification of significant deviations from the mean in data sets. The red areas on the graph represent data points that have values much higher than the mean, typically exceeding one standard deviation above, indicating substantial deviations from the anticipated baseline activity. These discrepancies may potentially arise from distinct brain responses or events. Blue patches, on the other hand, indicate data points that exhibit a large variation below the mean, typically exceeding one standard deviation, suggesting intervals of diminished brain activity or responses that fall below the anticipated baseline level.

The z-score bar highlights the statistical significance of the differences, indicating that separate neural processes are responsible for each action. ERP activity seems more positive in the grasp condition than in the mimic start condition at the beginning of the plot. There may be a variation in cognitive processing between the two conditions at the beginning. In addition, the ERP activity seems to be more negative during the grasp condition compared to the mimic start condition in the latter part of the plot, suggesting a potential additional distinction in the cognitive processing that takes place in the two conditions at a later stage. The z-score bar indicates that this difference is statistically significant at certain time points. It is crucial to note that this interpretation relies on data from a single subject, which may be influenced by individual differences. Collaborative research yields more robust evidence and examining particular channels with established functional connections can provide a more profound understanding.

4.1.2 Preprocessing

4.1.2.1 Independent Component Analysis

Firstly, the aim is to capture independent components that represent common brain activity during both "grasp" and "mimic" conditions. Independent Component Analysis (ICA) is a method used to estimate independent source signals from recordings where the source signals were combined in unknown proportions. It can be applied to EEG/MEG analysis, where multiple sensor channels record physiological activities such as blinks, heartbeats, brain activity, and muscular movements. If the source signals are statistically independent and non-Gaussian, it is typically feasible to separate them using ICA and then reconstruct the sensor signals by excluding the unwanted sources.

```python
from mne.preprocessing import ICA

# Initialize ICA with a specified number of components
n_components = 5  # Adjust this
ica = ICA(n_components=n_components)
```
MNE-Python offers three distinct ICA algorithms: **fastica** (default), **picard**, and **infomax**. FastICA and Infomax are commonly used algorithms, while Picard is anticipated to converge more quickly and be more resilient when dealing with sources that are not entirely independent. In order to identify and distinguish statistically independent sources, the data undergoes initial processing using Independent Component Analysis (ICA). Whitening and dimensionality reduction are the next steps after ICA. In whitening, the ICA components are further normalized to unit variance, and in dimensionality reduction, the components that contribute the most to the whitened ICA outputs are concentrated using Principal Components Analysis (PCA). The ICA will receive the optimal number of components needed to explain the specified fraction of total variance. Once the Independent Components (ICs) have been visualized and any capturing artifacts have been excluded, the sensor signal can be reconstructed by using the `apply()` method of the ICA object.

**Figure 5.** Spatial distribution of the first five Independent Component Analysis (ICA) components. The topographic maps are associated with specific ICA components (ICA000 to ICA004), which depict unique distributions of electrical activity throughout the scalp.

**Independent Components (ICs):**

Each column on the plot corresponds to an independent component (IC), which is a statistically distinct signal extracted from the EEG data using ICA. These components represent either brain activity or artifacts. The quantity of components extracted is contingent upon the parameters selected and the intricacy of the data. In the experiment, 5 components were
selected, indicating that the ICA algorithm detected 5 statistically independent signals in the data.

The elbow method is used to determine the optimal number of components in this experiment comparing grasp and mimic actions. ICA is conducted using varying numbers of components, such as 5, 10, 15, and 20. The explained variance is calculated for each analysis, indicating the proportion of overall data variance accounted for by the chosen components. The explained variance is graphed as a function of the number of components. The "elbow" point is the point where the explained variance begins to level off, suggesting that further addition of components does not significantly contribute to new information. The exact elbow point may vary based on the data's unique characteristics and analysis tools.

Topographical maps:

Each column is accompanied by a scalp map illustrating the spatial distribution of activity for that component. This aids in illustrating the specific area on the scalp where the component exhibits the highest level of activity. Red represents increased activity, while blue represents decreased activity. Areas with darker shading on the plot represent regions where the component exerts a more significant impact.

An EEG topomap is a visual representation of electrical activity on the scalp, with each electrode's color corresponding to the amplitude or intensity of the recorded activity. To interpret the topomap, one must analyze both color intensity and spatial arrangement of colors on the scalp. Red color signifies regions with increased amplitude, suggesting increased neural stimulation or excitatory function, while blue color signifies regions with reduced amplitude or increased negative activity, suggesting reduced neural activation or inhibitory function. Localized colors indicate focused electrical activity in specific areas of the scalp, while gradual color changes suggest broader or more widespread electrical activity. Colored regions on the topomap indicate electrode locations on the scalp, with each region associated with electrode location. The configuration and organization of colored areas correspond to the electrode montage used in EEG recording.

Figure 6. Using a simplified model of the scalp, the International 10–20 System for EEG electrode placement shows electrode placements in relation to cranial landmarks such the Nasion and Inion. Adapted from 'The international 10–20 system indicates the positions of the electrodes to be placed for EEG recordings' (n.d.), ResearchGate. Available at:
Each component probably corresponds to a distinct source of brain activity that is engaged during the task. The colors' intensity on the maps indicates the activity's strength in each Independent Component at various locations on the scalp. More specifically:

- **ICA000**: This component displays low overall activity as it appears entirely blue, which could indicate an artifact, hindering its interpretation.
- **ICA001**: This component exhibits pronounced activity in the frontal central and right parietal and posterior temporal regions. It seems to coordinate different information streams. Its function in the frontal central region indicates participation in planning and decision-making while grasping. The activation in the right parietal lobe suggests directing attention toward the observed action and adapting one's body schema for the next movement. Moreover, the activity in the posterior temporal region suggests the processing of grasping sounds and their integration with visual information. This component illustrates multimodal integration, which involves combining different sensory inputs.
- **ICA002**: This component exhibits pronounced activity in the frontal and anterior temporal as well as the right occipital areas of the scalp. This component seems to interpret the observed action. Its frontal activity corresponds to the comprehension and coordination of the grasping movement. The activation in the anterior temporal lobe indicates a possible role in memory formation. The right occipital activity suggests visual processing of the observed action and object recognition.
- **ICA003**: This component exhibits pronounced activity in the left posterior temporal regions. This component can be considered as an observer of the brain, detecting the important memory encoding details necessary for successful understanding.
- **ICA004**: This component exhibits pronounced activity in the left parietal regions and right frontal areas. It is crucial for the spatial and attentional aspects of the actions observed. The left parietal activity indicates directing attention to particular locations and adjusting the body schema for movement. Right frontal activation corresponds to executive control and decision-making, directing the actions toward the desired goal. This component functions as the spatial choreographer and decision-maker, ensuring precise placement of the action to be done if needed at the correct time.
Figure 7. Detailed analysis of the properties of the Independent Components. The topomaps and their corresponding plots provide detailed information on five specific properties of the components obtained from EEG data. Every set consists of an ERP/Image plot, a joint probability plot, a power spectrogram, and an evoked response plot. The evoked response plots demonstrate unique ERP waveforms for various components, indicating diverse cognitive processes. Notably, there are prominent ERP peaks observed at between 200 and 300 milliseconds. The ERP/Image plots demonstrate a steady rise in response, emphasizing the brain's ability to adapt to repeated inputs. Joint Probability plots verify the validity of signals free of lost segments, and Power Spectrum plots illustrate frequency distribution, perhaps revealing an alpha rhythm (8-10 Hz) suggesting relaxed wakefulness and beta activity (10-15 Hz) linked to cognitive engagement.

Properties Plots:

The extra plots shown together with the topomaps could offer more detailed information about the attributes of each component, including:

- **Evoked Response** (Event-related potential (ERP) averages) calculated for each component, may reveal its significance in particular event-related responses in the experiment. It involves examining the usual brain activity pattern linked to the component to recognize its distinctive waveform. The fact that the ERPs are different for the different components suggests that they may be reflecting different cognitive processes.

- **ERP/Image**: This plot illustrates the component's response to various stimuli or events over time. Observing the brain's electrical activity changing in response to stimuli provides clues about the function of the component. The study reveals a consistent rise in ERP over time, indicating the brain's growing recognition of images due to repeated presentation. The timing of ERP and peaks is also interesting, with the ERP peak occurring around 200 milliseconds and around 300 milliseconds.

- **Joint Probability plot** integrates details regarding both the spatial (location on the scalp) and temporal (changes over time) characteristics of the component. It involves assessing the likelihood of observing specific electrical patterns on the scalp at particular moments to analyze the independence and reliability of neural signals. It aids in determining if the component reflects an authentic brain signal or simply noise. The zero dropped segments percentage indicates the percentage of trials that were excluded from the analysis due to artifacts or other issues. Intra-component variance measures the change in activity within a single component over different epochs, indicating varying activation patterns based on the trial's context. Observations of changes in variance can provide light on the ways in which various brain networks interact with one another and with the task at hand. Higher values in the distribution for a
particular epoch (in this case the 20th one) indicate that the activity pattern was strong and prominent at that time. Examining different time periods can reveal changes in patterns that may indicate variations in brain activity or reactions.

- Power spectrum displays how the component's activity is distributed across various frequencies, aiding in the identification of prominent frequency bands linked to the component. Also, displaying the various frequencies found in the signal aids in determining whether the component is associated with slow or fast brain activity, providing insights into its source.

Electrical interference spikes at 50 and 100 Hz are often caused by power lines or electrical equipment, which can corrupt EEG recordings and mask authentic brain signals. Muscle activity may also be affecting the EEG signal if spikes align with muscle artifacts like eye blinks. Muscle artifacts usually show strong power at frequencies that align with muscle contractions that come in contrast with the prominent frequency. Furthermore, physiological rhythms can indicate authentic brain activity when spikes occur at specific frequencies. However, the spikes at 50 and 100 Hz which are displayed in these plots are unlikely to reflect natural brain rhythms and are typically viewed as interference.

The EEG spectrum consists of negative and positive spikes, in all of the 5 components, which may indicate the alpha rhythm, a repetitive pattern during calm wakefulness. The peaks in the spectrum between 8-10 Hz likely represent the alpha rhythm, a distinct repetitive pattern seen during a state of calm wakefulness. Positive spikes at slightly higher frequencies (10-15 Hz) may suggest a modulation or variation in the alpha rhythm. Negative peaks followed by positive peaks may indicate shifts between distinct brain states or cognitive processes. Negative peaks may indicate a reduction in alpha activity linked to increased attention or cognitive involvement, followed by a rise in beta activity (10-15 Hz) associated with active cognitive processing or task involvement.

Specific frequency patterns in the EEG spectrum can indicate physiological or pathological phenomena, such as alpha-beta transitions or cross-frequency coupling. Alpha-beta transitions are a phenomenon that occurs during cognitive activities like working memory, decision-making, and motor planning. Fluctuations in alpha and beta activity can align with cognitive processing or motor preparation, while decreases may occur during information encoding or consolidation. Alpha-beta transitions indicate the dynamic interplay among brain regions and functional networks, with oscillatory activity in the alpha and beta frequency bands indicating changes in neural synchronization, information transmission, or network connectivity that support cognitive and behavioral functions. Neuropsychological conditions like ADHD, schizophrenia, and Alzheimer's disease exhibit abnormalities in alpha-beta transitions, which may indicate changes in neural circuitry or cognitive functions related to these conditions.
The alpha-beta transitions that were observed in the EEG data during cognitive engagement can also align with concurrent mu suppression over the sensorimotor cortex. That is proposing a dynamic relationship between cognitive processing and motor-related activity in tasks that engage motor mirror neuron function. Motor action execution, or, with practice, motor action visualization, causes people to suppress mu rhythms. This phenomenon is known as the desynchronization of brain waves, as EEG wave patterns result from the synchronized firing of numerous neurons. Mu is a rhythmic pattern detected in a standard human electroencephalogram (EEG), commonly identified as the frequency range of 8–13 Hz, believed to originate from the sensorimotor regions. Modifications in mu power, which refers to the intensity of the mu frequency band, have been utilized in contemporary research to investigate the human mirror neuron system (MNS).

So both alpha waves and mu rhythms are neural oscillations found in the human brain, particularly in the EEG signal. Alpha waves are rhythmic electrical activity in the 8 to 12 Hz frequency range, often observed in the posterior regions of the brain, particularly over the occipital lobe. They are associated with wakeful relaxation, calmness, and reduced mental arousal. They can be modulated by factors like attention and can decrease in response to external stimuli or cognitive engagement. Mu rhythms, on the other hand, are rhythmic electrical oscillations in the 8 to 13 Hz frequency range, often centered around 10 Hz. They are particularly prominent during rest and decrease in amplitude when an individual performs or observes motor actions. Mu rhythms are thought to reflect motor cortical activity and play a role in motor planning, execution, and action observation.

To distinguish between these phenomena, analyzing the spectral and temporal characteristics of EEG signals recorded over the sensorimotor cortex is helpful. In the case of mu suppression, the power of the mu band would be reduced during motor tasks or action observation, whereas alpha-beta transitions would cause changes in the alpha and beta bands to occur simultaneously during cognitive engagement or motor planning.

4.1.2.2 Principal Component Analysis

Independent Component Analysis is a crucial step in EEG data analysis, separating and eliminating artifacts and extracting significant independent sources from the data. It helps in isolating EEG signals into distinct components representing various neural or non-neural sources, such as brain activity, eye movements, muscle artifacts, or environmental noise.

Principal Component Analysis (PCA) is then applied to further decrease the data's dimensionality or focus on specific components of interest. PCA reduces dimensionality by identifying principal components that capture the highest variance in the data, offering a more concise representation of the data while preserving crucial information about its variability. PCA identifies components explaining most variance in EEG data, potentially capturing common patterns across electrodes and time points. It doesn't directly relate to ICA, which separates independent sources. However, the explained variance ratio can assess component
importance and compare it to ICA results. So, PCA might be sufficient if the overall variance isn't strong, while ICA may be more advantageous for separating and analyzing distinct brain activities with independent origins.

Applying PCA after ICA in EEG analysis serves multiple purposes. It reduces the number of features or channels in EEG data, leading to more efficient computational analysis and reducing the risk of overfitting. It also allows focusing on specific components identified through ICA, such as temporal patterns or spatial arrangement. PCA also reduces residual noise or artifacts in the independent components obtained from ICA, simplifying the representation of EEG signals. Also, given the limited sample size of 20 trials per condition and a total of 40 trials, the impact on the Independent Component Analysis separation results may not be significantly different from the application of ICA to each condition separately.

```python
from mne.decoding import UnsupervisedSpatialFilter
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt

data = epochs.get_data()

# Reshape the data for PCA (epochs, channels, time points)
data_reshaped = data.transpose(1, 0, 2).reshape(data.shape[1], -1) #(channels, epochs * time points).

# Perform PCA on the reshaped data
n_components = 5 # Number of PCA components to keep
pca = PCA(n_components=n_components)
pca.fit(data_reshaped)
comp = pca.components_

# Extract components from 2 to 4 (inclusive)
components_2_to_4 = comp[1:3] # Components are zero-indexed, so 1 to 3 represents the 2nd to 4th component

# Extract explained variance ratios for components 2 to 4
explained_variance_2_to_4 = pca.explained_variance_ratio_[1:3]

# Print the components and their explained variance ratios
for i, (component, explained_variance) in enumerate(zip(components_2_to_4, explained_variance_2_to_4), start=2):
    print(f"Component {i} (Explained Variance Ratio: {explained_variance:.2f}):")
    print(component)
print()

# Plot the explained variance ratio for all components
plt.plot(pca.explained_variance_ratio_)
plt.xlabel('Component')
plt.ylabel('Explained Variance Ratio')
plt.show()
```
Conducting Principal Component Analysis (PCA) on EEG data with the MNE-Python starts with `scikit-learn` libraries. The EEG data is first acquired from the epochs object by utilizing the `get_data()` method. The data is reformatted for PCA analysis to have dimensions representing epochs, channels, and time points. This restructuring enables a thorough analysis of the data's temporal and spatial attributes. After reshaping the data, PCA is used to reduce the dimensionality of the EEG data. Here, the number of principal components to keep is established as 5. PCA is utilized on the reformatted data to derive the principal components.

