The Perception of Exercisers vs Non-Exercisers Using EEG Analysis

By

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Abstract

Obesity rates and other chronic diseases continue to rise due to the lack of physical activity and exercise exerted by Americans annually. Although recommendations from the American College of Sports Medicine (ACSM) and other exercise science organizations have published numerous studies about how to keep up a healthy lifestyle, most Americans tend to not follow them. With this in mind, we wanted to know if there were any innate neurobiological differences between a population that exercises regularly and one that is sedentary. In order to evaluate this phenomenon, we used EEG analysis focusing on functional connectivity and graph theory when both groups evaluated images displaying both physically active and inactive behaviors. Our results show that exercisers and non-exercisers evaluate the concept of physical activity through very different neurocognitive mechanisms. These results have the potential to inform the way that agencies can distribute information in a more targeted fashion, hopefully reaching the broader population more effectively.

The Perception of Exercisers vs Non-Exercisers Using EEG Analysis

A Thesis

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In Partial Fulfillment of the Requirements for Exercise Physiology

by

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Table of Contents

Chapter I: Introduction

Within the United States, all states and territories had more than 20% of adults with obesity in 2020 (CDC, 2021) and remains high with sixteen states that now have an adult obesity prevalence at or above 35% (CDC, 2021). This is partially due to COVID-19 quarantine protocols for several sequential months in the year 2020, but also most American's sedentary activity and poor nutritional lifestyle choices in the past decades. The American government provides ample amounts of information on how to cease the epidemic trend from continuing including being at a higher risk for fatal diseases from impaired immune function. Having obesity increases the risk of severe illness from COVID-19 and people who are overweight may also be at increased risk (CDC, 2021). There is abundant evidence supporting the health benefits of physical activity, including reduced risk for cardiovascular disease, stroke, some cancers, type 2 diabetes, osteoporosis, hypertension, high cholesterol, obesity, osteoarthritis, and all-cause mortality (U.S. DHHS, 2002). In today's society, the top two leading causes of death are obesity and diabetes and their associated comorbidities. Many people know that exercise alone can be used as a remedy to help control the severity of these diseases, yet the obesity trend continues to rise. With exercise, there is a decreased percentage of an individual having either of these diseases.

In order to combat these diseases, the American College of Sports Medicine (ASCM) guidelines recommend that all healthy adults aged 18-65 years should participate in moderate intensity aerobic physical activity (PA) for a minimum of 30 min on 5 d/wk or vigorous intensity aerobic physical activity for a minimum of 20 min on 3 d/wk for the prevention of weight gain and to sustain current weight loss along with 2 d/wk of muscle-strengthening exercises that incorporate all major muscle groups (ASCM 10th ed.). Even though these recommendations have been out for the public since 1975, Americans are still not following the guidelines, which has led to a higher percentage of premature mortalities nationwide. About 12% of all deaths in the United States can be attributed to physical inactivity (McGinnis, n.d.) and has been estimated that the direct costs of physical inactivity account for approximately $24 billion, or 2.4% of US health-care expenditures (U.S. DHHS, 2002; Colditz, 1999) and has only increased over the years. There have been numerous studies on why individuals aren't meeting the activity guidelines, however, this study aims to see if there are individual components for this occurrence. This includes psychological factors, whether the sedentary individual is neurobiologically predisposed to encode physical activity as compared to their chronically active counterparts, which may suggest how ACSM presents materials might not be effective for exercise adherence in all individuals. This study focuses on potential neurological differences and how it relates to the perception of exercise to both an avid exerciser group who follow the guidelines as well as a sedentary non-exerciser group in a cross-sectional study design.

Different cultures, experiences, and environments shape the perception of developing individuals from infancy to adulthood. Other human beings differ from all other "stimuli" by their great similarity to the perceivers themselves (Hari & Kujala, 2009). This study will test both Theory of Mind (ToM) and Social Cognitive Theory (SCT). When we watch someone perform an action, we group the movements into coherent subunits or parts with some of them subordinate to others (Grafton, 2009). Generally, individuals need to have their own experience about an observed action before understanding the action themselves. In terms of physical activity and exercise, some motor skills do not come as easily to others but need extensive practice to understand a movement pattern. The proponents of enactive perception acknowledge the close connections between perception and action, who consider the content of perception to rely on the subject's sensorimotor experience (Hari & Kujala, 2009). Certain cortical areas in humans can be attributed to the mirror-neuron system (MNS) (Hari & Kujala, 2009), that will be discussed in a later section. This MNS mapping can be seen on an electroencephalogram (EEG) to make stronger inferences about correlations between an action observation.

The purpose of this study looks at a group of avid exercisers and a sedentary non-exerciser group using EEG analysis by analyzing the differences in perception between brain activity when presented with images showing physical and sedentary behaviors, as well as the neuronal pathways that are activated when viewing the active and inactive images. By doing so, this study should distinguish if there are any innate neurobiological differences between the two groups. Within this study, there were two groups: the exercisers and non-exercisers, and two conditions: physically active and sedentary images. The differences between the exerciser group alone and the non-exerciser group alone will also be looked at. The central hypothesis of this thesis is that exercisers and non-exercisers will have differentiated neuronal pathways when evaluating active and inactive images. To achieve this, we examined functional connectivity and graph theory between the two groups and within groups.

Chapter II: A Review of the Literature

Humans are born to be physically active since the beginning of time. However, over time society has been driven away from this idea and has been distracted by modern day technology, which is always evolving. With this, society tends to spend more time behind a cellular phone, computer, or television rather than being physically active and moving their bodies. While there is a portion of the population that still engages in regular physical activity, we wanted to know if there is a neurological difference between the active individuals and the sedentary individuals.

Transtheoretical Model

The transtheoretical model (TTM) of behavior change (de Freitas et al., 2009) assesses the stages of readiness an individual has before beginning an exercise regimen. It has long been considered a useful interventional approach in lifestyle modification programs, such as smoking reduction (Aveyard et al., 2009), weight management (de Freitas et al., 2020), but for this study it was used for physical activity adherence. The TTM consists of five sequential stages: precontemplation (no intention to change), contemplation (intension to change within the next 6 months), preparation (intention to change in the next 30 days), action (engaged in the behavior for <6 months), maintenance (behavioral change sustained for >6 months, Ren et al., 2021). There is also a relapse stage, most will go through a few times before conquering the maintenance stage. These stages were used to reference the participants who volunteered in this study to show how they identify themselves. Participants who are in the precontemplation, contemplation, and preparation stages were recruited for the non-exerciser group of this study. Meanwhile, participants in the maintenance stage of exerciser self-identified themselves as exercisers.

Theory of Mind

It is common to visualize oneself as another person, including their beliefs, desires, emotions, and behaviors. This usually begins when we infer emotions, intentions, and beliefs of the other person (Adolphs, 2009). This concept refers to "theory of mind", the attribution of mental states to others (Hari & Kujala, 2009; Keysers & Gazzola, 2006). It can be thought of as "walking in someone else's shoes" as every human has the ability to think, feel, react, and behave to the environment around us. Mentalizing the other person's understanding of the world is connected to the ability to make first and third person views (Hari & Kujala, 2009). This theory compares with the simulation theory, imagining in one's mind that the actions, emotions, and sensations of others are 'translated' into the neural language of our own actions, emotions, and sensations (Keysers & Gazzola, 2006). It is natural to envision other's lives as humans are curious individuals. Interpreting behavior in terms of underlying mental causes, or 'mindreading,' is widely agreed to be crucial to our ability to succeed in complex social environments: in order to predict and interpret behavior, we need to be able to reason about the hidden, mentalistic causes of action (beliefs desires, intentions, etc.) (Westra, 2019).