![Figure 8. Plot of PCA Explained Variance Ratios.](image)

These components identify the main sources of variability in the EEG data and offer insights into its fundamental structure. Then analyzing principal components 2 to 4 takes place after extracting them. This information helps to comprehend the significance of each component in capturing the variability found in the EEG data based on the explained variance ratios for all components. Greater explained variance ratios suggest that the associated components contain a larger amount of information, rendering them more pertinent for further analysis or interpretation.

```python
pca = UnsupervisedSpatialFilter(PCA(5), average=False)
pca_data = pca.fit_transform(data)
ev = mne.EvokedArray(
    np.mean(pca_data, axis=0),
    mne.create_info(5, epochs.info['sfreq'], ch_types='eeg'))
ev.plot(show=False, window_title="PCA", time_unit="s")
```
To reduce the dimensionality of EEG data and display the spatial patterns of extracted components PCA is applied. A PCA object is created with 5 components using scikit-learn's PCA class. An unsupervised spatial filter, a type of image processing technique that is used to remove noise or enhance certain features in images, is generated by utilizing MNE-Python's UnsupervisedSpatialFilter class, which includes the previously set up PCA object. The 'average=False' parameter enables PCA to be applied separately to each EEG channel, facilitating a detailed analysis of spatial patterns across channels. The EEG data is processed with a PCA spatial filter to create a reduced-dimensional representation using principal components. The EvokedArray object is created by calculating the average spatial patterns of each PCA component across trials after the transformation. This object represents the average spatial activity of the PCA components and is generated with pertinent channel information using MNE-Python's create_info function. The evoked data, data that are generated in response to a specific stimulus or event, are plotted to display the average spatial patterns of the PCA components.

![EEG (5 channels)](image)

**Figure 9.** Principal component analysis (PCA) of EEG data during a task that featured grasping and mimicking actions. This PCA-derived EEG plot shows the intricate interplay of sensory, motor, and cognitive processes involved throughout the task. The negative fluctuation detected after task initiation (onset event at 4 seconds) indicates strong brain activity, which could be suggestive of motor execution and initial sensory processing. The subsequent negative deflection, which occurred 1.5 to 2 seconds later, may indicate a more in-depth mental assessment of the activity. A significant positive deviation occurring 4 seconds after the event indicates a later stage of cognitive processing, possibly related to the integration of the task outcome.

The components in PCA represent spatial patterns of brain activity, reflecting variation throughout the dataset. These variations are considered significant instances of brain activity in response to tasks, including sensory processing, motor execution, and cognitive assessment. The temporal patterns of these variations indicate a series of brain processing phases, starting from initial action execution to more profound cognitive processing. The potential implications of the observed fluctuations, whether negative or positive, may provide insights into the cerebral processes involved.

The highest degree of variability related to the experiment's task occurs around the event at the 4-second mark suggesting that the physiological reaction of the brain to the initiation of the grasping or imitating action is a fundamental characteristic of the data. The noticeable negative fluctuation around 1 second after the onset event (~5 seconds on the timeline) may indicate the brain's continuous processing of motor execution and sensory data.
from the task. This may entail integrating sensory information and doing an initial mental evaluation of the action's consequence. A following negative deflection recorded 1.5 to 2 seconds after the event (approximately between 5.5 and 6 seconds on the timeline) might indicate deeper cognitive processing such as classification, recognition, or assessment of the action taken. This might represent the brain's additional examination and integration of the task within the larger context of the experiment, as well as the subject's psychological state. Then, around 4 seconds after the task begins, a positive deviation in the PCA components is detected. The difference might represent a critical period in the cognitive or sensory processing connected to the task, possibly representing the effective integration of the activity within the framework of the experiment or an acknowledgement of task completion. This positive deviation, which occurred well after the task's initial execution, may indicate a higher-order cognitive function. It might indicate a condition of cognitive awareness, reward processing, or contentment with executing the activity as directed. Alternatively, it might reflect relaxation or return to a baseline state following intense task involvement. The findings indicate that the principal component analysis (PCA) has effectively detected a notable instance of brain activity pertaining to the task, comprising not only the motor movement but also potentially the correlated sensory processing and cognitive assessment.

4.1.3 Features Extraction

Feature extraction is a process that converts EEG signals into numerical data that captures brain activity. Common features include time-domain features like mean, variance, skewness, and kurtosis, frequency-domain features like power spectral density, time-frequency features like spectral power, spatial features like spatial distribution or connectivity between electrodes, and statistical features like higher-order statistics computed over EEG epochs. These features are often extracted from specific frequency bands, time windows, or spatial locations.

4.1.3.1 Time domain analysis

Analyzing the brain activity's amplitude over time to identify variations between conditions within specific time frames is a common EEG analysis method. The method involves computing EEG features within specific time windows or regions of interest and correlating these with evoked responses. This helps researchers identify EEG components related to specific cognitive processes or sensory events, providing insights into neural mechanisms responsible for task performance or perception.

4.1.3.1.1 Average responses across channels for each trial

Calculating the average response from epochs synchronized to a particular event or condition produces the evoked data, showing the average neural activity linked to that specific event or condition. This data usually represents the neural processes influenced by the
Experimental changes. In simple terms, Event Related Potentials (ERPs) and Evoked data are equivalent.

```python
# Compute evoked responses for each condition
evoked_grasp_start = epochs["grasp_start"].average()
evoked_mimic_start = epochs["mimic_start"].average()

# Plot and compare evoked responses with butterfly plot and custom colors and linestyles
plt.plot(evoked_grasp_start.times, evoked_grasp_start.data.T, color='blue', label='grasp_start')
plt.plot(evoked_mimic_start.times, evoked_mimic_start.data.T, color='red', linestyle='--', label='mimic_start')
plt.xlabel('Time (s)')
plt.ylabel('Amplitude')
plt.title('Comparison of Evoked Responses')
plt.legend()
plt.grid(True)
plt.show()
```

Comparing the average evoked responses for the "grasp_start" and "mimic_start" conditions facilitates the interpretation of differences or similarities in the neural responses triggered by these events. To start, the average evoked responses are calculated for the two conditions, after preparing an epochs object. Then the evoked responses for each condition are displayed on a single plot to simplify the comparison process. The line plots for the time course of the evoked responses are created using `plt.plot()`.
The utilization of a butterfly plot is helpful in obtaining a comprehensive understanding of the overall activity patterns observed in all sensors inside an EEG recording. It facilitates the rapid identification of significant features or patterns within the dataset, such as responses associated with events or oscillatory behavior, without placing emphasis on individual channels as in a simple plot. In simpler terms, a simple plot provides a detailed view of data from every single channel, whereas a butterfly plot provides a more aggregated view by displaying the grand average over all channels. The selection between the two options is contingent upon the objectives of the investigation, with simple plots being suitable for in-depth examination of individual channels, while butterfly plots offer a comprehensive perspective on the overall activity pattern of the data.
Analyzing the butterfly plot of EEG data to identify shared and distinct brain activity patterns between the "grasp start" and "mimic start" conditions showed that both conditions probably exhibit similar brain activity patterns, as shown by the overlapping sections of the butterfly plot.

Both situations exhibit consistency in response patterns across trials, showing a persistent brain response to both grasping and mimicking. Notably, 'grasp_start' trials have a greater positive amplitude, indicating that brain activation is more strong during the actual execution of a grasp than during a mimic. During the time from -3 to -2 seconds, there is a significant overlap in brain patterns between the two circumstances, which may indicate similar neural processes in task preparation. However, a noticeable difference occurs between -2.6 and -2 seconds, when the mimic condition exhibits a positive amplitude greater than that of the grasp condition, indicating differential brain activity as the individual distinguishes between goal and non-goal-oriented movement. Both situations start to exhibit parallel patterns again as the task beginning countdown approaches, which could mean that the brain is finishing up its preparations. The grasp condition is characterized by higher negative fluctuations immediately after the event begins, most likely reflecting the complicated brain activity required, which involves a delicate interaction of feedback and motor control systems that is not as apparent in the mimic state. In the post-event timeframe ranging from +1 to +4 seconds, both conditions resume overlapping action. This period could indicate the brain's integration and processing of the action's outcome, regardless of whether it was a goal or not oriented task.

Despite sharing similarities in their preparatory stages, the evidence shows that the two motor control actions of grasping and imitating are fundamentally different when observed. However, the butterfly plot shows only mean responses. Also, brain activity can differ greatly among individuals considering the limited data. Statistical tests are necessary to establish whether the observed variances are statistically significant, indicating that they are improbable due to random occurrences.
4.1.3.1.2 Average responses across trials for each channel

Averaging responses across channels for each trial provides a unique perspective that emphasizes the overall state of brain activity during a single session. This way broad patterns and trends that might otherwise be lost in the specificity of channel-specific data can be highlighted. Simplifying EEG data in this manner can provide clarity to complex datasets, making broad-stroke comparisons easier. On the other hand, averaging responses over trials for each EEG channel is a crucial technique for determining the precise brain activity associated with specific events or stimuli. This method reduces random noise and transitory artifacts, allowing researchers to map the brain's activity with great spatial accuracy. It is particularly useful when studying localized reactions, which are critical for understanding the brain's functional architecture.

```python
# Compute the difference between evoked responses
evoked_difference = mne.combine_evoked([evoked_congruent, evoked_incongruent], weights=[1, -1])

# Plot the difference waveform
evoked_difference.plot()
```

The process is initiated by investigating the neural responses in the two experimental conditions. To calculate the mean evoked response for the congruent condition, the command `epochs['grasp_start'].average()` is used to extract and average epochs labeled 'grasp_start', and the same method is called for 'mimic_start' condition. After completing the extraction and averaging processes, the disparity is calculated between the evoked responses of both conditions. This is accomplished by utilizing the command `mne.combine_evoked([evoked_congruent, evoked_incongruent], weights=[1, -1])`. This command effectively subtracts the incongruent response from the congruent response by applying weights of 1 and -1 respectively. The resulting differential waveform is crucial in understanding the differences in neural processing caused by congruent and incongruent stimuli. To display this distinct waveform the command `evoked_difference.plot()` is used.
Identifying specific patterns that can be directly linked to mirror neuron activity in the cluttered plot is challenging without additional data processing, such as signal averaging, filtering, or source localization. Source localization techniques, such as sLORETA or beamforming, may also be required to determine the specific regions of the brain that exhibit the highest level of activity during each condition. This plot exhibits visual complexity as a result of the overlapping of multiple channels, making it challenging to discern the activity of each individual channel. To conduct a thorough analysis, it would be beneficial to reduce the number of channels displayed simultaneously or use an interactive viewer that allows for individual selection of channels.

4.1.3.1.3 Reduction of the number of channels and interactive view

The objective is to present the responses as time series, with each channel having its own time series, and visualize in an interactive manner. This is essential for evaluating the neural activity across various EEG channels during specific experimental phases.

```python
#displaying the averaged responses or waveforms of EEG. Visualize epoched data as
time series (one time series per channel)
epochs["grasp_start"].plot(butterfly=True, group_by="position")
epochs["mimic_start"].plot(butterfly=True, group_by="position")
```

To visually represent averaged responses or waveforms derived from data linked to the 'grasp_start' event the command `epochs["grasp_start"].plot(butterfly=True, group_by="position")` is utilized. The `butterfly=True` parameter is used to generate a 'butterfly' plot, which displays all channels on a single graph, providing a clear visualization of the temporal dynamics of the data across all channels. The argument "group_by" with the value "position" is used to arrange channels according to their physical location or position. This allows for a spatially informed analysis of the EEG data. Similarly, the command
epochs['mimic_start'].plot(butterfly=True, group_by='position') is executed. This facilitates a comparative examination of the two conditions, enabling distinguishing the disparities in neural activity caused by the two distinct stimuli or task requirements.

Figure 13. Top Image: EEG Epochs for 'Grasp Start' – The plot depicts a dense butterfly display of EEG epochs linked with the 'grasp_start' condition. Bottom Image: EEG Epochs for 'Mimic Start' - The plot depicts the EEG epochs for the 'mimic_start' condition.

Noticing decreases in activity in the frontal and parietal lobes and an increase in the occipital lobe around 3 seconds in the "mimic start" condition butterfly plot is intriguing. The negative peaks in the frontal and parietal lobes may suggest reduced activity associated with observing the action. This may indicate a redirection of focus from visual processing in the occipital lobe to other cognitive processes. The frontal lobe is engaged in these processes. The decrease may not indicate a total end of activity, but rather a redirection of focus towards essential areas for preparing to predict the upcoming action. The parietal lobe is responsible for spatial processing and mental visualization. So, the decrease may indicate a transition from
focusing on the external stimulus (observed action) to internally practicing the action in readiness for imitation or prediction. The peak in activity in the occipital lobe may reflect a temporary surge in focus on particular visual aspects of the grasping movement at that moment possibly connected to detailing encoding specifics. The subject may be concentrating on specific elements of the movement, such as hand position or object manipulation, in preparation for understating or imitating. It is crucial to confirm the observed action before transitioning focus to planning or execution. Furthermore, negative peaks in the frontal and parietal lobes may indicate a change in focus from watching the action to planning or mental visualization, which could cause processing demands to decrease and lead to an increase in mu rhythm (suppression). This is because the sensorimotor cortex may be less involved in analyzing the current visual aspects of the action being observed. Both conditions exhibit comparable mu suppression patterns, which may indicate that observing the grasping action activates the mirror neuron system to a similar degree for this subject, regardless of the starting point.
The EEG signals in the above plots highlight the sensorimotor cortex, a crucial brain region involved in the processing and execution of motor motions. The consistent appearance of waveforms across these channels over the trials indicates coordinated activity within this brain region during the tasks. Examining such data longitudinally can yield valuable insights into the cognitive processes involved in the initiation, execution, and completion of motor tasks. The 'grasp_start' condition depicted in the top image typically exhibits a gradual increase in activity leading up to the point when the action is initiated. This may appear as a consistent pattern of rising amplitude or frequency in the EEG signals as the motor cortex becomes increasingly engaged. After the activity, a return to the initial levels would usually be noticed, signifying the end of the motor work. The 'mimic_start' condition is expected to have a distinct temporal pattern, as imitating an action may not entail the same degree of motor execution or be more focused on observation and mental simulation.

EEG signals are visual representations of electrical activity recorded by scalp electrodes, showing voltage changes as waveforms. These waveforms represent different brain states and functions, with alpha waves, which have slower, high-amplitude oscillations, typically associated with peaceful wakefulness, and beta waves, which have faster, compressed waveforms, indicating intensive cognitive engagement or muscular activity. EEG signals can be associated with distinct frequency bands, including delta, theta, alpha, beta, and gamma, which correlate to specific brain rhythms. Understanding these signals requires careful analysis of waveform characteristics, as specific alterations can indicate shifts in cognitive processes or reactions to stimuli. In order to accurately measure the frequency and intensity of the waveforms, additional analysis techniques such as Fourier transforms or wavelet decompositions are employed for transforming the time-domain data into the frequency domain.

Furthermore, during the mimic condition, the EEG signals suggest a pattern that may be consistent with alpha wave activity, typically associated with a calm and relaxed state. This could imply that the subject might be resting or passively observing, which aligns with the known role of the sensorimotor cortex in movement planning and its involvement with mirror neurons during observational tasks. Conversely, the EEG data from the 'grasp_start' condition seem to demonstrate a denser, more frequent fluctuation in the EEG signal, which could be suggestive of beta wave activity. Although beta waves are better identified by their frequency in the spectral domain, their potential presence here—indicated by a more rhythmic and finely spaced waveform pattern—may reflect an active state of sensorimotor engagement. The increased fluctuation with more defined peaks, in comparison to the 'mimic_start', is indicative of what might be expected during tasks requiring focused attention and motor coordination. This pattern hints at a shift from a more passive observational state to an active engagement, possibly involving the physical execution of the movement.

Consequently, a typical pattern of motor engagement when performing the "grasp" task, and a decrease in this engagement when performing the "mimic" task, has been observed. The inhibition of the mirror neuron system during motor tasks or the observation of such tasks is regarded as proof of activation in sensorimotor brain regions. Statistical analysis is necessary...
to ascertain the significance of observed disparities in the EEG responses, involving the comparison of EEG responses across conditions at each channel and time point.

4.1.3.1.4 Averaging across all channels and all trials

To improve the examination of neural patterns associated with particular cognitive or motor functions, using averaging techniques can make data representations easier to observe.

```python
# compare the average responses for each channel of the two Evoked objects
mne.viz.plot_compare_evokeds(dict(grasp=evoked_congruent, mimic=evoked_incongruent), show_sensors="upper right")
```

To generate a distinct comparative representation of the brain's electrical activity in the two distinct experimental conditions the function `mne.viz.plot_compare_evokeds` is invoked with a dictionary parameter that associates the two conditions, with their corresponding evoked response data. In this context, 'evoked' data refers to the mean neural response that is synchronized with a stimulus or an action, reflecting the brain's activity in response to specific events. The function also includes a parameter to visually represent the sensor layout on the resulting figure, indicating the placement of the EEG sensors on a representation of the head. This graphical representation, positioned in the top right corner of the graph, assists in comprehending the spatial arrangement of the documented brain reactions.

![Figure 15. Comparative Evoked Responses for Grasping vs. Mimicking. This graph depicts the average EEG responses for two circumstances, 'grasp' (blue) and 'mimic' (orange), across all channels and all trials. The data covers a time period of 4 seconds before and after the event, indicated by the vertical dashed line at time zero. It captures the brain activity related to](image-url)
grasping and mimicking actions. The peaks in the plot signify instances of increased electrical activity. The inset in the top right corner displays the arrangement of sensors on the scalp, offering information on the spatial source of the recorded data.

The 'grasp' condition exhibits greater peaks after the stimulus, suggesting a stronger brain response to observing the act of grasping in comparison to the act of touching. This may indicate a greater involvement of the mirror neuron system, which is specifically triggered by actions that have a clear objective and involve interactions between the hand and an object, such as grabbing. The 'mimic' condition, although it still demonstrates increased activity following the stimulus onset, seems to produce a slightly reduced amplitude response. This implies that the neural representation of the mimicking touch action is less intense or potentially processed in a distinct manner compared to the grasping action. The graph's timeline demonstrates that the brain's reaction is both immediate and enduring for several seconds after the stimulus. This suggests that the act of observing these actions involves a prolonged cognitive process, which may include elements such as attention, recognition, and motor planning, even when not physically performing the observed actions. The presence of variability over time in both conditions indicates the dynamic nature of the cognitive processes involved in observing and processing the two distinct actions.

The plot_image() function is executed for each condition with the picks="eeg" parameter, indicating that only EEG channels should be incorporated into the visualization. The input combine=mean specifies that the signal from the chosen channels should be averaged. As a result, there is one image for each condition. Each row in the image shows the average response for a certain epoch, which is a slice of the EEG data that is time-locked to an event. The x-axis denotes time, and the color of each pixel indicates the average signal amplitude at that specific time point across all epochs. Next, the plot_topo_image() function is employed to generate a topographic image map for every condition. This map presents the data from all EEG sensors at the same time, showing how brain activity is distributed across the scalp. The resulting plots offer a clear and easy-to-understand visual representation of the spatial patterns of brain activity elicited by each condition, across all channels. Topographic maps are particularly valuable for determining the areas of the brain that exhibit the highest levels of activity during the 'grasp_start' and 'mimic_start' events. This adds a spatial context to the temporal patterns noticed in the previous image plots.
Figure 16. Top Image: 'Grasp Start' Evoked Response - A heatmap showing the variation in brain activity during the 'grasp start' task, with a line graph below it summarizing the average EEG signal over epochs, revealing a particular neural engagement pattern throughout grasp preparation and execution. Bottom Image: 'Mimic Start' Evoked Response - This section displays a heatmap representing the neural response evoked during the 'mimic start' condition, alongside its corresponding average waveform. Notable is the negative variation between -4 and -3 seconds, which contrasts with the 'grasp start' condition and suggests different brain processing during the anticipation of replicated movement.

From the grasp epochs image, the display exhibits a heatmap-like representation of activity across multiple trials. The differences in color intensity between trials reflect the magnitude of voltage fluctuations at each specific time point. Significantly, there is a region of intense red color that appears shortly after the stimulus is presented, indicating a consistent upward shift in electrical activity across multiple trials in response to the mental visualization of grasping. The black line represents the mean of all trials, mitigating individual deviations to expose the shared pattern of brain response. The abrupt deviation that occurs immediately after the introduction of the stimulus may be linked to sensory processing or cognitive recognition of the grasping action, potentially involving the activation of mirror neuron systems that are sensitive to perceiving actions with functional goals.
In the mimic condition the individual trials in this section exhibit variability, with a greater range of red and blue patches, representing positive and negative voltages, respectively. The distribution implies that the neural response to the mimic condition is less consistent across trials compared to the grasp condition, potentially suggesting less reliable processing of the mimicking action over periods. The average brain response in the mimic condition is less prominent, suggesting a more suppressed or scattered brain response. This implies that the mimic action, although still recognized as an action, may not activate the mirror neuron system to the same degree as the grasp action, or it may involve a wider range of neural processes beyond those usually linked to observing actions.

The stronger response observed in the grasp condition indicates that this action may hold greater significance or captivation for the observer, potentially owing to its purposeful nature. Conversely, the mimic condition, which represents a touch that is not aimed at achieving a specific goal, produces a less strong average response. The grasp condition demonstrates a higher level of consistency in response patterns across trials, which may indicate a more consistent cognitive or perceptual processing of the observed action. The implications for mirror neuron activity are that if mirror neurons show a greater response to actions that have a specific goal in mind, this increased activity may be evident in the larger average deflection observed during the grasp condition. The diminished deflection observed in the mimic condition suggests that these neurons, or the brain regions linked to action comprehension, are less engaged when the action lacks a specific goal.

Both conditions show significant variability in individual epochs, a common occurrence in EEG data due to variations in brain activity among individuals, minor movements, and other noise sources. The most notable distinction between the two conditions is the magnitude of the mean reaction following the stimulus initiation. The 'grasp' condition has a higher mean deflection, suggesting a more robust neural reaction to grasping images. The pre-stimulus baseline shows a relatively consistent level of activity, confirming that the response observed after the stimulus presentation is solely caused by the stimulus itself. Also, during the mid-four to three-second interval before the event marker at zero seconds, it seems like the 'mimic' and 'grasp' conditions produce quite distinct EEG responses. More precisely, the 'mimic' condition exhibits a noticeable decrease—a noticeable decline in the waveform—when contrasted to the 'grasp' condition. This could imply that, in contrast to the grasp action's preparation phase, there is a distinct pattern of neuronal inactivation or distinct brain processing occurring during the period preceding the mimic action.

By analyzing the timing, magnitude, and spatial distribution of brain activity linked to various experimental conditions, it is possible to visually discern and interpret the disparities in evoked responses.

```python
# Alternatively, plot the difference topomap
evoked_difference.plot_topomap()

evoked_difference.plot_joint()

evoked_difference.plot_image()

evoked_difference.copy().apply_baseline((None, None)).plot_joint()
```
To gain a better understanding of these outcomes, it’s crucial to integrate spatial and temporal information. Firstly, the function `evoked_difference.plot_topomap()` is used, to produce a topographic map displaying the differences in the evoked data. In this application, a topographic map represents the potential field on the scalp, displaying the distribution of electrical activity across various locations at distinct time points. Next, the function `evoked_difference.plot_joint()` is utilized. This approach offers a full perspective by integrating both the topomap(s) and time series plots into a single picture. Usually, it displays specific topographic maps at important time intervals alongside the waveforms of Event-Related Potentials (ERPs) or Event-Related Fields (ERFs). After that, the function `evoked_difference.plot_image()` is called. The execution of this command generates a visual representation of the data in the form of an image plot. In this plot, the data is arranged in a matrix format, with one axis usually indicating time and the other axis representing channels. The image’s color intensity corresponds to the magnitude of the signals. Ultimately, the code duplicates the `evoked_difference` object, performs baseline correction using the `.copy().apply_baseline()` method, and subsequently invokes the `.plot_joint()` function on the changed object to compare the results with and without baseline. Baseline correction involves estimating and subtracting the baseline noise of the signal to enhance the brain’s responses. The parameters `(None, None)` indicate that the baseline correction should utilize the full time interval before the event marker as the baseline period. This guarantees that the displayed data in the joint plot is adjusted to a baseline level, which may result in more distinct interpretations of the evoked responses by eliminating any interfering background noise.

![Figure 17. Analysis of EEG channel activation and its corresponding scalp topographies. The heatmap illustrates variations in voltage across 58 channels during an 8-second period, while the topographical maps underneath indicate specific brain](image)

Figure 17. Analysis of EEG channel activation and its corresponding scalp topographies. The heatmap illustrates variations in voltage across 58 channels during an 8-second period, while the topographical maps underneath indicate specific brain...
activity in different regions at four specific time points. The color variations on the maps correspond to the magnitude of electrical activity recorded in microvolts (μV).

The concentrated red regions observed at specific channels and time points indicate that, in these cases, the 'grasp' condition evoked a considerably more robust reaction compared to the 'mimic' condition. In contrast, any regions colored blue would indicate instances where the 'mimic' condition evoked a more intense response. However, based on the provided plot, these occurrences seem to be less frequent or noticeable. The high frequency of the color red in the plot, particularly after the stimulus is presented, indicates that the 'grasp' condition generally elicits a more powerful neural reaction compared to the 'mimic' condition. This could be interpreted as the brain's increased response when observing a functional grasp in comparison to a touch that imitates the action. This is consistent with theories that propose that the brain's mirror neuron system is more strongly activated when observing purposeful actions, such as grasping, compared to actions that lack a clear goal, such as mimicry. The plot suggests that the variations in brain response are specific in terms of both location and time. Specific areas of the brain and specific time intervals show increased responsiveness to the 'grasp' condition. This may indicate the involvement of neural networks responsible for processing purposeful motor actions and their cognitive and psychological significance.

It is possible that the significant deviations between these conditions derive from some channels, which could be indicative of neural responses of interest or potential artifacts such as eye blinks, muscle activity, or technical noise. The nature of these deflections cannot be determined without further context or information about data processing methods. A possible way to further explore the data would be to focus on time intervals that hold theoretical significance for the cognitive processes under investigation. Statistical significance refers to the evaluation of the importance of the observed activity, which can be determined using statistical tests such as t-tests or ANOVAs. The results of these tests can be displayed on the plots to indicate specific channels and time points that exhibit significant differences between conditions.

4.1.3.1.5 Statistical analysis

Statistical analysis is crucial in EEG experiments, as it helps identify genuine neural signals amid background activity. This enhances the accuracy of interpreting EEG results, allowing attributing observed changes in brain activity to specific cognitive processes or experimental conditions. However, due to the large volume of data produced by multiple electrodes and the precise timing of EEG, there is a risk of false positives from multiple comparisons. Statistical methods mitigate this risk by ensuring the results are not false due to multiple tests.

The choice between a t-test and an ANOVA (Analysis of Variance) is contingent upon the experimental design and the specific inquiries being addressed. A t-test is a statistical test used to compare the means of two groups and determine if they are significantly different from each other. So, it is preferable when conducting a comparison between the averages of two distinct groups or conditions. ANOVA is applicable in situations where there are more than two groups or conditions, or when one wishes to examine the impact of multiple independent variables and their interactions. Since the region of interest is in comparing the two conditions ('grasp_start' and 'mimic_start') at each time point for each channel, a t-test is the appropriate statistical test based on the given information. However, if there were more than two levels
within a condition (such as different types of grasping or mimicking) or if there were additional factors to take into account (such as subject groups or task difficulty), then an ANOVA would be a more appropriate choice. ANOVA is capable of simultaneously comparing multiple groups and can also uncover interaction effects between factors.

```python
# t-test for all timepoints for each channel #around 5min

import numpy as np
import matplotlib.pyplot as plt
from scipy import stats
import mne

data_grasp = epochs['grasp_start'].get_data()  # Shape: [n_epochs, n_channels, n_times]
data_mimic = epochs['mimic_start'].get_data()  # Same shape

n_channels, n_times = epochs.info['nchan'], len(epochs.times)
t_vals = np.zeros((n_channels, n_times))
p_vals = np.zeros((n_channels, n_times))

# Define significance threshold
significance_threshold = 0.05

# Perform t-tests at each channel and time point
for ch_idx in range(n_channels):
    for time_idx in range(n_times):
        # T-test between conditions
        t_stat, p_val = stats.ttest_ind(data_grasp[:, ch_idx, time_idx],
                                        data_mimic[:, ch_idx, time_idx], nan_policy='omit')
        t_vals[ch_idx, time_idx] = t_stat
        p_vals[ch_idx, time_idx] = p_val

# Identify significant channels without correction
significant_channels = []
for ch_idx in range(n_channels):
    if np.any(p_vals[ch_idx, :] < significance_threshold):
        significant_channels.append(epochs.ch_names[ch_idx])

print("Significant Channels (without correction):")
for ch in significant_channels:
    print(ch)

# Plotting
plt.figure(figsize=(10, 5))
for ch_idx in range(n_channels):
    if np.any(p_vals[ch_idx, :] < significance_threshold):
        plt.plot(epochs.times, t_vals[ch_idx, :], label=epochs.ch_names[ch_idx])

# Highlighting significant points without correction
```
The objective is to perform a series of statistical t-tests between two conditions, grasp_start and mimic_start, across all channels and timepoints in the dataset. The number of channels and time points are derived from the structure of the epochs object. Next, two arrays, \texttt{t_vals} and \texttt{p_vals}, are created to store the outcomes of t-tests conducted across all channels and time points. The arrays are populated by iterating through each channel and time point and performing separate t-tests between the 'grasp_start' and 'mimic_start' conditions for each combination. Upon conducting the t-tests, the p-values are compared to a predetermined significance threshold (0.05) in order to ascertain the statistical significance of the results. The channels that display at least one significant time point are gathered and stored in a list called "significant_channels". A graphical representation that illustrates the t-values as they change over time for each channel is displayed. The epoch object is used to plot channels that have produced significant results.

![Image of significant T-values over time](image)

**Figure 18.** Significant T-values between grasp and mimic conditions across all channels and timepoints without correction applied. The channel names are displayed alongside the corresponding channels, and any data points that are considered significant are highlighted in red.