There are shared circuits in the brain controlling three systems—actions, sensations, and emotions that are perceived in the premotor and motor cortex and the inferior parietal lobule interconnected with the superior temporal sulcus (STS) for actions, the insula for the emotion of disgust, the anterior cingulate cortex (ACC) and anterior insula for pain, and the somatosensory cortices for touch (Keysers & Gazzola, 2006). By observing how others feel or do, we reflect on our mental representation of how we would feel or do in a similar circumstance. Through the connectivity of these shared circuits, the brain then adds specific first person elements to each situation (Keysers & Gazzola, 2006). To provide examples, it is possible to witness another individual experience pain, so the ACC and anterior insula add a sense of pain; the somatosensory cortices would add a sense of touch when witnessing another individual pet a fluffy dog, and the insula would add a sense of disgust if witnessing someone else eats rotten food. The shared circuits relate these sensations to the brain and body in order to internally simulate the situations. Current brain imaging is converging neuroscience with various behaviors involving human social cognition and interaction (Hari & Kujala, 2009), leading to a better understanding of the human mind and these shared circuits within brain connectivity.

Social Cognitive Theory

Humans are social in their day-to-day lives as it is practically impossible to be withdrawn from others as there are interactions at work, school, or within the family. We want to know what is going on in the world as well as what is going on with ourselves and our bodies. This idea is known as embodied cognition, the idea that cognition depends upon the kinds of experience that comes from having a body with various sensorimotor capacities, and that these individual sensorimotor capacities are themselves embedded in a more encompassing biological, psychological, and cultural context (Garbarini & Adenzato, 2004). Therefore, both the mind and body are interconnected and influence each other on motor behavior.

The sensorimotor concept involves the sensory inputs from the body and producing a motor function from the nervous system as a response. Hari & Kujala, (2009) discussed how the sensorimotor cortex is involved in a circuitry that includes the parietal lobe, and its close connections with frontal areas. This circuitry involves the ventral intraparietal area (VIP) which is coupled to area F4, and controls hand and mouth movements on the basis of visual input. Hari

& Kujala, (2009) explains that the anterior intraparietal area (AIP), which projects to area F5, is considered to be related to affordances, the qualities of objects that are perceived as action possibilities and this AIP-F5 network forms the core of the mirror-neuron circuitry. F5 also receives input from parietal area PF, which itself receives input from the superior temporal sulcus (STS).

Human social cognition encompasses all cognitive processes relevant to the perception and understanding of conspecifics including, but not restricted to, the cognitive processes involved in the understanding of perceived actions performed by conspecifics (Jacob & Jeannerod, 2005). To make stronger inferences about the kind of simulation that takes place in action observation, many groups have begun to incorporate electrophysiological methods aimed at defining the functional anatomy of embodied cognition and the circumstances where there is strong overlap between action, perception, and understanding (Grafton, 2009). As an observer of an action, the brain engages in a bilateral network of cortical brain regions including the bilateral posterior STS, inferior parietal lobule (IPL), inferior frontal gyrus (IFG), dorsal premotor cortex, and ventral premotor cortex known as the action observation network (AON) (Grafton, 2009). A small perceptual stimulus can elicit an extensive recruitment of these numerous parts of the brain. This network likely supports many subtasks, including the formation of perceptions to action, the simulation of observed movements in relationship to known movements, and the storage of physical knowledge (both of self and objects) that can be used for simulation (Grafton, 2009).

Social Identity Theory and Identity Theory

This study will take Social Identity Theory and Identity Theory approach by placing individuals into exercisers and non-exercisers groups. In social identity theory and identity theory, the self is reflexive in that it can take itself as an object and can categorize, classify, or name itself in particular ways in relation to other social categories or classifications. This process is called *self-categorization* in social identity theory, and *identification* in identity theory (Stets & Burke, 2000). Through this process, an identity is formed within oneself. A social group is a set of individuals who hold a common social identification or view themselves as members of the same social category (Stets & Burke, 2000). A narrower view to look at these theories is if a person partakes in a running group, they will most likely identify as a runner. Members who are similar will categorize themselves as in-group and label others who differ as an out-group. With this, members of an in-group will enhance their self-esteem by evaluating the in-group positively and the out-group negatively. In this case, the exerciser group would probably assess themselves as the in-group as they like to focus on physical fitness and health, while the group of non-exercisers would be the out-group as they portray that they do not care to focus on this matter. This accentuation occurs for all the attitudes, beliefs and values, affective reactions, behavioral norms, styles of speech, and other properties that are believed to be correlated with the relative intergroup categorization (Stets & Burke, 2000). This study is expected to have participants that view themselves as an exerciser or non-exerciser based on how they categorize themselves and perceive exercise as part of their identity.

Mirror Neuron System

When observing or engaging with another individual, one (or both) might be involved in “mirroring” the actions and intentions of the other. Our ability to perceive the goals and intentions of others from watching their movements is often ascribed to mirror neurons (Frith & Frith, 2007). The "mirror neurons", possibly responsible for such behavior, were first reported in the monkey frontal lobe, in the ventral premotor cortex area F5 (Hari & Kujala, 2009) and fire when performing or observing an alike action. This mirror neuron system (MNS) was found to be true in humans as well. Such interconnected brain areas form the human MNS, consisting of a frontoparietal sensorimotor network that is considered to support implicit understanding of other persons' actions (Hari & Kujala, 2009). While there is no direct correlation between monkeys and humans, both species use the MNS, but with different regions of the brain.

The activation of MNs is a type of social cognitive process that is driven by perception, which is different in both humans and monkeys. In monkeys, by automatically matching the agent's observed movements onto her own motor repertoire without executing them, the firing of MNs in the observer's brain stimulates agent's observed movements (Rizzolatti et al., 1995; Rizzolatti et al., 2001; Rizzolatti et al., 2004). In humans, the MNs led to a new way of thinking about how we generate our own actions and how we monitor and interpret the actions of others (Kilner & Lemon, 2013). By examining the MNs in monkeys, researchers have discovered more of the mirror system in humans and have raised the prospects of a 'motor theory of social cognition', whose goal is to derive human social cognition from human motor cognition (Gallese et al., 2003; Wolpert et al., 2003; Blakemore & Decety, 2001; Metzinger & Gallese, 2003; Gallese & Goldman, 1998). This theory relates back to executing a specific action and observing the same action that fire the MNs, and therefore allows the understanding of the perceived action. It should be understood that there is a differentiation between human mindreading and the psychological process of understanding perceived actions by the MNs.

Neuroanatomy

The primary motor cortex, premotor cortex and cerebellum are all a part of the motor system used in our everyday lives, especially when involved in exercise. Exploring brain function increases scientists' comprehension of this mysterious system and may facilitate the diagnosis of neuropsychological diseases and, for many years, the central theme of brain function was that of functional localization, i.e., each separate region of the cerebral cortex dictates a specific function (Zhang et al., 2014). Therefore, it would be hypothetically feasible to delineate the region of the cortex that implements a certain function, but electrophysiological techniques were applied to validate such functional localization (Zhang et al., 2014). Within these parts of the brain, as well as others, we will be looking at certain parts that are involved in action perception. The medial prefrontal cortex (MPFC) is activated when thinking about mental states of self and other (Amodio & Frith, 2006; Saxe 2006), which is tied in with ToM. The anterior cingulate cortex (ACC) and anterior insula (AI) are associated with experience of emotions, also tied into the SCT (Wicker et al., n.d.; Singer et al., 2004). The inferior frontal gyrus (IFG) and intraparietal sulcus (IPS) are associated with action execution and action observation (Hamilton, 2006; Rizzolatti & Craighero, 2004). The tempo-parietal junction (TPJ) is associated with perception (Blanke, 2005; Aichhorn et al., 2006) and the posterior superior temporal sulcus (pSTS) is used for action observation when reading intentions from actions (Puce & Perrett, 2003; Pelphrey et al., 2004; Saxe et al., 2004).