This plot depicts a plot of T-values obtained from an EEG experiment. The experiment involved comparing two conditions, "grasp_start" and "mimic_start," at each time point across various channels. The T-values exhibit a substantial level of variation throughout the entire
time span, ranging from -4 to 4 seconds. This indicates significant variability in the disparities between the two conditions over time. The red dots indicate time points and channels that exhibited a statistically significant disparity between the two conditions prior to any adjustment for multiple comparisons. The concentrated grouping of red dots indicates a large number of occurrences of statistical significance in all the channels.

The code does not incorporate any adjustment for multiple comparisons, thereby evaluating each test independently without accounting for the increased likelihood of false positives that arise from conducting multiple statistical tests. EEG data analysis often involves correcting for multiple comparisons to account for the numerous tests conducted across multiple channels and time points.

Multiple comparisons are a common issue in statistical testing, where the likelihood of obtaining significant outcomes due to random chance increases with each additional test. To ensure accurate results, correction for multiple comparisons is crucial. By implementing these corrections, confidence in the results is enhanced, ensuring the reproducibility of scientific findings. By striking a balance between statistical power and error control, corrections help detect genuine effects while minimizing the likelihood of false positives. Various methods provide varying degrees of stringency, such as Bonferroni being stronger and FDR being more lenient.

The Bonferroni correction serves to manage the family-wise error rate in multiple comparisons, reducing the chance of false positive results (Type I errors) as the number of tests increases. However, this approach can also diminish the statistical power of individual tests, especially with a large number of comparisons, increasing the potential for incorrect negative results (Type II errors) and possibly overlooking real effects. The Bonferroni correction's precise formula involves dividing the standard significance level (0.05) by the total number of comparisons (channels × time points) and then using this corrected threshold to identify significant sensors. Although this method is conservative, it is suitable for controlling the family-wise error rate when conducting multiple comparisons.

Given its conservative nature, the Bonferroni correction might be excessively stringent in scenarios like EEG studies that involve many comparisons. Initial findings indicating differences suggest that effects or patterns worthy of further exploration exist. However, after applying Bonferroni correction, the lack of significant differences post-correction in this case means that the observed differences do not meet the stricter criteria for statistical significance. This does not denote the absence of real differences but indicates that the evidence does not strongly support these differences under the high standards set to mitigate the increased risk of false positives in multiple testing scenarios.

The Bonferroni correction, in this experiment, displays a significant degree of caution; for EEG data encompassing numerous channels and time points, it's also preferable to explore less conservative correction methods, like the False Discovery Rate (FDR) but still effectively control the error rate. These alternatives can provide insights into the data and the effects under examination, including effect magnitude and variability, significant fluctuations, sample size considerations, and the precision and reliability of data.

```python
for all timepoints for each channel with correction fdr

import numpy as np
```
import matplotlib.pyplot as plt
from scipy import stats
import mne
from mne.stats import fdr_correction

# Epochs is epochs object containing both 'grasp_start' and 'mimic_start' conditions
data_grasp = epochs['grasp_start'].get_data()  # Shape: [n_epochs, n_channels, n_times]
data_mimic = epochs['mimic_start'].get_data()  # Same shape

n_channels, n_times = epochs.info['nchan'], len(epochs.times)
t_vals = np.zeros((n_channels, n_times))
p_vals = np.zeros((n_channels, n_times))

# Perform t-tests at each channel and time point
for ch_idx in range(n_channels):
    print(ch_idx)
    for time_idx in range(n_times):
        # T-test between conditions
        t_stat, p_val = stats.ttest_ind(data_grasp[:, ch_idx, time_idx],
                                        data_mimic[:, ch_idx, time_idx], nan_policy='omit')
        t_vals[ch_idx, time_idx] = t_stat
        p_vals[ch_idx, time_idx] = p_val

# Correct for multiple comparisons using FDR
p_vals_flat = p_vals.flatten()
reject_fdr, p_vals_fdr_corrected = fdr_correction(p_vals_flat, alpha=0.05)
reject_fdr = reject_fdr.reshape(n_channels, n_times)  # Reshape back to original shape

# Identify and print significant channels
significant_channels = []
for ch_idx in range(n_channels):
    if reject_fdr[ch_idx, :].any():
        significant_channels.append(epochs.ch_names[ch_idx])

# Plotting
plt.figure(figsize=(10, 5))
for ch_idx in range(n_channels):
    # Plot only channels that have at least one significant time point
    if reject_fdr[ch_idx, :].any():
        plt.plot(epochs.times, t_vals[ch_idx, :], label=epochs.ch_names[ch_idx])

# Highlighting significant points
significant_points = np.argwhere(reject_fdr)
for point in significant_points:
    plt.plot(epochs.times[point[1]], t_vals[point[0], point[1]], 'ro')  # 'ro'
for red dots

plt.xlabel('Time (s)')
plt.ylabel('T-value')
plt.title('Significant T-values Over Time')
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left')
plt.tight_layout()
plt.show()

Essentially, a thorough approach is provided to examine and display the variations in EEG response between two experimental conditions. Also, the statistical challenge of conducting multiple comparisons across the EEG dataset is addressed. The EEG data for both conditions, namely 'grasp_start' and 'mimic_start', is obtained from a pre-defined 'epochs' object, encompassing all recorded epochs, channels, and time points. A t-test is conducted on each individual channel at every time point, resulting in a matrix of t-values and p-values that represent the variations between conditions across the entire EEG dataset. This leads to a multitude of statistical comparisons, due to the large number of channels and time points. In order to mitigate the issue of multiple comparisons and maintain control over the false discovery rate, the p-values undergo an FDR correction. This correction guarantees that the percentage of false positives remains below a predetermined threshold, which in this case is set at 0.05. This step modifies the significance threshold to be more strict, taking into account the number of tests conducted. Channels that display a significant difference after correction are identified and recorded. Subsequently, these discoveries are graphically represented in a plot, where the significant disparities are emphasized through distinct channels. The time series of t-values for each channel are plotted, and significant time points are highlighted with red dots to draw attention.

Figure 19. T-value distribution across time points for each channel after FDR correction. No significant differences were detected between 'grasp_start' and 'mimic_start' conditions.
Since the application of the False Discovery Rate correction does not reveal any substantial disparities, similar to the Bonferroni correction that was also applied, it may indicate various aspects of the data and the effects that are examined. In cases where effect sizes are minimal, differences between conditions might not be discernable given the sample size, possibly due to insufficient statistical power. Variability within conditions can mask true effects, complicating the identification of consistent patterns. Ensuring data accuracy and consistency is crucial, requiring proper preprocessing and analysis. Both permutation t-tests and FDR corrections rely on specific assumptions, highlighting the importance of adhering to these assumptions in data analysis.

Aggregating data within a specified time frame to calculate average values before conducting a t-test can help minimize variability, emphasize long-term trends, and enhance statistical power. This technique can be beneficial in data environments with noise, where short-term fluctuations can obscure long-term patterns. Averaging data over a specific time frame allows for a more consistent estimation of mean values, focusing on general patterns among different conditions or groups. This approach also simplifies analysis and interpretation, making it easier to communicate and understand differences. Aligning statistical analysis with study objectives is also beneficial, especially when evaluating the impact of an intervention or condition over a specified period.

```python
#averages the data across a time range before testing, reducing the analysis to one dimension (channels)
from mne.stats import permutation_t_test, fdr_correction

# Set a significance threshold
significance_threshold = 0.05

# Define the number of permutations
n_permutations = 100

# Define the time window of interest
tmin = -4.0  # Start time
tmax = 3.998  # End time

# Convert the time values to indices manually
tmin_idx = np.argmin(np.abs(epochs.times - tmin))
tmax_idx = np.argmin(np.abs(epochs.times - tmax))

# Perform permutation t-test for condition 1 and 2
data_condition1 = np.mean(epochs['grasp_start'].get_data()[:, :, tmin_idx:tmax_idx], axis=2)
data_condition2 = np.mean(epochs['mimic_start'].get_data()[:, :, tmin_idx:tmax_idx], axis=2)

# Perform permutation t-test for condition 1 and 2
T0_condition1, p_values, _ = permutation_t_test(data_condition1 - data_condition2, n_permutations)

# Apply FDR correction
```
The above code does not actually conduct a t-test for each channel individually across all time points. Instead, it aggregates the data within the specified time window by taking the average before performing the t-test. This implies that the t-test is conducted only once for each channel, utilizing the average values within the specified time range, instead of conducting a t-test for each individual time point. This process involves choosing a specific time range (tmin to tmax) and calculating the average of the data within this range for each channel. The permutation t-test is utilized to analyze the averaged data for each channel, yielding a single p-value for each channel. The FDR correction is applied to the array of p-values from the t-test, specifically to account for multiple comparisons across channels. It is important to note that the correction is not applied to multiple comparisons across time points, as the time dimension has been averaged out. Also, the channels that exhibit a statistically significant difference between the two conditions, taking into account the false discovery rate (FDR) correction are identified. Lastly, the visualization displays the negative log-transformed FDR-corrected p-values on a topomap, improving the legibility and highlighting channels that exhibit significant differences.
In neuroscience and similar fields dealing with complex data, it's not uncommon to find no statistically significant differences even after applying multiple comparison corrections. When variations in channel signals are observed between conditions (e.g., grasping and mimicking) in an EEG experiment before correction, but vanish post-correction (using Bonferroni or FDR), it suggests several implications about the experiment and the nature of the observed effects. If the plot is empty following correction, it indicates that the observed disparities may be attributable to random variation rather than a consistent impact of the conditions. This is a frequent result when a strict multiple comparisons correction is implemented, particularly with a substantial number of tests, which raises the probability of false positives. Also, the lack of substantial results following correction may indicate that the neural reactions to grasping and mimicking are not as discernible as initially proposed, or that the experiment lacked sufficient statistical power to detect the disparities.

To summarize, although the initial results indicate numerous notable disparities, the implementation of a correction technique has invalidated these findings, indicating that they do not exceed the revised threshold for significance. The lack of heterogeneity in the observed patterns of brain activity may be due to the similarity between the actions of 'grasp' and 'mimic'. This result highlights the significance of applying multiple comparison corrections in EEG data analysis and emphasizes the need for a cautious interpretation of the findings.

In order to effectively analyze EEG data by taking advantage of the inherent spatial and temporal correlation structure of the data cluster thresholding is applied. By analyzing clusters instead of individual data points, the likelihood of making type I errors (false positives) during multiple comparisons is minimized.

```python
# exploratory mass-univariate analysis at all sensors and time points.
# This requires correcting for multiple tests.
# MNE offers various methods for this; amongst them, cluster-based permutation
# methods allow deriving power from the spatio-temporal correlation structure of
# the data.
# Here, we use TFCE.

import matplotlib.pyplot as plt
import numpy as np
from scipy.stats import ttest_ind

import mne
```
from mne.channels import find_ch_adjacency, make_1020_channel_selections
from mne.stats import spatio_temporal_cluster_test

# Calculate adjacency matrix between sensors from their locations
adjacency, _ = find_ch_adjacency(epochs.info, "eeg")

# Extract data: transpose because the cluster test requires channels to be last
# In this case, inference is done over items. In the same manner, we could
# also conduct the test over, e.g., subjects.
X =
    epochs["grasp_start"].get_data().transpose(0, 2, 1),
    epochs["mimic_start"].get_data().transpose(0, 2, 1),
]  
tfce = dict(start=0.4, step=0.4)  # ideally start and step would be smaller

# Calculate statistical thresholds
T_obs, clusters, cluster_pv, h0 = spatio_temporal_cluster_test(
    X, tfce, adjacency=adjacency, n_permutations=100
)  # a more standard number would be 1000+
significant_points = cluster_pv.reshape(T_obs.shape).T < 0.05
print(str(significant_points.sum()) + " points selected by TFCE ...")

# plotting
time_unit = dict(time_unit="s")
evoked_difference.plot_joint(
    title="Grasp vs. mimic condition", ts_args=time_unit,
    topomap_args=time_unit
)  # show difference wave

# Create ROIs by checking channel labels
selections = make_1020_channel_selections(evoked_difference.info, midline="12z")

# Visualize the results
fig, axes = plt.subplots(nrows=3, figsize=(8, 8))
axes = {sel: ax for sel, ax in zip(selections, axes.ravel())}
evoked_difference.plot_image(
    axes=axes,
    group_by=selections,
    colorbar=False,
    show=False,
    mask=significant_points,
    show_names="all",
    titles=None,
    **time_unit,
)
plt.colorbar(axes["Left"].images[-1], ax=list(axes.values()), shrink=0.3,
label="μV")
The objective is to conduct an exploratory analysis on all sensors (EEG channels) and time points to detect disparities between two conditions, 'grasp_start' and 'mimic_start'. First, the matrix of adjacency that represents the spatial relationship between EEG channels is calculated. This is employed to compensate for the phenomenon that neighboring channels may detect comparable signals as a result of the spatial distribution of electrical fields across the scalp. Then data preparation involves extracting EEG data for the two conditions from the epochs object and rearranging it by transposing it to ensure that the dimensions of the data (trials, time points, channels) are in the correct order as required by the cluster test function.

TFCE, or Threshold-Free Cluster Enhancement, is a technique that enhances clusters of potentially significant values without the need for an arbitrary threshold. The parameters (start and step) determine the manner in which the cluster enhancement is implemented. The `spatio_temporal_cluster_test` function is utilized to execute the cluster-based permutation test on the data. This approach employs permutation testing to establish significance levels while also utilizing spatial and temporal clustering to account for multiple comparisons.

Significant points (time-point and channel combinations) are determined by evaluating the cluster p-values (`cluster_pv`) against the pre-defined significance level (in this case, p < 0.05). The total count of significant points is displayed. The `evoked_difference.plot_joint` method is utilized to visually represent the disparities between the two conditions as a time series and a topomap at specific time points. Regions of interest (ROIs) are determined by using the `make_1020_channel_selections` function, which is based on the standard 10-20 system channel labels. The `evoked_difference.plot_image` method is employed to generate a heatmap-style image for each ROI, illustrating the temporal variations for each channel group. The significant time points are masked to highlight the statistically significant disparities.

![Grasp vs. mimic condition](image)

*Figure 21. Comparison of Event-Related Potentials under the 'Mimic' and 'Grasp' Conditions. The above topography maps illustrate variations in brain activation at distinct time intervals, while the multi-colored waveform below displays the EEG signal across different channels over time. The signal's peaks align with prominent changes in the topography, indicating instances of substantial variations in brain activity between activities.*
Figure 22. Spatiotemporal Cluster-Based Permutation Test Findings. Significant clusters are depicted throughout the left, midline, and right channels during a 8-second time frame. In the left image, the enlarged view displays the specific timing of substantial activity within a 0.25-second timeframe, around 3 sec prior to the event.

The TFCE analysis is categorized into three regions: left, midline, and right, each representing distinct brain areas. The time frame is represented on the horizontal axis, focusing on the pre-stimulus period just before a stimulus is introduced. The colored clusters correspond to the intensity and orientation of the disparity in brain activity between the two conditions being contrasted. It indicates that only a small portion of the data exhibited statistically significant differences. For example, the midline region showed 99.9% of points masked, implying that only 0.1% of data points (combinations of time and channel) exhibited notable variations. The presence of notable activity in all three brain regions during the pre-stimulus period indicates discernible variations in brain activity between the two conditions even before the stimulus presentation. That could indicate distinct anticipatory brain processes between ‘grasp’ and ‘mimic’ conditions. After the event, no significant differences were observed which validated the same findings as the significant differences found in the t-t-tests.

As can be seen, significant disparities are observed in the pre-stimulus period when employing a technique such as TFCE, but not when using a standard t-test, even after adjusting for multiple comparisons like FDR, it emphasizes the contrasting sensitivity and methodology of these approaches. The TFCE method exhibits high sensitivity, particularly in cluster-based permutation tests, towards detecting patterns of activity that are distributed across time or space. It has the ability to detect larger patterns of importance that may not be observed when examining individual time points or sensors separately, as is the case with t-tests. This approach capitalizes on the inherent structure of the data, which may unveil substantial disparities in the period prior to stimulation that may not be as evident when examining each individual data point in isolation. Thus, t-tests, especially when applied separately to each time point or sensor, may fail to detect these larger patterns. By implementing FDR correction to account for the false discovery rate resulting from multiple comparisons, the threshold for significance is tightened. If the variations are inconspicuous or spread out across multiple points rather than concentrated at specific points, the t-test may not identify them as statistically significant. However, if this distinction is only evident when employing more refined, multivariate techniques such as TFCE, as opposed to univariate methods like t-tests, it could suggest that the disparities are subtle and integrated within the overall pattern of activity, rather than confined to specific points.

Butterfly plots in EEG analysis have limitations, as they assume the EEG signal is consistent throughout the recording period. However, frequency analysis is essential for a thorough understanding of brain function. It distinguishes between different brain states, such
as wakefulness, sleep, and specific cognitive activities, by identifying specific bands and their temporal patterns. Additionally, it records short-lived events, which can be accurately identified and analyzed using wavelet transforms.

### 4.1.3.2 Frequency domain analysis

While butterfly plots provide a simple representation of EEG activity over time, frequency analysis is essential for revealing important frequency-related information necessary for a thorough comprehension of brain function. Spectral power analysis is frequently utilized to examine alterations in neural activity patterns linked to various cognitive states, tasks, or neurological conditions. Spectral power is the magnitude of a signal at various frequencies within a defined range. Spectral power in EEG analysis indicates the level of electrical activity in the brain across various frequency bands. The information pertains to the amplitude or magnitude of brain oscillations across different frequency ranges, including delta, theta, alpha, beta, and gamma frequencies.

```python
# plot spectral power estimates across sensors as a scalp topography
spectrum_grasp = epochs["grasp_start"].compute_psd()
spectrum_grasp.plot_topomap()

spectrum_mimic = epochs["mimic_start"].compute_psd()
spectrum_mimic.plot_topomap()
```

To enable the comparison of spectral power distribution across sensors between the two conditions ("grasp_start" and "mimic_start") their scalp topographies were displayed. The scalp electrode array reveals frequency-specific neural activity patterns associated with each condition. The spectral power estimates for the "grasp_start" condition are calculated from the epochs data using the `compute_psd()` method. This function computes the power spectral density (PSD) for each sensor or channel. The PSD data is saved in the `spectrum_grasp` variable. The `plot_topomap()` method is then applied to `spectrum_grasp`, producing scalp topographic plots that display the distribution of spectral power across the scalp specifically for the "grasp_start" condition. The same procedure is followed for the "mimic_start" condition.
Figure 23. Comparative topographical maps of brain activity during the 'grasp' and 'mimic' conditions across different EEG frequency bands. The topographic maps depict the distribution of power across different frequency ranges (delta, theta, alpha, beta, and gamma) and highlight the unique patterns of brain activity observed during the two tasks. These patterns may indicate cognitive processes that are specific to the activity, with the 'Grasp' task potentially including more intricate circuits for motor and sensory integration.

The tables below (table 3 and table 4) shows the limits of power frequencies of different brain waves in two conditions: grasp and mimic.

Table 3. Limits of power frequencies in grasp condition

<table>
<thead>
<tr>
<th>FREQUENCY BAND</th>
<th>GRASP CONDITION (MAX)</th>
<th>GRASP CONDITION (MIN)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Delta (0-4 Hz)</td>
<td>7358.276</td>
<td>1385.540</td>
</tr>
<tr>
<td>Theta (4-8 Hz)</td>
<td>939.728</td>
<td>178.287</td>
</tr>
<tr>
<td>Alpha (8-12 Hz)</td>
<td>992.451</td>
<td>227.762</td>
</tr>
<tr>
<td>Beta (12-30 Hz)</td>
<td>536.475</td>
<td>108.077</td>
</tr>
<tr>
<td>Gamma (30-45 Hz)</td>
<td>618.279</td>
<td>98.754</td>
</tr>
</tbody>
</table>

Table 4. Limits of power frequencies in mimic condition

<table>
<thead>
<tr>
<th>FREQUENCY BAND</th>
<th>MIMIC CONDITION (MAX)</th>
<th>MIMIC CONDITION (MIN)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Delta (0-4 Hz)</td>
<td>6847.303</td>
<td>1431.597</td>
</tr>
<tr>
<td>Theta (4-8 Hz)</td>
<td>1012.469</td>
<td>177.340</td>
</tr>
<tr>
<td>Alpha (8-12 Hz)</td>
<td>936.438</td>
<td>212.386</td>
</tr>
<tr>
<td>Beta (12-30 Hz)</td>
<td>460.923</td>
<td>101.223</td>
</tr>
<tr>
<td>Gamma (30-45 Hz)</td>
<td>516.385</td>
<td>86.728</td>
</tr>
</tbody>
</table>

The data suggest that although similar brain regions were engaged in both grasping and mimicking tasks, the brain activity patterns varied between the two conditions. Differences in average power of various brain wave frequencies are evident when comparing grasp and mimic. Increased power in delta, beta, and alpha brain waves during grasping indicates that the brain may be involved in more profound cognitive processing compared to mimic. This may be attributed to the need for planning and carrying out the motor actions required for grasping. Also, greater power in beta and gamma waves while grasp condition suggests increased focus, alertness, and cognitive processing compared to mimic condition. This is in line with the idea that understanding a first-time stimulus requires concentrated attention and active processing of sensory information.
The power levels in various frequency bands are consistent between the grasp and mimic conditions. The consistency indicates that the overall activity levels in the respective brain regions are similar in both conditions. This finding is consistent with the mirror neuron hypothesis, which suggests that specific neurons activate not only when an action is executed but also when the same action is implied. The activation of common brain regions during both grasp and mimic conditions indicates that these regions may be involved in both conditions. Thus, while the same brain areas were involved in both tasks, their functioning varied depending on the requirements of each task. Comprehending, which involves more motor planning and execution, resulted in a distinct brain wave pattern compared to mimic condition.

The delta band (0-4 Hz) shows the highest power levels in both conditions, suggesting significant low-frequency activity related to motor processing and sensorimotor integration. Higher power is shown during the grasping condition, suggesting increased cognitive processing demands for understanding and interpreting observed grasping actions. Delta waves are usually linked to deep sleep and unconscious mental processes, but in this case, they could indicate higher cognitive exertion during the grasping task. The theta band (4-8 Hz) exhibits elevated power levels associated with cognitive processing and attention and increased power during mimic condition was shown due to its association with internal processing, memory retrieval, and mental planning. The rise in theta power during mimic may indicate increased involvement in these processes as individuals decode the observed action into their motor plan. With moderate power levels, the alpha (8–12 Hz) and beta (12–30 Hz) bands indicate the presence of higher cognitive functions as well as sensory and motor processing. In the grasp condition, the beta band displays slightly elevated power levels in comparison to the mimic condition, suggesting a potential increase in motor planning and execution during grasping. Alpha Band shows increased power during grasp condition due to the association of alpha waves with inhibitory processes and relaxed wakefulness. The rise in alpha power while observing grasp may suggest increased inhibition of irrelevant information and improved concentration on decoding the observed action since it is the first stimulus. Beta waves show increased activity during grasp condition, indicating higher levels of motor planning, execution, and attention. Beta power increases during mimic correspond to the activation of motor regions responsible for planning and executing actions. The gamma band, ranging from 30 to 45 Hz, shows lower power levels compared to other frequency bands in both conditions. Gamma oscillations are linked to cognitive processes like attention, memory, and perception. Gamma Band shows increased power during grasp condition. Their rise indicates improved communication and coordination among various brain regions responsible for observing, planning, and carrying out the action.

In general, these findings indicate that the grasp and mimic conditions participate in comparable neural processes. These processes include motor planning and execution, as well as cognitive functions. The consistency in power levels across various frequency bands
provides evidence for the idea of shared neural mechanisms that are responsible for both observed and imitated actions, as suggested by the mirror neuron hypothesis.

The information of the topomap solely provides the power of various brain wave frequencies. Although these frequencies provide some understanding of general brain function, they do not provide specific information about the precise range within the alpha band or power dynamics within that range. However, the higher beta and gamma wave power observed during grasping could be seen as indirect evidence of the motor cortex and possibly the mirror neuron system's involvement since these frequencies are commonly linked to increased motor activity and cognitive processing. Therefore, the topomaps’ demonstration of increased alpha band power during the grasping condition and diminished power during the mimic condition does not definitively establish or refute mu suppression. Furthermore, this is a limited dataset and further research is necessary to validate these results. Also, statistical tests are required to determine if any observed differences in power between conditions are significant.

Analysis of mu suppression typically involves using visualization tools like butterfly plots to examine changes in power within the specific mu rhythm band. Visualizing spectral power across sensors, specifically focusing on the grasp and mimic conditions can be helpful in order to understand better the regions that are activated and comprehend their behavior.

#plot spectral power across channels
spectrum_grasp.plot()
plt.title('Spectrum for Grasp Start Condition')
spectrum_mimic.plot()
plt.title('Spectrum for Mimic Start Condition')

#comparisson plot
fig, ax = plt.subplots()
# Plot spectrum for "mimic_start" condition with solid line style
spectrum_mimic.plot(axes=ax, show=False)
for line in ax.lines:
    line.set_linewidth(2)
# Plot spectrum for "grasp_start" condition with dashed line style
spectrum_grasp.plot(axes=ax, show=False)
for line in ax.lines[-len(spectrum_grasp.freqs):]:
    line.set_linestyle('--')
# Customize the plot
plt.legend(['Mimic Start', 'Grasp Start']) # Add legend
plt.xlabel('Frequency (Hz)') # Label x-axis
plt.ylabel('Power Spectral Density (dB/Hz)') # Label y-axis
plt.title('Comparison of Spectra for Mimic Start and Grasp Start Conditions') # Add title
First, spectral power for both conditions is visualized separately using the `plot()` function. A comparison plot is generated by utilizing Matplotlib's `subplots()` function to create a single figure with two subplots. The spectral power for the "mimic_start" condition is represented by a solid line and for the "grasp_start" condition by a dashed line. Both spectra are shown on the same axes in the comparison plot, enabling a direct comparison between the two conditions. The width of each line is modified to enhance visibility, solid lines indicate the mimic condition, and dashed lines indicate the grasp condition. Enhancing the interpretability of the comparison plot can be achieved by adding legends, labeling the axes, and providing a title as additional customizations.

![Frequency Spectrum Analysis in EEG for "Grasp Start" and "Mimic Start" Conditions.](image)

*Figure 24. Frequency Spectrum Analysis in EEG for "Grasp Start" and "Mimic Start" Conditions. The figures illustrate the spectrum power comparison across a range of frequencies, indicating that both circumstances exhibit similar patterns of spectral distribution. The included topographic map display the spatial arrangement of spectral power throughout the scalp.*
Based on the power spectral density (PSD) plots derived from EEG data for a single subject during this experiment and depicting the scalp plot with numbered electrodes and their corresponding colors the findings can be analyzed as follows.

All spectra exhibit a standard distribution pattern for EEG data, showing a decrease in power as frequency rises. This is anticipated due to the fact that the energy in EEG signals is usually focused at lower frequencies, typically below 50 Hz. When comparing the spectra of the two conditions, there are no significant differences observed initially, suggesting that the brain activation patterns for imagining an action and preparing to observe an action may be alike. Furthermore, the composite plot which compares the spectra for both conditions with multiple trials superimposed, indicates some variability in the EEG responses across different trials. However, the overall trends appear consistent. Both conditions exhibit similar PSD patterns throughout the frequency spectrum.

Although based on the topomap data there isn’t any explicit demonstration of mu suppression, it can be utilized alongside other information to implicitly support the presence of mu suppression and its connection to motor mirror neurons. As already mentioned, if the power values for the alpha and beta bands (which typically exhibit inverse relationships with mu) are greater in the mimic condition than in the grasp condition, it could indirectly indicate the existence of mu suppression. According to the theory of mirror neurons, there should be a decrease in the power of the mu rhythm, known as mu suppression, during the mimic condition in comparison to the grasp condition. The decrease in activity can be attributed to increased engagement in the sensorimotor cortex, a region responsible for performing and perceiving actions.
Figure 26. Composite Power Spectral Density Curves for 'Grasp Start' and 'Mimic Start' Conditions Over 58 EEG Channels within the lower frequency range of 2-14 Hz.

The butterfly plot confirms the motor system's involvement in interpreting incomplete actions. Mu suppression is lower in the 8-12 Hz range in the "Mimic Start" condition compared to the "Grasp Start" condition, indicating a decrease in mu activity during imitating actions. The mu rhythm is predominantly observed at approximately 10 Hz, which falls within the expected range. The existence of mu suppression provides further evidence that patterns of brain activity indicate the involvement of the motor system in both observing an action and observing the same action when it is incomplete. Other frequency bands (theta, beta, gamma) also contribute to this understanding, with the theta band suggesting increased internal processing, memory retrieval, and mental planning, the alpha band indicating improved suppression of irrelevant information and enhanced focus, while the beta band is associated with motor planning, execution, and attention and gamma band linking to enhanced communication and coordination during the mimic condition. However, task specificity and inter-individual variability must be considered.

The analysis of the EEG results using the 10-20 system for placing electrodes is crucial to understanding the neural processes underlying action observation and predicting mimicking actions. Activity in the central to parietal regions (greenish lines), plays a role in combining sensory information and potentially in the coordination of motor activities. The increased activity observed in the grasp condition may indicate improved processing associated with the integration of sensory information and the planning of motor actions when observing a grasping movement. The presence of cortical areas being activated during the observation of a grasping action suggests widespread involvement, potentially encompassing not only the sensorimotor areas but also visual and possibly associative regions.

The parietal to occipital regions (blueish lines) are known to be associated with visual processing and spatial perception. Since the amplitude of purple electrodes is greater at a frequency of 10 Hz during the grasp condition, it may indicate an increase in alpha brainwave activity. This increase in alpha activity could be associated with enhanced visual attention or a distinct cognitive state when observing an actual grasp as opposed to mimicking it.
The presence of brain activity in the frontal to central regions (reddish lines), encompassing the prefrontal cortex and motor areas. The decrease in activity at a frequency of 10 Hz during the mimic condition may suggest mu suppression, which aligns with the notion of imagined or prepared motor activity. Along with a rightward shift, it may suggest mu suppression linked to motor imagery or preparation. This could potentially involve a stronger engagement of the right hemisphere or a lateralized timing of the neural response.

The 30 Hz alternation of higher frequencies in the grasp condition rather than the lower frequencies in the mimic condition in beta activity indicates that different brain regions are involved in different ways depending on whether the subject is observing an action or trying to decode an incomplete but somehow familiar action. Fluctuating activity at this frequency across the scalp could suggest intricate dynamics in how various brain regions participate in observing and imitating actions. If this alternation exhibits a spatial pattern that aligns with sensorimotor regions, it could indicate varying degrees of involvement in these areas during the two conditions.