The brain is no longer considered to work via individual regions but rather by several regions working cooperatively (Varela et al. 2001). The cerebral cortex in the human brain is a 2-4 mm thick sheet of gray matter that generally has 5 or 6 layers with pyramidal neurons aligned in the same direction perpendicularly along the surface of the cortex, in which there are at least

10^{10} neurons (Kida et al., 2016), making them the most populous cell type. They have long, thick apical dendrites that can generate strong dipoles along the somatodendritic axis that induces substantial ionic flow in the extracellular medium. Therefore, neurons that generate open fields, such as pyramidal cells, make a sizable contribution to the extracellular field (Buzsáki et al., 2012). When large numbers of neurons with the same orientation in restricted cortical layers are synchronously activated by trans-synaptic inputs, it is possible to detect the resulting magnetic fields using magnetic field sensors placed near the scalp.

The precuneus is a region in the brain that rests between the occipital lobe and parietal lobe in the medial surface of the cerebral hemisphere. The precuneus, along with the adjacent areas within the posteromedial parietal cortex, is among the most active cortical regions according to the “default mode” of brain function during the conscious resting state, whereas it selectively deactivates in a number of pathophysiological conditions (ie, sleep, vegetative state, drug-induced anesthesia), and neuropsychiatric disorders (ie, epilepsy, Alzheimer’s disease, and schizophrenia) characterized by impaired consciousness (Cavanna, 2007). One method that has been of particular interest is the default-mode network (DMN), comprising the posterior cingulate cortex (PCC) and precuneus, medial prefrontal cortex, and bilateral temporoparietal junction (TPJ) (Utevsky et al., 2014). This portion of the brain seems to correlate with self-reflection processes, possibly involving mental imagery and episodic/autobiographical memory retrieval (Cavanna, 2007). Studies have shown that PCC/precuneus exhibits increased activation during many tasks—including autobiographical memory retrieval (Maddock et al., 2001), reward outcome monitoring (Hayden et al., 2008), and emotional stimulus processing (Maddock et al., 2003—all from Utevsky et al., 2014)—further challenging the association of DMN with task disengagement, and highlighting the differences between the functional core of DMN and the network more broadly (Utevsky et al., 2014). The precuneus has long remained one of the less accurately mapped areas of the whole cortical surface (Cavanna, 2007). Its strategic location and widespread connectivity patterns suggest that it is a major association area that may subserve a variety of behavioral functions, which the modern era of neuroimaging has begun to unravel (Cavanna, 2007). The researchers found that during the baseline resting state, a neural network comprising the precuneus and posteromedial parietal region, along with lateral parietal, ventromedial prefrontal, mid-dorsolateral prefrontal, and anterior temporal cortices, exhibits a remarkably high metabolic activity (so-called hotspots) (Cavanna, 2007). Moreover, the tonic level of activity in the precuneate cortex and of the other regions of the brain characteristically decrease when subjects are engaged in goal-directed cognitive processing or perceptual tasks (task-induced deactivations (TIDs) (Cavanna, 2007). One possibility that TIDs and selective hypometabolism in pathophysiological conditions affecting consciousness relate to resting-state mentation is that when an individual is awake and alert and yet not actively engaged in particular cognitive task, the precuneus and interconnected posterior cingulate and medial prefrontal cortices subserve continuous information-gathering and representation of the self and external world (Cavanna, 2007).

When non-self-referential goal-directed processes are interrupted, reflecting a necessary reduction in resources devoted to general information gatherings and evaluation (Cavanna, 2007). It is suggested that precuneus activity during conscious resting states supports conceptual processing operating on internal stores of information (endogenous signals) rather than "perceptual" functions (concerned with sources of information external to the brain) (Cavanna, 2007). This area seems to contribute to the self-referential "thought" processing that humans experience during resting consciousness (Cavanna, 2007). This is otherwise known as episodic memory retrieval tasks, the ability to consciously recall personal past events and being able to relate to them. This has highlighted clear dissociation between the precuneus and the neighboring posterior cingulate cortex, which have traditionally been grouped together as a functional unit within the medial parietal region (Cavanna, 2007). Yonelinas and colleagues found that the precuneus was related to familiarity whereas the posterior cingulate was related to recollection (Cavanna, 2007). Overall, during the baseline resting state this neural system is likely to be engaged in higher mental functions involving something similar to contemplative thought against a background of general body awareness, upon which any extended consciousness is constructed (Cavanna, 2007).

Brain Connectivity and Mapping

The brain network is a complex system that is constantly working whether we realize it or not. Neurons in the brain do not function independently, rather they rely on interacting with different brain regions using afferent and efferent connections to enable different sensorimotor and cognitive tasks to be performed (Horwitz, 2003). The network is defined as a collection of nodes (vertices) and links (edges) between pairs of nodes (Rubinov, 2010). The nature of nodes and links in individual brain networks is determined by combinations of brain mapping methods, anatomical parcellation schemes, and measures of connectivity (Rubinov, 2010). Brain connectivity is an elusive concept that refers to different interrelated aspects of brain organization (Horwitz, 2003) and is normally divided into three different categories: anatomical or structural, functional (FC) and effective connectivity (EC) (Niso et al., 2013). For this study, we used FC, the statistical dependence between the signals stemming from two (or among many) distinct units within a nervous system (from single neurons to whole neural networks), while EC refers to the causal interactions between (or among) them (Friston, 1994; 2011). Neither FC nor

EC involve physical connections, but rather the existence of a relationship between these signals. While both are related to the stability of phase relationships of two independent signals (channels) or the coherent phase difference between them (Niso et al., 2013), EC relies on the probability that the history of one signal can change the probability of another, threin creating the causal relationship. Both FC and EC can be observed from multivariate neurophysiological signals by analyzing the interdependence between time series. These connectivity measurements are used to examine relationships between two time series experimentally recorded from, for example, different brain regions, from a brain region and muscle, from cortical and subcortical regions, from a subcortical region and muscle (i.e., electromyographic activity), and from a cortical region and kinematics (i.e., acceleration of movement) (Kida et al., 2016).

Using EEG Analysis

Electroencephalography (EEG) is one of the oldest and most widely used methods for the investigation of electric activity in the brain (Buzsáki et al., 2012). The millisecond temporal resolution of EEG measurements makes using this technique an ideal candidate to study the brain as a dynamic system (Nolte et al., 2004). Temporal resolution may be considered in two manners; one is as an aspect of the measuring device, while the other is as a physiological aspect depending on its electromagnetic properties and the temporal profile of underlying neuronal activity (Kida et al., 2016). EEG is a classical tool that has been used for nearly 100 years since its first application to humans (Berger, 1929), but in years past, there has been more recognition when it comes to interpreting rhythmic EEG to determine brain connectivity. EEG also considers a measure of ‘interaction’ that is probably the simplest and most popular measure at a specific frequency known as coherence, a generalization of correlation to the frequency domain (Nunez et al., 1997, 1999). Coherence is studied as a relation between EEG or MEG channels (Nolte et al., 2004) while EEG always needs a reference similarly to the electrode pairs being studied that can contribute significantly to the coherence, and thus, relative power changes may also affect coherencies without reflecting a change in coupling (Fein et al., 1988; Florian et al., 1998). Coherency between two EEG channels is a measure of the linear relationship of the two at a specific frequency (Nolte et al., 2004).