To gain a comprehensive understanding of the outcomes, it is crucial to establish a baseline or control condition for the purpose of comparison. Furthermore, it is necessary to perform statistical analysis in order to ascertain the significance of the observed differences.

4.1.3.3 Time-Frequency domain analysis

Combining time and frequency analysis, such as time-frequency analysis, offers a more comprehensive and detailed insight into the intricate and ever-changing characteristics of brain activity observed in EEG recordings. This integrated method enables researchers to identify distinct brain states and their transitions and study neural connections related to cognitive functions and behavior by recognizing and categorizing particular brain patterns. In this section a thorough time-frequency analysis is conducted, providing information about the rhythmic patterns of the brain’s EEG activity across the scalp and over time, both before and after an event. Also, the consistency of these patterns across various experimental trials is also assessed.

The time-frequency transform function in MNE-Python offers methods for analyzing EEG data frequency characteristics. The tfr_morlet() function is recommended for a trade-off between time and frequency resolution, especially for frequency ranges with waveshape significance. The tfr_multitaper() function mitigates spectral leakage and provides accurate power estimates over a broad frequency spectrum. The tfr_stockwell() function ensures consistent resolution across all frequencies, making it useful for identifying and describing events at both low and high frequencies. Thus, because examining particular frequency ranges that involve wave shape significance, such as alpha or beta rhythms, morlet was preferred. More specifically, the FFT-based Morlet wavelet approach is preferred due to its ability to balance temporal and spectral resolution, its computational efficiency, scalability, and compatibility with various software packages. Also, it has been extensively used in EEG experiments, ensuring reliability and comparability of results across different studies.

```python
from mne.time_frequency import tfr_morlet
freqs = np.logspace(*np.log10([6, 35]), num=8)
```
To perform time-frequency analysis initially, a range of frequencies spanning from 6 to 35 Hz is established using the `np.logspace` function. This function generates an array of 8 frequency values that are evenly spaced on a logarithmic scale within the specified range. This selection effectively captures essential brain rhythms, including Alpha and Beta waves. The number of cycles in the wavelet is determined for each frequency by setting it to half of the frequency value, as indicated by the equation \( n_{\text{cycles}} = \frac{\text{freqs}}{2.0} \). This ratio guarantees that every wavelet utilized in the analysis maintains a suitable equilibrium between time and frequency resolution. Next, the `tfr_morlet` function is invoked, taking as input the epochs of EEG data, the array of frequencies, and the corresponding number of cycles for each frequency, and setting `use_fft=True` to utilize the Fast Fourier Transform for the calculations, to convert EEG data from the time domain to the frequency domain. The presence of the `return_itc=True` parameter signifies that the function will calculate inter-trial coherence (ITC) as well. ITC is a metric that quantifies the consistency of phase across multiple trials. The data is reduced by a factor of 3 (`decim=3`), which decreases the sampling rate in order to accelerate computations without a substantial loss of information. The power and ITC obtained are graphically represented in multiple formats. The `power.plot_topo` function generates a topographic map that displays the average power across all channels in relation to the baseline period. It utilizes a logarithmic ratio for baseline correction. This provides a comprehensive analysis of the spatial arrangement of power within the designated frequency range. Next, a figure with two subplots is created using the `plt.subplots` function. The dictionary `plot_dict` specifies the precise frequency ranges for Alpha (8-12 Hz) and Beta (13-25 Hz) rhythms. The loop
subsequently iterates through the dictionary, generating topographic maps for each frequency band by utilizing the `power.plot_topomap` function. Subsequently, the function `power.plot_joint` generates a unified graph illustrating the mean power over time and frequencies. The inter-trial coherence (ITC) is displayed using `itc.plot_topo`, with a 'Reds' colormap representing the degree of phase-locking consistency across trials. This visualization assesses the reliability of the observed brain responses.

![Figure 27. Topographic Time-Frequency Representations for EEG Data. Applying Morlet wavelet analysis to the EEG channels within a logarithmic frequency range of 6 to 35 Hz reveals clear variations in average power for each channel. The color-coded log-ratio values represent changes in power compared to the baseline, showing the fluctuating patterns of brain activity in different regions.](image)

This plot represents the average power spectral density analysis over multiple trials with each sub-plot representing data from a different channel. The homogeneity observed in power levels across all channels suggests a consistent pattern of brain activity throughout the scalp. Almost all channels (with a slight difference noticed in the right temporoparietal region) exhibit similar patterns of power changes. Consistent patterns observed in sensors may suggest that these regions are working together, potentially indicating the simultaneous activation of brain networks involved in observing the grasp and mimic actions.

Based on the time-frequency plot displays the average activity of channels the specific frequency bands associated with mirror neuron activity, such as the mu (8-13 Hz) and beta (13-30 Hz) bands can be examined. The EEG patterns observed in the alpha and beta frequency bands in response to a stimulus event can offer insights into the brain's anticipatory, reactive, and restorative processes. At first, a rise in the alpha band before the stimulus indicates a preparatory stage, in which the brain is in a state of 'standby', potentially marked by increased attention and alertness. Upon presentation of the stimulus, the alpha band exhibits a decline, signifying a transition from anticipation to engagement, as the brain actively analyzes the incoming sensory information or readies itself for a motor response. The active involvement is indicated by event-related desynchronization (ERD) in the alpha frequency range, which represents the cognitive activation to focus on and engage with the stimulus. Since the alpha band continues to be reduced as the task progresses, it indicates a prolonged period of cognitive or motor activity, which helps the brain maintain its attention on the current task. After the stimulus, there is a rise in the beta band, which is called event-related synchronization (ERS).
This indicates a clear shift to a post-active state, indicating the end of the immediate task requirements and a return to a resting state. The phenomenon known as ‘beta rebound’ can also be linked to internal assessments of the action taken or the analysis of feedback received from the task performed.

The pattern shows a decrease in the alpha band at the same time as the stimulus, indicating mu suppression. Mu suppression is a clear sign of sensorimotor engagement that starts when the stimulus is presented and continues even after it is no longer present, suggesting ongoing task involvement. The continued presence of this decrease in alpha brainwave activity, combined with the increase in beta brainwave activity after the stimulus, strengthens the idea that the suppression of mu brainwaves is closely connected to the cognitive and motor processes involved in the task. Beta rebound generally indicates the conclusion of active movement or engagement in a task. So, the occurrence of mu suppression during the stimulus indicates the active involvement of the mirror neuron system. This suppression, which is comparable to the event-related desynchronization (ERD) in the alpha frequency range, indicates the brain’s engagement in sensory processing and motor planning. Since this suppression continues after the stimulus, it indicates ongoing motor involvement, and the subsequent rise in beta band activity indicates the end of movement and the return to a normal neural state.

![Figure 28. Time-Frequency Heatmap and Scalp Topography during a Peak Event. The heatmap displays temporal variations in power spectral density, with a prominent peak in the alpha frequency range (about 10 Hz) observed at roughly -3.74 seconds. This peak is emphasized in the topographic inset.](image)

With the event time set at 0 seconds the time-frequency plot displays power changes across various frequencies over time. The color bar serves as a visual representation of the power level, where red indicates an increase and blue indicates a decrease. The theta-range activity is highlighted by the topographical inset at a specific time and frequency of -3.74 seconds and 6.0 Hz, respectively. This point has been circled to indicate a significant event in
the data. Theta oscillations are linked to various cognitive functions, such as the encoding and retrieval of memories, attention, and internal mental processing. This notable activity taking place at -3.74 seconds (before the task commences at time zero), indicating the presence of anticipatory or preparatory brain activity. This may be associated with attentional processes preparing for the observation or performance of the task. This would suggest that the mirror neuron system is active, as the subject's brain might be 'simulating' the observed action.

There is a noticeable change in dominance in the alpha frequency band (about 10 Hz) before to the occurrence, specifically between -3.74 seconds and -1 second, as indicated by areas of red. This indicates a rise in alpha brainwave activity, which could be associated with the expectation of an upcoming task or a state of relaxation before engaging in a task. As the event approaches, there is a noticeable decline in strength in the alpha frequency band (shown by the color blue), which may suggest event-related desynchronization. ERD in the alpha band is frequently linked to increased cognitive processing or the activation of sensory or motor systems. After the event, there is a decrease in the prominent activity in the alpha band. The power output does not appear to reach the same maximum levels as during the pre-event period, although there are still variations that may be connected to the specific tasks being performed. However, following the event, there is an apparent increase in activity in the beta frequency range, which is around 16-35 Hz. The red regions signify an increase in intensity for particular frequencies, typically linked to engaged cognitive processing, sensory analysis, or motor planning and execution, depending on the specific occurrence. While the alpha band showed a significant decrease in strength soon after the event, indicating suppression of the more relaxed state associated with alpha waves, the beta band increased, indicating a change to a more attentive and engaged cognitive state. The existence of increased beta activity suggests that the event compelled the participant to engage in tasks that require attention, problem-solving, or motor response. This aligns with the conventional understanding of beta activity, which involves the utilization of higher frequencies during levels of mental activity and engagement.

Since the participant is getting ready to learn, decode or memorize the action that is about to be observed, then theta waves may be relevant to this situation. The topographical map shows the distribution of power across the scalp at this point in time. The observed phenomenon seems to be concentrated in a particular region, indicating the involvement of a localized brain network. The region aligns with areas known to contain mirror neurons, such as the premotor cortex or inferior frontal gyrus, providing additional evidence for the participation of the mirror neuron system.

To understand the strength, consistency, and spatial distribution of brain activity both power and Inter-trial coherence have to be analyzed. ITC is a measure of the consistency of EEG activity over multiple trials. For example, a decrease in alpha power and significant ITC could suggest a suppression of neural oscillations, while an increase in beta power and strong ITC indicate consistent cognitive or motor processes in response to an event. This data can be used to create a topographic map to identify brain responses associated with specific tasks.
Color intensity signals indicates the strength of coherence, with higher intensity indicating a higher level of alignment. This means that the phase of the EEG signal is consistently aligned across trials at that specific time-frequency point. A consistent red hue signifies a level of coherence that surpasses the zero line but remains below the maximum value of 0.4. The absence of diversity in color intensity among channels and within each channel plot indicates a consistent synchronization of phases across various channels within the displayed frequency range. Consistency across channels suggests that the neural response phase remains constant across various locations on the scalp, suggesting a global neural mechanism at work during the task.

Within the context of mirror neuron activity, these patterns can describe the brain's progression through stages of anticipation, execution or observation, and then reflection or relaxation. This aligns with the suggested roles of mirror neurons in not only aiding in the comprehension and imitation of observed actions, but also in the internal practice and subsequent acquisition of knowledge from those actions.

Conventional time-frequency techniques provide a fundamental understanding of the temporal pattern and modulation of neural activity in EEG data analysis. Nevertheless, these methods might struggle to handle the intricate interactions, non-linearity, and high dimensionality that are characteristic of EEG datasets. Machine learning is a supplementary factor that demonstrates proficiency in maneuvering through these complex streams of data. It can reveal subtle patterns and relationships that more traditional techniques lack, providing a more detailed understanding of the brain's activity.

The true potential of machine learning becomes apparent when it not only complements but also verifies the observations made through time-frequency analyses. The cross-methodological confirmation provided enhances confidence in the outcomes, guaranteeing that
they are authentic representations of neural dynamics rather than mere artifacts. The collaboration between machine learning and conventional EEG analysis not only reinforces the existing knowledge but also advances it by facilitating accurate delineations of brain states. When the results of both approaches align, it strengthens the credibility of the conclusions, which can lead to further developments in a more profound understanding of the cognitive mechanisms involved.

4.1.4 Classification

The machine learning models can provide valuable insights for creating more accurate and precise algorithms that can detect and classify neural patterns related to intricate behaviors. The model presented below is fine-tuned to optimize its performance, and its ability to differentiate between two distinct mental states related to grasp and mimic actions is evaluated.

```python
from mne.decoding import Vectorizer
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import make_pipeline
from sklearn.model_selection import cross_val_score, train_test_split, GridSearchCV, StratifiedKFold
from sklearn.metrics import classification_report, accuracy_score, precision_recall_fscore_support

# Models
from sklearn import svm
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.linear_model import LogisticRegression

# Load and preprocess data for "grasp_start" and "mimic_start" conditions
epochs_GS = epochs["grasp_start", "mimic_start"]
data_GS = epochs_GS.get_data()
labels_GS = epochs_GS.events[:, -1]
train_data_GS, test_data_GS, labels_train_GS, labels_test_GS = train_test_split(data_GS, labels_GS, test_size=0.3, random_state=42)

# SVM for "grasp_start" and "mimic_start" conditions
clf_svm_pip_GS = make_pipeline(Vectorizer(), StandardScaler(), svm.SVC(random_state=42))
parameters_GS = {'svc__kernel': ['linear', 'rbf', 'sigmoid'], 'svc__C': [0.1, 1, 10]}
gs_cv_svm_GS = GridSearchCV(clf_svm_pip_GS, parameters_GS, scoring='accuracy', cv=StratifiedKFold(n_splits=5), return_train_score=True)
gs_cv_svm_GS.fit(train_data_GS, labels_train_GS)

print('Best Parameters for Grasp_Start and Mimic_Start: {}'.format(gs_cv_svm_GS.best_params_))
print('Best Score for Grasp_Start and Mimic_Start: {}'.format(gs_cv_svm_GS.best_score_))
```
# Prediction
predictions_svm_GS = gs_cv_svm_GS.predict(test_data_GS)

# Evaluation
report_svm_GS = classification_report(labels_test_GS, predictions_svm_GS, target_names=['Grasp_Start', 'Mimic_Start'])
print('SVM Classification Report for Grasp_Start and Mimic_Start:
{}
'.format(report_svm_GS))

acc_svm_GS = accuracy_score(labels_test_GS, predictions_svm_GS)
print("Accuracy of SVM model for Grasp_Start and Mimic_Start: 
{}").format(acc_svm_GS))

precision_svm_GS, recall_svm_GS, fscore_svm_GS, support_svm_GS = precision_recall_fscore_support(labels_test_GS, predictions_svm_GS, average='macro')
print('Precision: {0}, Recall: {1}, f1-score: {2}'.format(precision_svm_GS, recall_svm_GS, fscore_svm_GS))

Aiming at distinguishing EEG patterns related to two distinct actions: "grasp_start" and "mimic_start" machine learning is used. The EEG signal data is extracted using the get_data() function, while the corresponding labels are obtained from epochs_GS.events[:, -1]. The dataset is subsequently partitioned into a training set, from which the machine learning model will acquire knowledge, and a test set, which will be employed to assess the model's performance. The data split is performed using the train_test_split function from scikit-learn, with 30% of the data allocated for testing.

Subsequently, a Support Vector Machine (SVM), which is a machine learning model specifically designed for classification tasks, is established within a pipeline. The Vectorizer converts the EEG data, which is initially represented as a 3D array (trials x channels x time), into a 2D array (trials x features). This conversion is necessary because machine learning algorithms in scikit-learn require data to be in a 2D format. The StandardScaler is employed to standardize the data, guaranteeing that each feature has a mean value of zero and a variance of one. In order to determine the optimal settings for the Support Vector Machine (SVM), a grid search (GridSearchCV) is conducted across a predefined range of parameters (parameters_GS). The SVM uses grid search to explore different kernel types and C values to classify data. The kernels change class boundaries, while C values determine strictness in classification. Lower values prevent overfitting, while higher values can lead to overfitting. This range encompasses various kernel types (linear, rbf, sigmoid) and different values for the regularization parameter C (0.1, 1, 10).

This optimization process employs cross-validation with StratifiedKFold to ensure that the proportion of each label remains consistent across folds. Its objective is to determine the parameter combination that yields the highest accuracy for the model. The grid search prints the best parameters and their corresponding best score after training. These provide information on the most effective settings used during the process of training the model.
The SVM model that has been trained is subsequently employed to forecast the labels of the EEG data in the test set, resulting in predictions referred to as \texttt{svm\_GS}. The model's performance is evaluated by comparing the true labels and the predicted labels. A 	exttt{classification\_report} offers a comprehensive breakdown of precision, recall, and F1-score for each action, while the \texttt{accuracy\_score} function provides a summary of the overall accuracy. Ultimately, the macro-averaged precision, recall, and F1-score are computed using the \texttt{precision\_recall\_fscore\_support} function. This yields a singular score for each metric that treats all classes equally, regardless of their respective sizes.

![Table of SVM Classification Report](image)

The output displays the outcomes obtained by employing a Support Vector Machine (SVM) model to categorize EEG data into two distinct groups: "Grasp\_Start" and "Mimic\_Start". The model underwent optimization using a grid search, which determined that the optimal parameters are C=10 (representing the regularization strength) and the sigmoid kernel (a specific type of function used for data point separation). The cross-validation score, which represents the mean accuracy achieved on various subsets of the training data, was approximately 74.67%. Accuracy achieving a score of 58.33% represents the ratio of correct predictions to the total number of predictions made. Out of all the EEG events classified by the model, 58.33% were accurately identified as either Grasp\_Start or Mimic\_Start. The model achieved a precision of 75% for Grasp\_Start, meaning that 75% of its predictions for this category were correct. The precision of Mimic\_Start was 50%, indicating that only half of the predictions made for Mimic\_Start were correct. Precision is a metric that quantifies the proportion of correctly identified positive cases among all the cases that were predicted as positive. The recall for Grasp\_Start is 43%, meaning that the model accurately detected 43% of all Grasp\_Start events. The recall for Mimic\_Start was 80%, indicating that the model performed better in identifying Mimic\_Start events compared to Grasp\_Start events. Recall, also known as sensitivity, quantifies the number of true positives that were accurately detected. The F1-Score is a metric that combines precision and recall to provide a single measure of test accuracy. It takes into account both precision and recall equally. The F1-score for Grasp\_Start was 0.55, while for Mimic\_Start it was 0.62. The macro-average F1-score for both categories was around 0.58, suggesting a moderate equilibrium between precision and recall for the
overall model. The macro-average values give equal weight to both categories, indicating an overall precision of 62.5%, recall of 61.43%, and F1-score of 58.04%. These averages provide valuable insights into the model's performance across all categories, without disproportionately emphasizing the larger ones.

The findings indicate that the model is adequately proficient in differentiating between Grasp_Start and Mimic_Start, but there is still potential for enhancement. Specifically, it faces greater difficulty in accurately identifying all Grasp_Start events (as indicated by the lower recall), while it demonstrates relatively better performance in recognizing Mimic_Start events. The model exhibits a higher level of precision for Grasp_Start, indicating that when it predicts an event as Grasp_Start, it is highly reliable. However, its ability to accurately detect all Grasp_Start events (recall) is somewhat limited. On the other hand, it successfully detects the majority of the Mimic_Start events. However, it is less confident in its predictions of an event being Mimic_Start compared to its predictions of Grasp_Start.

Possible enhancements could include fine-tuning parameters, investigating alternative models, or improving the extraction and selection of features to capture the inherent disparities more accurately in brain activity between the two conditions. It is essential to build EEG-based prediction models using machine learning that can differentiate between various mental states or tasks, but it is also of great matter to select the right model for EEG data analysis. It is intriguing to explore the integration of linear and non-linear models or ensemble methods to capture intricate neural patterns. Thus, additional refinement and investigation are necessary to enhance the accuracy of classification.

```python
from mne.decoding import Vectorizer
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import make_pipeline
from sklearn.model_selection import train_test_split, GridSearchCV,
StratifiedKFold
from sklearn.metrics import classification_report, accuracy_score,
precision_recall_fscore_support
from sklearn import svm
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.linear_model import LogisticRegression

# Function to evaluate the model
def evaluate_model(clf, parameters, X_train, y_train, X_test, y_test,
cv_folds=5):
    grid = GridSearchCV(clf, parameters, cv=StratifiedKFold(n_splits=cv_folds),
return_train_score=True, scoring='accuracy')
    grid.fit(X_train, y_train)
    best_params = grid.best_params_
    best_score = grid.best_score_

    # Make predictions on the test set
    predictions = grid.predict(X_test)

    # Evaluation
```
report = classification_report(y_test, predictions)
accuracy = accuracy_score(y_test, predictions)
precision, recall, fscore, _ = precision_recall_fscore_support(y_test, predictions, average='macro')

# Print the results
print(f'Best Parameters for {clf.steps[-1][0]}: {best_params}"
print(f'Best Cross-Validation Score: {best_score}"
print(f'Accuracy of {clf.steps[-1][0]} model: {accuracy}"
print(f'Classification Report for {clf.steps[-1][0]}:
{report}"
print(f'Precision: {precision}, Recall: {recall}, f1-score: {fscore}"

return grid, predictions, accuracy

# Load and preprocess data for "grasp_start" and "mimic_start" conditions
epochs_GS = epochs['grasp_start', 'mimic_start']
data_GS = epochs_GS.get_data()
labels_GS = epochs_GS.events[:, -1]
test_data_GS, labels_test_GS = train_test_split(data_GS, labels_GS, test_size=0.3, random_state=42)

# Define the models and parameters
models = {
    'SVM': (make_pipeline(Vectorizer(), StandardScaler(), svm.SVC(random_state=42)), {
        'svc__kernel': ['linear', 'rbf', 'sigmoid'],
        'svc__C': [0.1, 1, 10]
    }),
    'LDA': (make_pipeline(Vectorizer(), StandardScaler(), LinearDiscriminantAnalysis()), {
        'lineardiscriminantanalysis__solver': ['svd', 'lsqr', 'eigen']
    }),
    'LogisticRegression': (make_pipeline(Vectorizer(), StandardScaler(), LogisticRegression(random_state=42)), {
        'logisticregression__C': [0.1, 1, 10],
        'logisticregression__penalty': ['l2'],
        'logisticregression__solver': ['lbfgs']
    })
}

# Run the function for each model
results = {}
for model_name, (model, parameters) in models.items():
    print(f'Evaluating model: {model_name}"
results[model_name] = evaluate_model(
    model, parameters, train_data_GS, labels_train_GS, test_data_GS, labels_test_GS)
The `evaluate_model` function is a grid search and cross-validation tool that generates optimal parameters, highest cross-validation score, and accuracy for each classifier. It uses a dictionary with model names and corresponding tuples containing the pipeline and parameter grid. The loop iterates through the models dictionary, invoking the `evaluate_model` function for each element. The results are stored in a dictionary for further analysis. The function also assesses accuracy, precision, recall, and f1-score by making predictions on the test set. The `classification_report` provides a comprehensive evaluation of each label's performance.

Evaluating model: SVM
Best Parameters for svc: {'svc__C': 10, 'svc__kernel': 'sigmoid'}
Best Cross-Validation Score: 0.7466666666666668
Accuracy of svc model: 0.5833333333333334
Classification Report for svc:

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<th>f1-score</th>
<th>support</th>
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<td>weighted avg</td>
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<td>0.58</td>
<td>0.57</td>
<td>12</td>
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</tbody>
</table>

Precision: 0.625, Recall: 0.6142857142857143, f1-score: 0.5804195804195804

Evaluating model: LDA
Best Parameters for lineardiscriminantanalysis: {'lineardiscriminantanalysis__solver': 'svd'}
Best Cross-Validation Score: 0.58
Accuracy of lineardiscriminantanalysis model: 0.5
Classification Report for lineardiscriminantanalysis:

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</table>

Precision: 0.7272727272727273, Recall: 0.5714285714285714, f1-score: 0.4375

Evaluating model: LogisticRegression
Best Parameters for logisticregression: {'logisticregression__C': 10, 'logisticregression__penalty': 'l2', 'logisticregression__solver': 'lbfgs'}
Best Cross-Validation Score: 0.7866666666666667
Accuracy of logistic regression model: 0.6666666666666666

Classification Report for logistic regression:

<table>
<thead>
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<th>recall</th>
<th>f1-score</th>
<th>support</th>
</tr>
</thead>
<tbody>
<tr>
<td>11</td>
<td>0.80</td>
<td>0.57</td>
<td>0.67</td>
</tr>
<tr>
<td>21</td>
<td>0.57</td>
<td>0.80</td>
<td>0.67</td>
</tr>
<tr>
<td>weighted avg</td>
<td>0.70</td>
<td>0.67</td>
<td>0.67</td>
</tr>
</tbody>
</table>

Precision: 0.6857142857142857, Recall: 0.6857142857142857, f1-score: 0.6666666666666666

Based on the output, it is evident that:

- The Logistic Regression model achieved the highest cross-validation score and test accuracy. The model demonstrated a favorable balance between precision, recall, and F1-score metrics, suggesting its ability to accurately identify positive cases and generalize to the test data.

- The Support Vector Machine (SVM) with a 'sigmoid' kernel and a regularization parameter (C) set to 10 achieved a satisfactory cross-validation score. However, its test accuracy was comparatively lower than that of Logistic Regression. The precision, recall, and F1-score exhibit a moderate balance.

- The 'svd' solver exhibited the poorest performance in terms of cross-validation score and test accuracy for Linear Discriminant Analysis. Although it exhibited the highest precision, its recall and F1-score were comparatively lower, suggesting that it was more cautious in predicting positive labels but less successful overall.

The summarized results provide insights into the performance of various machine learning models in differentiating between the "grasp_start" and "mimic_start" conditions. The effectiveness of logistic regression in differentiating between grasping and mimicking indicates a distinct linear correlation in the EEG signals associated with these actions. This suggests that the brain's reaction to observing a non goal specified action (mimic) as opposed to a goal specified (grasp) exhibits clear and distinguishable patterns that can be separated linearly. These findings imply that mirror neurons, may contribute to both types of actions. However, there are identifiable patterns in their neural activity that can be accurately represented using linear models.

The SVM model with a sigmoid kernel has achieved a moderate level of success, indicating that there are non-linear complexities in the EEG data that are only partially captured by this model. The SVM's attempt to create a non-linear decision boundary may resemble the complex behavior of mirror neurons and the corresponding brain regions, which exhibit distinct responses to goal-oriented and non-goal-oriented actions. Nevertheless, the partial achievement suggests that further improvements in the model or selection of features may reveal additional insights into these neural patterns.

Limitations of assuming homogeneity in variance-covariance structures across the two types of actions could be highlighted by the lower performance of LDA. Regarding EEG
analysis, this suggests that the electrical patterns produced by the brain during grasping and mimicking are not only different but also distributed in different ways.

The high efficacy of logistic regression indicates that linear models, when appropriately regularized and parameterized, can effectively capture the differences in brain activity between these two types of actions in your dataset. This observation has the potential to direct future investigations, enhance the accuracy of models, and facilitate the exploration of supplementary characteristics or alternative models in order to enhance the performance of classification.

```python
from mne.decoding import Vectorizer, SlidingEstimator, cross_val_multiscore
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import StandardScaler
import numpy as np
import matplotlib.pyplot as plt

# Assuming 'data_GS', 'labels_GS', and 'epochs_GS' are already defined and
# preprocessed as shown previously

def applyCrossValidation(data, labels, epochs, classifier):
    CV_score_time = None
    sl = SlidingEstimator(classifier, scoring='accuracy', n_jobs=1)  # Adjust
    n_jobs based on your machine's capabilities
    if np.isfinite(data).all() and not np.isnan(data).any():
        # Perform cross-validation over time
        CV_score_time = cross_val_multiscore(sl, data, labels, cv=3, n_jobs=1)  #
        Adjust n_jobs as needed
        plotCVScores(epochs.times, CV_score_time)
        else:
            print('Input contains NaN or infinity!')

    return CV_score_time

def plotCVScores(times, CV_score_time):
    plt.figure()
    plt.title('CV Scores Over Time')
    mean_scores = np.mean(CV_score_time, axis=0)
    std_scores = np.std(CV_score_time, axis=0)

    plt.fill_between(times, mean_scores - std_scores, mean_scores + std_scores,
                      alpha=0.5)
    plt.plot(times, mean_scores, '-o', label='Mean CV score', markersize=5)
    plt.xlabel('Time (s)')
    plt.ylabel('CV Accuracy')
    plt.legend()
    plt.show()

# Setup your classifier. Here LogisticRegression used.
clf = make_pipeline(Vectorizer(), StandardScaler(),
                    LogisticRegression(random_state=42))
```
This strategy utilizes commands such as `SlidingEstimator` and `cross_val_multiscore` to implement a sliding window technique. This technique is crucial for analyzing the changes in the predicted accuracy of the classifier at different time periods in the EEG data. The `SlidingEstimator` is used to systematically apply the classifier, which is a logistic regression model in this scenario, to each individual moment in the dataset. This sequential approach enables the investigation of the dynamic characteristics of EEG signals and their association with predetermined labels, revealing the periods of increased brain activity that are most relevant to the task or condition being studied.

In addition, the `cross_val_multiscore` function enables cross-validation at each time point, resulting in a comprehensive curve that illustrates the temporal progression of prediction accuracy. This curve, displayed using a specialized charting method, illustrates the average accuracy and its fluctuation over time, providing insights into the time-dependent nature of brain responses. The presence of preprocessing procedures like `Vectorizer` and `StandardScaler` in the classifier pipeline highlights the intricate nature of EEG data and the need for advanced analytical tools to decipher it.

The given code does not explicitly define the temporal size of the sliding window, such as in milliseconds. In the `SlidingEstimator` context, the term "window" specifically refers to the application of the classifier to the data at each particular time point, rather than using a standard window that includes many time points. This indicates that the analysis is performed at the level of individual time points within the EEG epochs, rather than combining data across a longer time period before classification.

This method enables precise temporal resolution in decoding analyses, accurately identifying the very moment when task-relevant information becomes distinguishable in the brain's electrical activity. However, the precise duration that each categorization examines is not determined by a typical "window" but by the level of detail in the time sample of the era. Given that the EEG data was collected at a rate of 500 Hz, each individual time point corresponds to a duration of 2 milliseconds (ms). When utilizing the SlidingEstimator as stated, the analysis accurately applies the classifier to the EEG signals at every 2 ms interval across the epochs. The use of a high sampling rate and the analysis of each time point individually allows for a thorough investigation of the brain's fast changes in response to a stimulus or task.
Figure 30. Trend and Variability of Time-Resolved EEG Analysis Cross-Validation Accuracy Scores. This graphic displays the cross-validation accuracy of LogisticRegression predictive model applied to EEG data over time. Each data point represents the accuracy at certain time intervals, while the line represents the average trend of these scores. The temporal axis ranges from -4 to +4 seconds with respect to the pivotal event, illustrating the variations in the model's performance over the periods preceding and succeeding this event.

The average cross-validation (CV) score, depicted by the line, offers a comprehensive assessment of the model's ability to forecast the task or stimulus conditions by analyzing the EEG signals at each given instant. Significantly, the precision varies over time but consistently surpasses the chance level (which is 0.5 for a binary classification task). This indicates that the EEG data includes pertinent information for the task that the model can acquire. In general, the model seems to possess a certain level of predictive ability, as seen by the average accuracy scores being higher than what would be expected by chance. The mean CV score line helps to visualize the overall trend and the average accuracy of the model throughout the experiment. The clustering of scores around certain times could imply periods of more consistent predictive performance.