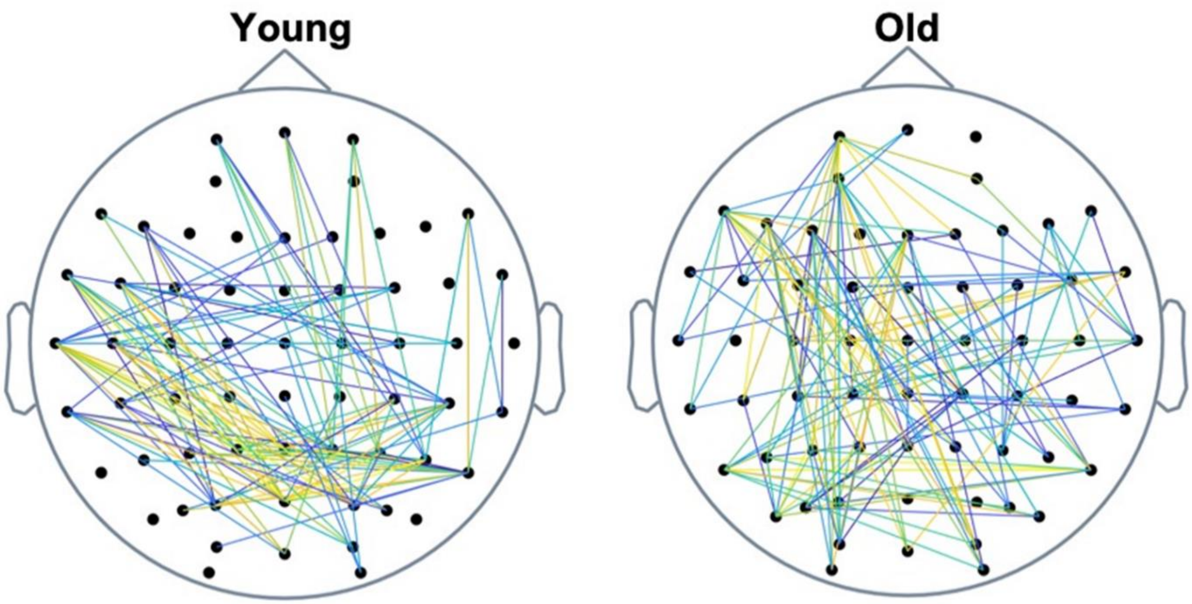
Although used for many years, coherence is essentially a version of the Perasron's correlation statistic. One of the challenges this presents is the concept of volume conduction, or that two electrodes can show artificial coherence simply due to their relative proximity to a point-source of activity. This source creates electrical activity that spreads through extracellular space and can be measured by multiple electrodes simultaneously, leading to a misinterpretation of their true connections. More advanced measures have been developed that control volume conduction through various normalization techniques. For this work, we will focus on the weighted phase lag index (wPLI), which normalizes the real part of the cross spectrum against the imaginary part of the cross spectrum, thereby removing the potential influence of volume conduction. This study intends to interpret the wPLI between EEG channels and their interaction between different brain sites.

When a large number of neurons with the same orientation in restricted cortical layers are synchronously activated by trans-synaptic inputs, it is possible to detect the resulting magnetic fields using magnetic field sensors placed near the scalp (Kida et al., 2016). These trans-synaptic inputs induce a primary current, which is related to the movement of ions due to their chemical concentration gradients, and passive ohmic current (also called volume current), which occurs in the surrounding medium, in the brain as a volume conductor, with the latter current completing the loop of ionic flow in order to prevent the buildup of charge in the conductor (Hämäläinen et al., 1993). Electric fields generated in the brain spread in space via different conductor media (volume conduction), and, thus, EEG signals recorded by different scalp sites include an electric field derived from a common current source (Kida et al., 2016).

EEG records the time series of a potential difference (voltage) between two sites (recording and reference sites) while the signals mainly include volume current originating from both radical and tangential current scores (Kida et al., 2016). The most important factor is that the most advanced EEG systems can detect signals with a sampling rate faster than 1 kHz and can record subtle and swift changes in neuronal activity, an important advantage, hence, EEG can provide precise measurements of brain activity (Zhang et al., 2014) that will be needed for this type of research.

Essentially, the EEG cap builds a "roadmap" for how information is transmitted across the brain and is debated whether it uses holism or localizationism to determine this phenomenon. Holism is the idea that discrete brain functions are distributed across the brain, while localization is when discrete brain functions are solely controlled by discrete regions of the brain. Despite which concept of brain function it is thought to be, this study aims to look more into which of these ideas supports this research. Below is an example used from a different study of how a young and an old population distributes information throughout the brain using functional connectivity.

Example of Connectivity Analysis



Weighted Phase Lag Index

One of the central theories of this study is to determine how the brain talks to itself and information is traveled throughout. It has been found that functional connectivity (FC) using weighted phase lag index and graph theory can explain such a phenomenon. Modern network science, a mixture of dynamic systems theory, graph theory and statistics, has been applied to the study of the functional and structural brain connectivity network under various states and conditions (Ismail & Karwowski, 2020). The theoretical framework for understanding large-scale networks is given by 'modern network theory', a branch in graph theory, in which networks are represented by a set of nodes (vertices) and connections (edges) (Stam et al., 2009). The modern era of graph theory began in the late 1990s with the discovery of small-worldness (Watts & Strogatz, 1998) and scale-free network models (Barabasi & Albert, n.d.), enabling the quantification of brain connectivity patterns (Ismail & Karwowski, 2020). He stated that small-world networks have a relatively high amount of so-called 'local clustering', meaning that nodes are often connected to their neighbors, combined with relatively short ‘path lengths’, which means that from any node it takes just a few steps to reach any other node in the network (Stam et al., 2009). Well-ordered networks are strongly clustered and show large path lengths, in contrast, random networks are weakly clustered with small path lengths (Stam et al., 2009).

Graph theory provides models of complex networks in the brain, and allows one to better understand the relations between network structure and the processes taking place on those networks (Stam et al., 2009). This study used the Alpha band, due to its involvement in visuomotor processing and widespread distribution. The “connectome” refers to the connectivity among different brain regions and the manner by which information is transferred among these regions (Sporns, 2011). Functional connectivity (wPLI) was used to determine the statistical interdependencies between physiological time series recorded from different brain regions (Friston et al., 1993; Friston, 1994), however, the functional brain connectivity and network topology in the context of cognitive neuroscience in the context of physical activity is largely unknown (Ismail & Karwowski, 2020). The first proposal of graph theory for EEG data was reported by Stam et al., 2009. who compared the functional brain network of control individuals and patients with Alzheimer’s disease (Ismail & Karwowski, 2020). EEG is capable of capturing the rich temporal information that aids identification of the directions of the flow of information among different brain regions (i.e., causal inference) (Hassan & Wendling, 2018). Since brain activity and behavior are determined by both neuronal spiking activity and the communications between neurons, we can expect that the firing activity and functional connectivity between neurons may also be highly regulated across behavioral states. It is probable that the coupling of the neuronal activity and behavioral states are based on the anatomical location of involved neurons when using the EEG coordinate (Olcese et al., 2016). Functional coupling between individual neurons that are measured in terms of firing rate fluctuations (Harris & Thiele, 2011), not only changes as a function of brain state, but is also highly dependent on distinct brain areas (neocortex vs hippocampus), distance between neurons (within and between brain regions), neural subtypes (excitatory vs inhibitory cells), and on functional properties of individual neurons that correlate highly localized processes (Olcese et al., 2016). Nevertheless, this study will give a brighter insight into this functional brain connectivity and how information is traveled throughout the brain.

Chapter III: Methods

Participants

Inclusion criteria for all participants are designated as: 1) healthy young males and females aged between 18 and 35 years, 2) right hand dominant, 3) healthy by self-report, 4) self-reported absence of previous neurological illness or injury, 5) self-reported absence of prescription medication usage. For this project, the term healthy is defined as any individual free of upper or lower extremity neuromuscular disability, as well as an absence of any neurological disease or obvious precursor to a neurologically debilitating disease. All participants have normal or corrected-to-normal vision. Specific exclusion criteria include: 1) a history of upper or lower extremity neuromuscular illness or chronic injury and 2) upper or lower extremity neuromuscular debilitating condition, 3) left-hand dominance. Exclusion criteria are designed to prevent extraneous factors from confounding the neural or behavioral activation patterns in healthy subjects, which are a primary focus of this work.

All research procedures will be performed in accordance with all regulations specified by the University and Medical Center Institutional Review Board (UMCIRB) of East Carolina University. Two groups of participants will be recruited for this study, each with 15 participants. The experimental group ("Exercisers") will consist of individuals who have engaged in a minimum of 150 minutes of moderate aerobic exercise (AE) a week for a minimum of 6 months. The control group will consist of healthy participants who do not regularly engage in AE, e.g., not more than 30 minutes per week. They have also engaged in a minimum of 2-3 days a week of muscle strengthening activities including all major muscle groups for a minimum of 6 months.

Once participants of this study came into the lab, they are required to review, sign, and date the informed consent as well as answer a self-assessment that were given to them by a member of the research team. The self-assessment includes a SAM scale-like self-report made by the researcher of their overall physical activity in the past 6 months, how they feel about exercise, and how important physical activity is to their lifestyle. This was another way, along with the TTM, to identify each participant and place them in either group. It is understood that the self-assessment that were given are poorly controllable by the researcher, such as insight, motivation, and the subject's honesty leading to the subjects that typically tend to answer in a more socially desirable way than could be presumed from their actions (Hari & Kujala, 2009). Therefore, this study was based on self-identity and is supported by the SIT. Participants were recruited by word-of-mouth and flyers around East Carolina University in Greenville, NC. We aimed to recruit 15 individuals for the exercise and non-exercise groups each, however totaled 17 exercisers and 13 non-exercisers.

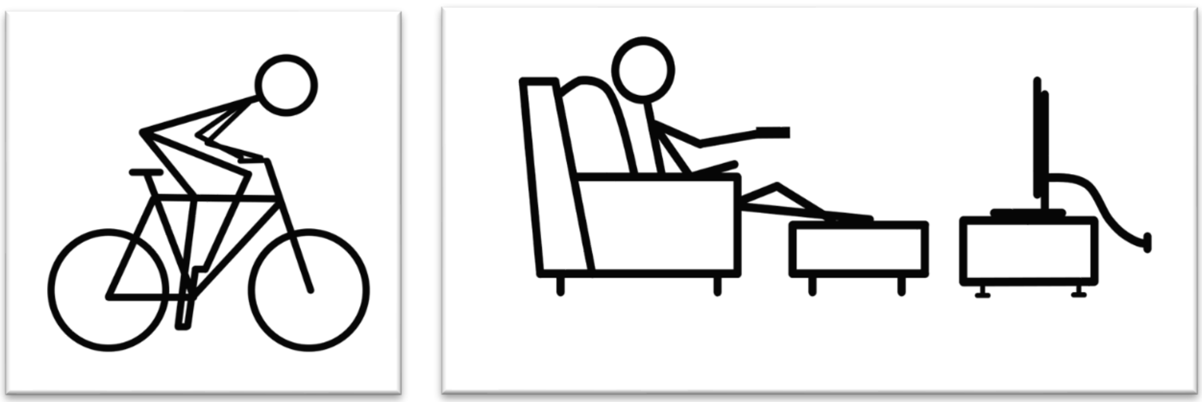
Procedures

Once the questions that were given to participants were analyzed and reviewed, participants visited the PI's research lab (Sensory-Motor Integration Laboratory; 170A Minges Coliseum, Greenville, NC, 27858) located on the Grady-White Boats Athletic Campus of East Carolina University. Participants were prepared to be set up to the EEG and rest for a few moments. For EEG preparation, participants were seated in a chair and any hair care products were removed from the hair and scalp with an alcohol-saturated cotton pad. The forehead was prepared by wiping the area with a cotton pad and a solution of pumice and Vitamin E, thereby removing any residual oil and dirt from the skin. The head was measured with a Gulick measuring tape from the naison to the inion. With that, the researcher made a small mark at 10% of the measurement, somewhere on the center of the forehead, as the universally known EEG head measurement. This is where the ‘reference’ electrode was placed, also known as Fz. Once the cap was securely on the head, the chin strap was attached and fastened. Participants were fitted with a 64-channel EEG cap (Compumedics Neuroscan, Charlotte, NC) to record neural activity using SynampsRT (Compumedics Neuroscan, Charlotte, NC). Once the cap was in place and properly aligned, the scalp under each electrode was prepared by first gently abrading the skin using the wooden end of a standard cotton swab with pumice and Vitamin E to reduce impedance to the electrode, and then applied a conductive gel with a 16-gauge blunt needle.

Various pictures were presented to them using stick-figure people performing activities including walking, hiking, lifting weights (physically active images) and sitting on the couch, sleeping, eating (physically inactive or sedentary images) etc. The stick-figure images were created to eliminate potential biases (i.e. weight, expression, connotation of “sedentary activities”), whereas using an overweight/obese or lean individual would potentially allow the participant to have different thoughts or perspectives of the activity based on their looks and size. Below is an example of a physically active image (A) and a physically inactive image (B) that were shown to the participants. There were 25 physically active images and 25 physically inactive images shown. Before each image appeared on the screen, a plus sign (+) and then a circle (○) would become visible in the middle of the screen to focus the participant’s eyes on the center. The computer was randomized to project the image within 2-5 seconds after centering the eyes. This was done to reduce anticipation from the participant of when the image would appear. A series of these physically active and inactive images would appear in random order until all 50 images were shown.

Examples of physically active (A) and physically inactive images (B)

A B



Eye movements were recorded with electrodes placed above and below the eyes to capture electrooculographic (EOG) activity. Data acquisition was performed using a common average reference at a sampling rate of 1KHz and filtered to DC-100 Hz. Potentials from the right and left ears will also be recorded and used (offline) for artifact correction. Participants were seated 1.8m (6') in front of a 119.38 cm (47") widescreen visual display for visual presentations. The display was placed in the middle of their visual field, and its height matched to the eye of the seated subject. The participant was instructed to use a Go/No-go task by using their index and middle finger. They were presented with images of simple stick-figure people performing static activities to distinguish how they view an active and inactive picture presented. The participant would recognize the action and use their index finger to click a button if they view the image as inactive, and the middle finger will click a button if they view the image as active. This was subjective based on all fifty images presented. Once the subject viewed all fifty images, the round was over. The participant was then able to relax, talk, and adjust themselves in their seats. There were two rounds completed for distractions and averages taken per participant.