The graph exhibits a broad spectrum of precision, ranging from approximately 0.2 to 0.8, with a few exceptional data points that approach 1.0. Understanding the consistency and reliability of the mirror neuron detection model could be facilitated by analyzing the distribution and range of these scores. If the mean CV score is consistently high over time, it indicates that the model is generally effective in predicting mirror neuron activity. On the other hand, if there is more variability in the CV score, it suggests that the model's predictions are influenced by the context or that mirror neuron activity is not always consistent across different actions or observations.

Furthermore, it is apparent that there is a noticeable increase in CV accuracy scores between approximately -4 to -3 seconds. The scores almost approach 1, indicating almost perfect classification. This suggests that during this time window, the EEG data contain highly predictive information about the conditions being tested. This peak may reflect a time period in which the neurological pattern of mirror neurons is highly noticeable and consistent across multiple trials and individuals, suggesting a strong phase of mirror neuron involvement. Since the condition involves seeing an action, the peak may indicate the moment when the...
brain's mirror neuron system is most engaged in analyzing the observed movement, allowing the classifier to make precise predictions. Alternatively, this could indicate that participants are expecting the forthcoming action during the interval before the stimulus, resulting in increased activity in regions linked to mirror neurons, such as the premotor and parietal cortices which is in sync with the time-frequency analyses. The temporal synchronization of this peak prior to the occurrence may possibly indicate preparatory brain processes that are involved in the mirroring function.

To visually represent the brain regions (channels) that have the highest predictive power for a continuous outcome variable at different time intervals is essential.

```python
from mne.decoding import Vectorizer, SlidingEstimator
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import StandardScaler
from mne.viz import plot_topomap
import numpy as np
import matplotlib.pyplot as plt

# Define the time points you are interested in (for example, at 100 ms intervals)
times_to_analyze = np.arange(-4, -2.8, 0.1)  # Adjust this as needed
topomap_coeffs = []

# Prepare the regression model
lr = LinearRegression()
vec = Vectorizer()
scaler = StandardScaler()

# Perform the sliding window analysis
for time_point in times_to_analyze:
    # Extract the data from the relevant time window
    time_idx = epochs_GS.time_as_index(time_point)
data_slice = epochs_GS.get_data()[:, :, time_idx]

    # Standardize the data and fit the linear regression model
    X = vec.fit_transform(data_slice)
    X = scaler.fit_transform(X)
    lr.fit(X, labels_GS)

    # Extract the coefficients for topomap plotting
    # Note: For linear regression, coefficients relate to the features in X
    coef = lr.coef_.ravel()
topomap_coeffs.append(coef)

# Now create a figure with subplots for each topomap
n_topomaps = len(times_to_analyze)
fig, axes = plt.subplots(1, n_topomaps, figsize=(2 * n_topomaps, 3))
for idx, time_point in enumerate(times_to_analyze):
    # Ensure that we are passing a 1D array to plot_topomap
```
ax = axes[idx] if n_topomaps > 1 else axes
plot_topomap(topomap_coeffs[idx], epochs_GS.info, axes=ax, show=False)
ax.set_title(f"{time_point:.2f} s")

plt.tight_layout()
plt.show()

The script utilizes a fitted epochs_GS object, which holds the EEG data divided into epochs, and a variable labels_GS that includes continuous labels for regression. It proceeds to construct a range of time points of interest using NumPy. Here, it examines the time range from -4 to -2.8 seconds at intervals of 0.1 seconds.

A linear regression model is constructed. It was preferred due to its high accuracy scores. The data was restructured using a vectorizer and normalized using a scaler. A sliding window analysis is conducted, wherein, for each specific time point of interest, the relevant segment of data is extracted from the epochs. Subsequently, this portion of data is transformed into a vector format and normalized. The processed data is used to fit the linear regression model with the continuous variable and are saved for creating topographic maps. Ultimately, a visual representation is generated, consisting of separate plots for each topomap that correspond to distinct time points. Each subplot exhibits the topographic representation of the regression coefficients, illustrating the changing significance of various sensors over time. The arrangement is optimized for a neat presentation, and the diagram is displayed using plt.show().

Figure 31. Sequential Topographic Maps of EEG Regression Coefficients from -4 to 3.5 Seconds Around the Event. The image is a set of topographic maps created by applying a sliding window method and linear regression to EEG data processing in order to comprehend the spatiotemporal dynamics of the brain’s reaction across time. The maps cover a time range of -4.00 to 3.50 seconds around an event, demonstrating the changing predicting abilities of several brain regions during this time period.

The sliding window regression analysis results applied to the EEG data are reflected in the series of topographic maps. Each map depicts the regression coefficients derived from the application of a linear regression model at various time points within a certain period associated
with a particular event. This suggests a possible correlation between the electrical activity and a continuous variable of interest. These maps display color intensities that correspond to the magnitude of the regression coefficients. The coefficients are calculated after the EEG signals have been vectorized and normalized. These coefficients can provide information about the specific regions of the brain that exhibit higher levels of activity or greater predictive power for the variable in question during specific time periods before and after the event. The diversity in patterns may indicate dynamic changes in brain activity, such as the involvement of distinct neural networks across a period of time.
5 In discussion

The study extensively utilizes MNE-Python for EEG analysis to investigate the neural dynamics involved in grasp and mimic actions. This work highlights the effectiveness of MNE-Python as a flexible tool in EEG analysis and also presents several opportunities for further research. This research has the potential to shed light on the complex functionality of the mirror neuron system. This research utilizes various analytical tools, including machine learning models, time-frequency analysis, and topographic mapping, to examine the specific temporal and spatial characteristics of EEG signals related to action observation. These findings enhance our comprehension of the neurological foundations of social cognition and provide empirical proof that supports the crucial function of mirror neurons in comprehending actions and acquiring knowledge through observation.

The application of SVM, LDA, and Logistic Regression models in this study is similar to the methodological approaches found in prior literature but without multiple parameters to be tested simultaneously. The results on mu suppression and its impact on mirror neuron activity are consistent with well-established hypotheses, such as those put out by Rizzolatti. These findings build upon previous research and further advance our understanding of the neural dynamics preceding stimulus occurrence in the context of action observation.

However, the study has limitations that are inherent to techniques based on EEG, especially with the precise identification of the location of brain activity. Potential future studies may involve incorporating fMRI or MEG technology to enhance the spatial precision of findings and authenticate insights acquired from EEG. Furthermore, the difficulties in interpreting the machine learning models' 'black box' character present an opportunity to investigate explainable AI frameworks. These frameworks can offer a more transparent understanding of the neural mechanisms underlying the models' decision-making processes. In order to improve the reliability and applicability of the results, future research should aim to expand the dataset to include a more diverse range of people. Additionally, it is recommended to investigate a wider range of machine learning models and statistical tests in order to better capture the intricate patterns of brain activity. These efforts hold the potential to provide more profound understanding of the neurological processes involved in social cognition. This knowledge can have significant consequences for the fields of neurorehabilitation, the creation of neuroprosthetics, and the progress of artificial intelligence systems that can imitate human social interactions.

These outcomes provide a comprehensive view of the brain processes involved in action observation and the mirror neuron system, representing a significant advancement in cognitive neuroscience research. The aim of this study is to enhance the ongoing discussion on the neurobiological basis of social cognition and motor control by exploring new analytical methods and suggesting future research directions. It also tries to establish a foundation for future advancements in neuroscience and technology.
6 Conclusions

The comprehensive examination and visualization of neural activity patterns not only validated the existence and operation of mirror neurons but also may have enhanced our knowledge regarding their ever-changing involvement in various motor and cognitive processes.

The utilization of Independent Component Analysis (ICA) and Principal Component Analysis (PCA) in the study of EEG data during observing grasping and mimicking of grasping tasks resulted in distinct findings that emphasize the intricate functionality of the brain. The ICA method identified signals that are specifically related to cognitive and motor tasks. These signals were then mapped to brain regions that are responsible for planning, decision-making, and sensory integration. This procedure successfully differentiated authentic brain activity from artifacts, hence improving the integrity of the data. PCA enhanced these findings by focusing on the primary factors contributing to data variability, revealing the sequential progression of brain reactions from initial action to cognitive processing. The comprehensive investigation identified the specific participation of the frontal and parietal lobes in task execution and the integration of sensory information from several modes, as well as the involvement of the temporal and occipital areas in processing and recognizing visual stimuli.

The findings from the time domain analysis demonstrated patterns of neural activation, with a notable increase in positive amplitude during "grasp_start" trials. This indicates a higher level of brain activation while executing an actual grasp. Remarkably, approximately -3 seconds before the start of an action, there is a noticeable difference in brain activity. The mimic condition exhibits a higher intensity, indicating subtle distinctions in how humans perceive and differentiate between motions that have a specific objective and those that do not. The butterfly plots focus on consistent response patterns observed in multiple trials, while also highlighting variations in amplitude that reflect the intricate interaction between feedback and motor control systems, particularly during grasping.

Statistical analysis techniques, namely t-tests and Threshold-Free Cluster Enhancement (TFCE) procedures, were employed to differentiate neural responses across all channels and timepoints between the "grasp_start" and "mimic_start" conditions using EEG data. At first, t-tests showed significant differences between conditions, indicating separate brain processes. However, this significance decreased after using multiple comparison corrections such as FDR, suggesting that the initial findings may have been overestimated or that there was not enough statistical power. On the other hand, TFCE, which utilizes the spatio-temporal correlation structure of EEG data, detected substantial clusters of activity approximately 3 seconds before the stimulus was presented. This suggests the presence of separate anticipatory brain mechanisms for each condition.

The spectral power analysis revealed separate brain activity patterns for the "grasp_start" and "mimic_start" circumstances, highlighting the effectiveness of frequency analysis in understanding brain activities. The presence of higher spectral strength in the delta, beta, and alpha frequency bands during grasping suggests a greater level of cognitive processing and motor planning in comparison to mimic. The investigation indicated that both
tasks activated the same brain regions, which supports the mirror neuron concept that suggests the activation of brain regions during both action execution and observation. Significantly, the grasping tasks exhibited increased delta wave activity, which is connected to cognitive effort, as well as increased alpha and beta activities, which are correlated with improved concentration and motor planning. In contrast, the mimic task had elevated theta power, indicating enhanced internal processing. Gamma oscillations, which are associated with cognitive abilities, exhibited increased power while grasping, thereby emphasizing improved brain coordination.

Furthermore, time frequency analysis using Morlet wavelets showed complex patterns of brain activity, showing a significant change in the alpha frequency range from -3.74 to -1 seconds prior to an event between the two conditions. This indicates a state of relaxation or increased concentration in preparation for task involvement. After the event, an increase in beta frequency activity suggested a shift towards a more focused and involved mental state, which is essential for tasks that require concentration, problem-solving, or physical response. Although brain activity was similar across trials, spectral power analysis revealed changes in power distribution between activities, reflecting different cognitive and motor demands and indicated greater task-relevant frequency power during grasping compared to mimicking.

A thorough method of data vectorization, standardization, and cross-validation to improve model accuracy, machine learning models—specifically, optimized Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), and Logistic Regression—were used in this extensive study to identify EEG patterns linked to "grasp_start" and "mimic_start" conditions. The logistic regression model outperformed the other models, attaining the maximum level of accuracy and showcasing a strong ability to linearly distinguish between the two conditions. This indicates the presence of distinct brain patterns that can be identified in EEG signals. Further research using sliding window methodology and regression techniques revealed temporal alterations in the ability to predict outcomes across different time periods and EEG channels. Notably, there was a peak period of prediction around 3 seconds before the event, which likely indicates a phase of increased activation of the mirror neuron system.

In summary, these findings underline the importance of mirror neurons in linking observation and action, as well as their role in social interaction, imitation learning, and the neurological underpinning of empathy. An in-depth examination and depiction of brain activity patterns not only validate the existence and effectiveness of mirror neurons but also enhance our comprehension of their active involvement in many cognitive and motor functions.

Neuron activity is not solely related to motor actions but also encompasses sensory and perceptual processes linked to these implicit actions. Within the premotor cortex, specific neurons, often referred to as mirror neurons, are activated when an individual performs a motor act or observes another person performing the same action. Observing an action prompts the observer to recall a mental motor representation that is consciously recognized and whose meaning is understood.

Mirror neurons do not respond uniformly to the observation of any action; rather, their activity intensifies when witnessing behaviors where the observer’s body interacts with objects. Furthermore, each neuron exhibits distinct behavior. Some may react to very specific actions, while others respond to two or three similar behaviors. They are activated both by the
observation of an action and the direct performance of that action. Essentially, mirror neurons encode the mental representations of one's own and others' motor actions in a sophisticated manner, considering variables such as the type, goal, and direction of the action. When an action is observed, it evokes neural activity corresponding to the action's representation when internally generated by the subject. Through observing an action, the subject discerns a kinetic representation they are familiar with and comprehends its meaning. The similarity between the internal and observed representations allows the observer to interpret the action and predict its outcome. Concerning mirror neurons' response to observing partial actions, we understand that neuron activation hinges not on the sensory modalities engaged, be it vision or hearing, but on the nature and meaning of the behavior. Partial observation and other sensory stimuli produce an analogous effect.

The experiment confirmed that in humans, the same brain areas are activated when observing an action and when executing it. Observations indicated a similar activation in certain brain regions during real and observed actions, with bilateral activation of the premotor cortex being particularly noteworthy. It seems that only actions within the observer's behavioral repertoire are recognized by the motor system and thus experienced personally. Those outside this repertoire are relegated to the cognitive system and are recognized based on their visual, auditory, and inferred characteristics, along with their intended outcomes or goals. An individual's behavioral repertoire, influenced by age and learned experiences, can vary widely. Consequently, there is an impact of motor experience on the brain's response to observing an action. Therefore, the mirror system integrates observed actions into the individual's personal motor repertoire, suggesting that the human brain understands the actions of others through the motor simulation of familiar actions. The mirror neuron system encodes the overarching intention correlated with the observed action, so the elements of this intention should modulate the activity in the brain regions housing these neurons. Thus, mirror neurons are implicated not only in recognizing motor actions but also in interpreting the intentions behind others' actions, depending on the context in which they occur.

The comprehensive analyses conducted, which encompass machine learning models, time-frequency analysis, and topography mapping, provide deep insights into brain activity that may be associated with mirror neurons. These observations may shed some light on the subtle function of mirror neurons in differentiating between observing goal-oriented and non-goal-oriented actions, indicating a distinct neuronal coding for intentionality and social cognition. The time-frequency analysis may have revealed the temporal patterns that indicate the stages of anticipation, engagement, and reflection, which correspond to the sequential activation of mirror neurons involved in action prediction and simulation. The mapping of topography in the brain may have shown specific activation of mirror neurons, indicating their extensive role in processing seen activities. The mirror neuron system's anticipatory involvement, necessary for preparing the brain to understand the action observed, presumably is highlighted by peaks in predicted accuracy before actions, as discovered using sliding estimator analysis. Furthermore, the consistency observed in all conditions may indicate the presence of a shared brain mechanism for both type of actions. These findings aim to reinforce the fundamental hypothesis of mirror neurons, which posits that these neurons play a role in enabling the understanding of actions, learning through imitation. Together, these observations not only support the presence and operation of mirror neurons but also enhance our understanding of their active involvement in cognitive and motor functions.
7 References


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