Instrumentation

Electroencephalography (EEG) gives researchers a tool to noninvasively evaluate both localized and widespread brain activity at a high temporal resolution in the time-voltage (ERP, VEP, MRCP) and time-frequency (power spectrum connectivity, ERD/S) domains. The MRCP is commonly used as an electrophysiological correlate of regional cortical involvement before and during voluntary movement (Shibasaki & Hallett, 2006). Similarly, the event-related potential (ERP) is a waveform of predictable shape, amplitude and latency that follow the onset of a stimulus, making it a powerful correlate of localized neural activations (Mizelle & Wheaton, 2011; J.C. Mizelle & L. A. Wheaton, 2010; J. C. Mizelle & L. A. Wheaton, 2010). As the ERP and MRCP are markers of brain activity in the time-voltage domain, changes in EEG signal strength in a particular frequency bandwidth (power spectrum, ERD/S) reflects regional brain activation in the time-frequency domain (Pfurtscheller & Aranibar, 1977). Most commonly, spectral studies are related to motor control within the alpha (~8-12 Hz), beta (~13-25 Hz) and theta (~4-8 Hz) frequency bands is described. Due to differences in temporal and spatial representation (Toma & Hallett, 2003), it is suspected that voltage and spectral properties represent different cortical processes underlying a particular movement or cortical process, thereby providing complimentary measures of movement related neuronal activation (Babiloni et al., 1999). As such, both time-voltage and time-frequency measures will be used in the current study.

As the EEG signal is related to activation of summed post-synaptic processes recorded at a high sampling rate, it has very fine temporal resolution. However, EEG is not recorded directly from the generators of this activity, causing a weaker spatial resolution. The Curry software package (Compumedics Neuroscan, Charlotte, NC) allows for sophisticated localization of cortical and grey matter linear solutions through the importation of template MRI scans to which EEG data can be co-registered for improved spatial accuracy of estimated neuroanatomical generator sources. Following the completion of data acquisition, the 3-D location of sensors will be recorded to allow for the merging of EEG and template MRI images. Three external indicator coils will be placed on the left and right pre-auricular points and the nasion. The exact location of these markers with respect to anatomical landmarks will be imaged with digital photography (e.g. a digital image, focused only on the marker and the surrounding anatomy, will be made of each marker with a high zoom factor; the subject will not be identifiable in the image), and the precise 3-D position of each sensor will be digitized using the Polhemus Fastrak following the recording session (Polhemus Fastrak, Colchester, VT). Following initial EEG processing and analysis, we will evaluate source activations at peak latencies identified in time- and frequency domain analyses described above. Statistical significance will be set at $p < 0.05$.

This study used a resting EEG to analyze the brain wave frequencies when activated by an external stimulus and have been shown to be reliable on regional brain activity. An EEG measures excellent temporal resolution, necessary for this degree of study, but are relatively poor in their spatial resolution (Grossmann & Johnson, 2007). Recording electrophysiological activity is one way that the relationship between resting-state and behavioral performance can be directly assessed (Rogala et al., 2020). Several studies have revealed correlations between certain EEG rhythms to differentiate cognitive performance. The MATLAB software was used to analyze the recordings of the brain waves as well as compare and contrast the data.

EEG studies have distinguished between two rhythms at rest, both of which occur in the alpha frequency range (8-13Hz) including alpha rhythm and a central mu rhythm (Rizzolatti et al., 2001). The posterior alpha rhythm is present when the sensory systems, particularly visual system, are not activated, and disappears on the presentation of sensory stimuli; while the mu rhythm is present during motor rest and disappears during active movements and somatosensory stimulation (Rizzolatti et al., 2001). Alpha oscillations have been proposed to clear sensory information from distractors, the beta to gamma band ratio can assure critical-state dynamics for optimal information processing and alpha and beta band activity can reduce attentional investment during rest (Rogala et al., 2020).

Design and Analysis

The researcher created codes for data computation in Matlab to assess the information. Brain activity was recorded with Compumedics Neuroscan CURRY8 and then analyzed using EEGLAB and custom software in Matlab to determine differences in brain connectivity within and between groups. By comparing both the neuronal pathways and brain waves, we can distinguish if there were significant neurobiological differences between the exercisers and non-exercisers that might lead to the reasoning of why one individual or population exercises, while another does not.

Data Processing

Offline, high pass (0.1 Hz) and low pass (45 Hz) filters was applied. Data was epoched from 1000 ms before the onset of the prime stimulus through 1000 ms after the target stimulus, which included the warning cue and the full duration of all stimuli. Time zero (0 ms) will be related to the onset of the prime stimulus, and each epoch will be baseline corrected over the interval from -250 to -550 ms. Based on the unique markers created in the SuperLab – SynampsRT interface for each stimulus, epochs will be sorted into their respective trial variants. The Artifact Subspace Reconstruction technique (ASR) was used to automatically remove ocular, muscular, electronic and other artifacts from the data (Mullen et al., 2015). Any trials with residual artifact were visually identified and removed from analysis.

The surface Laplacian was applied to the data to serve as a spatial filter, thus resulting in the calculation of the Current Source Density (CSD; Kayser & Tenke, 2006) of the scalp data and sharpening the spatial topography of the observed activations. In essence, the CSD maps represent the magnitude of the radial (transcranial) current flow from the brain to the scalp (source) and to the brain from the scalp (sink). As a net effect, the CSD transformation functions as a high-pass spatial filter that minimizes the electrical distortions produced by the mediums between cortical surface and sensor (electrode) such as skull and scalp, thus facilitating spatial separation of temporally overlapping components. Therefore, the benefits of a CSD transform are a reference-free, spatially enhanced representation of the direction, location, and intensity of current generators that underlie the recorded scalp potentials, and CSD provides topographies with more sharply localized peaks than those of the scalp potential, while eliminating volume-conducted contributions from distant regions and sources. CSD data was used for all subsequent procedures.

Data Analysis: Time-Frequency Domain

Changes in EEG signal strength in a particular frequency bandwidth reflects regional and interregional brain activation in the time-frequency domain (Pfurtscheller & Aranibar, 1977). Most commonly, ERD/S related to motor control within the alpha (~8-12 Hz), beta (~13-30 Hz) and theta (~4-8 Hz) frequency bands is described. Due to differences in temporal and spatial representation, it is suspected that time-voltage and time-frequency data represent different cortical processes underlying a particular movement, thereby providing complementary measures of neuronal activation (Babiloni et al., 1999). As such, both time-voltage and time-frequency measures were used in the current study.

Specifically for time-frequency measures, a complex Morlet wavelet transformation was used to extract instantaneous power and phase within all frequency bands (1 Hz resolution, 1-40 Hz range). A Morlet wavelet is defined as a sine wave tapered by a Gaussian. For time-frequency analysis, a complex Morlet wavelet was used, in which the Gaussian tapers a complex sine wave. The complex Morlet wavelet was then convolved with the time series signal, and the result of convolution is a complex-valued signal from which instantaneous power and phase can be extracted at each time point.

Wavelet convolution can be conceptualized as a “template-matching” procedure, in which each time point in the signal is compared against a template (the Gaussian-windowed sine wave), and the result of the convolution is a time series of “similarities” between the signal and the wavelet. There are several advantages of Morlet wavelets for time-frequency analysis. One is that the Morlet wavelet is Gaussian-shaped in the frequency domain. The absence of sharp edges minimizes ripple effects that can be misinterpreted as oscillations, which is a potential danger associated with plateau-shaped filters). Second, the results of Morlet wavelet convolution retain the temporal resolution of the original signal. Third, wavelet convolution is more computationally efficient and requires less code compared to other methods, because it involves the smallest number of computations, most of which are implemented using forward and inverse realizations of the fast Fourier transform.

Data Analysis: Functional Connectivity

From the analytic signal, the complex auto- and cross-spectrum for each channel and channel pair, respectively, was calculated for the theta, alpha and beta bands. Because the wPLI is a useful method to identify nonzero phase lag statistical interdependencies between EEG time series (from pairs of electrodes), it was used to identify neural interaction among brain regions in this work (Vinck et al., 2011). Because of likely non-normality, adjacency matrices derived through wPLI will be compared through nonparametric permutation statistics. Briefly, ground-truth adjacency data was used to create a null statistical distribution or a distribution that would be true if there was no dependence on specific channel pairs in the actual distribution of connectivity estimates. This was accomplished by randomly permuting electrode labels through 1000 iterations (McDonnell et al., 2021). A Fisher's Z-statistic map (Zmap) was then calculated, and a critical value ($t = 1.6449$ for $p < 0.05$) was used to threshold the Zmap, therein removing values falling below the critical value. The Zmap was then used to mask the ground-truth connectivity matrix, leaving only connectivity values that were statistically reliable according to the permutation test.

Data Analysis: Graph Theory

Network studies of large-scale brain connectivity have begun to reveal attributes that promote the segregation and integration of neural information (Sporns, 2013). To formally characterize interregional communication, the adjacency matrices derived through the permutation procedure were then subjected to graph theoretical measures. Graph theory focuses on the properties and behaviors of networks defined as systems consisting of a set of nodes (electrodes) linked by edges (connections or interactions) and has been used to distill multidimensional data sets into simpler, discrete numerical representations of global and local network integrity and function.

Two concepts are often used to describe the function of brain networks. The functional segregation of a network reflects local information processing and is often characterized by measures such as modularity and clustering coefficient. On the other hand, the functional integration within a network reflects global processing and can be characterized by measures such as global efficiency and characteristic path length. These concepts and specific measures will be central to this work to evaluate network properties.

Statistical Analyses

For connectivity measures, the nonparametric permutation statistics were applied as described above for the different conditions.

Chapter IV: Results

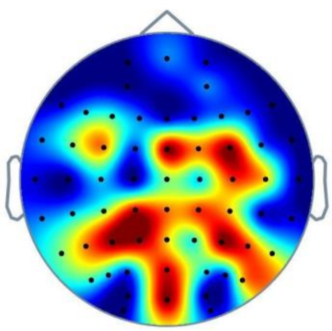
Within this study, there were two groups: the exercisers and non-exercisers, and two conditions: physically active and sedentary images. These consisted of: the exerciser group looking at physically active images (EP), the exerciser group looking at sedentary activity images (ES), the non-exerciser group looking at physically active images (NP), and the non-exerciser group looking at sedentary activity images (NS). Looking at the figures from an aerial point of view, there are no distinct correlations between all of the groups shown as none of the data look exactly alike and the "hotspots" are located in different areas of the brain, with a few exceptions. One of the most significant findings is that this study shows none of the groups think alike. The only similarity of both groups was that all of the hotspots are located in the parietal lobe as it uses interpretation of sensory information, primarily with the visual field.

The EP group revealed the most active FC out of all groups over the parietal and occipital lobes. This group showed strong visuomotor processing and widespread distribution among different brain regions including the frontoparietal lobes. This is believed to be supported by the MNS by using one's episodic memory to activate these neurons as this group has implemented these physical activities into their daily lives. When looking at the ES group compared to the EP group, there were overall less hotspots shown. The main area of focus for the EP group was a hotspot around the precuneus, an area that uses recollection, memory, and mental imagery. This could be the result of the exercisers imagining themselves participating in the sedentary activities shown.

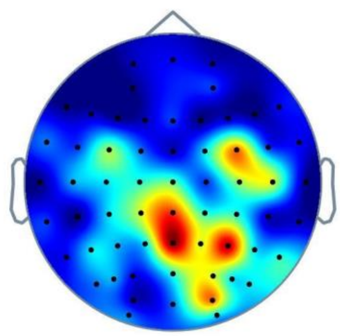
There was also one major hotspot located in the NS group around the precuneus area. It is similar, but not identical to the ES group. Using the idea that the brain was using recollection, it is possible to say that these areas were highly active due to the fact that everyone, whether highly active or sedentary, can relate to engaging in sedentary activities daily. This includes being on the phone, watching television, eating, sleeping, etc that were depicted in the images. There is slightly more surface area covered in the precuneus area in the NS group, while smaller hotspots are presented around in the ES group. We are unsure of why these hotspots appeared but believe it could be due to the ES group had to use more imagination of themselves partaking in these sedentary activities as they are less sedentary than the NS group. Therefore, the ES group was subconsciously influenced about behaving in this inactive manner by showing more active neurons firing in these spots.

Between the EP and NP group, there were similarities of hotspots around the IPL. In the NP group, it is the only major hotspot that we recognized. This area is known for perceiving a concept from a different point of view, agreeable with the idea of sedentary individuals having a different attitude toward the physically active images than the exerciser group.

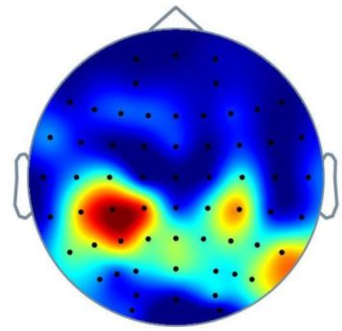
Figures from the data collected



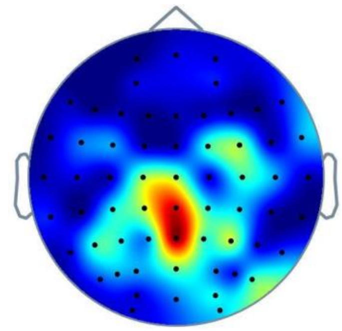
EP



ES



NP



NS

Chapter V: Discussion

The overall purpose of this work was to determine if there were any innate neurological differences between individuals who exercise regularly and commit to being an exerciser and sedentary individuals who do not like to participate in physical activity and exercise. This was done by using EEG looking at FC specifically. By doing so, we discovered that not everyone views exercise the same, however, everyone (in the study) viewed sedentary activities in the same region of their brains, the precuneus.

In the EP group, there were several hotspots, located on both hemispheres of the brain, and are pinpointed specifically along the parietal and occipital lobes, with some hotspots positioned in the frontoparietal lobes. The frontoparietal lobe was discussed earlier when talking about MNS, a frontoparietal sensorimotor network that is considered to support implicit understanding of one's actions. This finding would agree with Hari & Kujala's (2009) study and used episodic memory to activate these neurons as this group has implemented these physical activities into their daily lives.

The ES group had remarkably less hotspots than the EP group. The ES group resembles the NS group most as the precuneus area, located between the occipital lobe and parietal lobe in the medial surface of the cerebral hemisphere and adjacent to the areas within the posteromedial parietal cortex, contains the most similar hotspots as it is among the most active cortical regions according to the "default mode" of brain function during the conscious resting state when hooked up to the EEG. This data suggests that looking at sedentary activities is relatable to both an exercise and non-exercise population as all of society can associate to engaging in modern everyday innate sedentary activities such as sleeping, eating, using one's cell phone, etc., but with moderation from the ES group. However, there is one difference between the ES and NS groups as there are two smaller hotspots located to the right in the ES figure. The reason for these two hotspots are unknown, but it raises the possibility that it could be related to the ES population having less familiarity with these types of sedentary activities as they bring less attention to these occurrences daily than the NS group. Therefore, the ES group was subconsciously influenced about behaving in this inactive manner by showing more active neurons firing in these spots.

The NP group revealed a major hotspot in the left inferior parietal lobe (IPL). This area, along with the left temporo-parietal junction (TPJ) that overlap one another, is best known for tracking potential differences of perspective tasks (Arora et al., 2015). Existing evidence suggests regional specificity (Kanwisher, 2010) of different kinds of perspective tasks activate the left IPL (Almor et al., 2007). Therefore, this group of non-exercisers was sensitive to perspective differences of the physically active images, which is agreeable with ToM. The non-exercisers were not used to such physical activity in their everyday routines, activating the IPL and TPJ regions as they subconsciously envisioned themselves doing the activities presented in front of them.

Conclusion

The central hypothesis, exercisers and non-exercisers will have differentiated neuronal pathways when evaluating active and inactive images, was supported by the data collected. It is clear that the within groups analysis, the EP and ES groups showed hotspots in different brain regions. The exercisers looking at physical activity showed greater EEG activity when presented with active images compared to inactive images as there was possibly greater excitability in the brain due to viewing activities that the subject enjoys participating in. This figure shown has strikingly more hotspots than the other figures portrayed as the hotspots support the amount of brain activity that was found in the EEG analysis using functional connectivity. The ES figure showed most of its activity in the precuneus area.

When looking at the within groups of the NP and NS groups, there are also hotspots located in different brain regions. This analysis also supports the data as the NP group showed active hotspots in the left IPL area, and the NS group showed hotspots in the precuneus area. The reason why the NP group did not have any activity near the precuneus is because they had no past recollection of being physically active when looking at the images. Both these figures showed centralized hotspots in the parietal lobe, whereas the EP group alone showed multiple hotspots as a bilateral sensorimotor network.

There are comparable differences in the within-group analysis, but there are also similarities in the between-groups analysis. While the EP group showed hotspots all around the brain, there is one similar area of activity in the EP and NP groups in the left IPL. It is obvious that the precuneus was highly active in the ES and NS groups. This is very plausible as the precuneus area is known for self-reflection and mental imagery. Everyone, whether an exerciser or not, can relate to participating in sedentary activities. The average human partakes in sedentary activity daily, whether it is being on a cell phone, using a computer, sleeping, eating, etc. This supports the data shown in the precuneus area for both groups. Overall, none of the figures are exactly alike.

This concludes that the exerciser group had more EEG activity and functional connectivity when looking at both conditions presented in front of them. The non-exerciser group had mainly two areas of focus per figure, whereas the exerciser group showed many areas of hotpots throughout the brain. In conclusion, the exerciser group had greater areas of hotspots than the non-exerciser group.

All three theories, SCT, ToM, and SIT, supported the data in this study. The SCT was supported by the data by using strong overlap between action, perception, and understanding while viewing and comprehending each scenario presented in front of the participants. ToM was supported from the differences and similarities of the shared circuits in the brain being highlighted in the figures above. SIT was supported by participants using the SAM-scale when self-analyzing how they felt about exercise in general.

Overall, ToM supported the data the most. It is believed by the researcher that the reason for the way the figures were portrayed was due to the participants having attribution of mental states to others. This again, can be thought of as “walking in someone else’s shoes”. The exerciser group mentally imagined themselves being physically active as well as sedentary as they take part in these activities regularly. The non-exerciser group imagined themselves being physically active as they mentally imagined themselves exercising. They also, along with the ES group, imagined themselves being sedentary since they have physically done this before. Therefore, both groups looking at both conditions supported ToM as all the participants were subconsciously imagining themselves partaking in the activities shown in the images.

This research included many strengths and limitations. The strengths include a non-invasive evaluation of both localized and widespread activity at a high temporal resolution. There were both males and females who volunteered to participate including a wide age range with the oldest participant being 35 years old. The biggest strength of this research is that it has never been looked at before. This is the first time any study has looked at how the population looks at physical and sedentary activity. Some limitations of this research included self-reported physical activity when filling out the SAM scale as the researcher had no idea how truthful the participant was being. Another limitation included students solely from the East Carolina University campus. This research also has delimitations such as not recording height or weight to calculate the average BMI between the two groups. Age and race were not specifically recorded, as participants were only told they had to be 18-35 years old. More delimitations of this research included not having the same number of exercisers and non-exercisers recruited as it was more difficult than initially thought to find non-exercisers in a kinesiology-based program.

The implications for this study show it is evident that exercisers and non-exercisers do not view physical and sedentary activity the same way. Hopefully future research will explore more of this idea using these types of methods. It could be narrowed down to a specific group instead of a broad range of exercisers such as runners and non-runners. It could also be two different avid groups of exercisers comparing swimmers and boxers, for example. Other researchers could look at different age ranges such as how toddlers view physically active and inactive activities and have a follow up in their lives every 5 or 10 years to see if their views change. Another way of changing the dynamic of this study is to show a short 5 second video clip of the activities being performed. There could also be research based on left-handed exercisers and non-exercisers. This research is groundbreaking and could go in any direction in the future.

As stated before, a possible reason why some people do not exercise could be due to the way ACSM presents materials that might not be effective for exercise adherence in all individuals. Exercise should be presented to the public in a way that all Americans can relate to. For example, an obese woman running in the Runner's World magazine is more relatable to an average overweight or obese woman than the average thin woman that is typically shown on this platform. In this sense, the average obese woman will feel more inclined to participate in this type of exercise if another woman that is similar in size and shape is doing so. With this, ACSM and other exercise science organizations should think about the different ways that exercise recommendations can be marketed and individualized to different populations to make it feasible to all and encourage daily physical activity and the benefits that go with it.

In conclusion, we provided for the first time an idea of how a group of physically active individuals who exercise regularly, and a group of sedentary individuals view active and inactive activities using FC through EEG analysis. Our analysis demonstrates that exercisers and non-exercisers view physical activity differently as well as view sedentary activity through recollection and memory in different areas of the brain. Hopefully in the future, there will be more studies that will investigate why one population views or participates in exercise and why the other does not.

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Appendix A: IRB Approval Letter

EAST CAROLINA UNIVERSITY

University & Medical Center Institutional Review Board

4N-64 Brody Medical Sciences Building· Mail Stop 682

600 Moye Boulevard · Greenville, NC 27834

Office **252-744-2914** · Fax **252-744-2284** · **www.ecu.edu/ORIC/irb**

Notification of Initial Approval: Expedited

From: Biomedical IRB

To: Chris Mizelle

CC: Rachel Grantham

Date: 3/7/2019

Re: UMCIRB 19-000243

EEG Non-Exercisers and Exercisers Differences

I am pleased to inform you that your Expedited Application was approved. Approval of the study and any consent form(s) occurred on 3/6/2019. The research study is eligible for review under expedited category # 4,7. The Chairperson (or designee) deemed this study no more than minimal risk.

Changes to this approved research may not be initiated without UMCIRB review except when necessary to eliminate an apparent immediate hazard to the participant. All unanticipated problems involving risks to participants and others must be promptly reported to the UMCIRB. The investigator must submit a Final Report application to the UMCIRB prior to the Expected End Date provided in the IRB application. If the study is not completed by this date, an Amendment will need to be submitted to extend the Expected End Date. The Investigator must adhere to all reporting requirements for this study.

Approved consent documents with the IRB approval date stamped on the document should be used to consent participants (consent documents with the IRB approval date stamp are found under the Documents tab in the study workspace).

The approval includes the following items:

Name	Description
Exercise.NonExercise.Consent	Consent Forms
Exercise.NonExercise.Protocol	Study Protocol or Grant Application
Four Item Social Identification	Surveys and Questionnaires
Recruitment.Flier.Revised	Recruitment Documents/Scripts

The Chairperson (or designee) does not have a potential for conflict of interest on this study.