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Investigating the Impact of a Mindfulness Intervention on Rumination Patterns via a Source Imaging Approach

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Introduction

Self-reflection is an important cognitive process that involves thinking back and reflecting on one's experiences, and their corresponding feelings. It promotes self-awareness and provides individuals with the opportunity to grow and develop. Although self-reflection can be beneficial in forming adaptive behaviours, there are negative forms of self-reflection that may hinder one's behaviour. As per Mor and Winquist (2002), rumination was the form of self-reflection that was most consistently and strongly associated with negative affect, specifically depression, anxiety, and negative mood [1].

Defining Rumination

Rumination is rudimentarily defined as repetitive, persistent thoughts focused on oneself, that are commonly associated with negative moods, most notably depression. Initially, early researchers referred to rumination as a salient feature of depression involving negative automatic thoughts [2]. However, it was determined that rumination was more complex than simply a symptom of depression; Martin and Tesser (1996) broadly defined rumination as a "class of conscious thoughts" revolving around a common theme with a propensity to reoccur in the absence of direct environmental demands [3]. They declared that ruminations are indirectly cued by environmental needs and serve as an illustration of an individual's persistence and mental willpower for goal-related concepts [3]. Additionally, they determined that ruminative thoughts are not dependent on repeated cueing with an external environment. This is supported by further data differentiating rumination from negative automatic thoughts as it was previously defined by Beck et al. (1967) [2, 6]. Rumination has been characterized as a style of thought rather than thoughts with negative content [6]. Although the content may be similar to thoughts identified by earlier researchers, It was subsequently determined that the style of repetitive thinking in ruminative processes has a unique construct, specifically because rumination focuses on a negative emotional state rather than a negative event [6]. Consistent with this, in a study of survivors of the Loma Prieta earthquake those with a pre-existing negative emotional state had prolonged ruminations [4, 6]. The notion that rumination is a style of negative thoughts, rather than negative content itself has been used and proven in theoretical and empirical research.

Response Styles Theory of Depression

Rumination has been conceptualized through a variety of theories, one being the Response Styles Theory of Depression (1991). Here rumination is described as passive, repetitive thinking about the causes, and consequences of one's symptoms of depression [4]. According to this theory, it was hypothesized that those who engage in ruminative thoughts and focus on the causes, and consequences of their depression, will result in longer, more amplified periods of depression [4]. Their reasoning was that rumination amplifies the effects of one's negative affect on their cognition, resulting in cognitive fixation, preventing them from critically thinking and engaging in active problem-solving [4]. This is the basis of the Response Styles Theory of Depression; an individual's response to their negative affect impacts the severity and length of their negative affect [4]. This was explicitly seen in the Loma Prieta

Earthquake study (Nolen-Hoeksema and Morrow 1991). Students who had elevated levels of depression prior to the earthquake had elevated stress levels and depression symptoms for a prolonged period of time as they are hypothesized to be constrained by their cognitive fixation [5]. Within the Response Styles Theory of Depression, it was also hypothesized that distractions in response to negative mood, diminish one's negative emotional state. Both hypotheses were tested using the Ruminative Responses Scale (RRS) which assesses rumination through symptom-based rumination, introspection, and self-blame. The scale has been used in numerous studies thus far as a standardized quantitative measure of rumination and has been adapted over time [5, 7].

Differences in Levels of Rumination

Using the Ruminative Responses Scale developed by Nolen-Hoeksema (1993) as well as researcher observations, participants can be classified as ruminators and non-ruminators. Essentially, if an individual self-reports that they do not engage in any ruminative responses, they are classified as non-ruminators [7]. Further research investigated the differences between ruminators and non-ruminators by having participants engage in developing a plan to improve the community [8]. The researchers were able to determine that ruminators were more hesistant in comparison to non-ruminators when it came to devising a solution towards the problem and taking action [8]. The researchers hypothesized that this was due to ruminators exhibiting higher stress levels and diminished motivation, resulting in the increased hesistancy and inhibition of problem-solving behaviour [8]. Additionally, it was determined that ruminators exhibit dependency, neediness and assume responsibility for the well-being of others [5]. These are hypothesized to contribute to the elevated stress levels and social friction experienced by ruminators [5].

Rumination and Depression

Within literature, rumination has been shown to be connected to depression with many studies even demonstrating that rumination predicts amplified depressive symptoms. In a study researching how coping strategies used by bereaved men impact their depressive mood, the researchers determined that there was a correlation between rumination and depression, specifically with ruminative coping being associated with longer and more amplified depression levels [9]. This is consistent with the Response Styles Theory of Depression mentioned earlier. Additionally, empirical research has shown that rumination manipulations through the use of emotionally negative prompts significantly increases negative affect in depressive participants, whereas it has limited effect on non-depressive participants [10]. This provides further evidence on a possible association between depression and rumination. Similar findings were reported for patients after they underwent a distraction manipulation; it significantly decreased negative affect in depressive participants, whereas it had limited effect on non-depressive participants [10]. These findings not only support the Responses Styles Theory of Depression, but also provide strong evidence of the connection between rumination and depression.

Additionally, it was determined that rumination led to increased negative thinking about the past, present and future within depressive individuals [11]. Specifically, the researchers

determined that depressive participants tend to spontaneously recall more negative memories and events which could provide reasoning for the amplified and prolonged ruminative response in depressive individuals [11].

Physiology of Rumination

As understanding of ruminative processes grew, researchers started to investigate the neural physiology of rumination in depressed and healthy individuals through medical imaging. FMRI (Functional Magnetic Resonance Imaging) was used on depressed and healthy individuals, and the researchers found that during rumination, depressed participants had increased activation in the subgenual anterior cingulate, orbitofrontal cortex, and dorsolateral prefrontal cortex when compared to the healthy participants [12]. The researchers also observed increased activation in the amygdala, medial prefrontal cortex, and the parahippocampus for depressive participants during the rumination task [12]. Thus, there is an association between rumination and the activation between limbic structures and regions of the prefrontal cortex within depressive participants [12]. The findings by Cooney et al. (2010) were further examined by Sin et al. (2018) where they found that the gray matter of the anterior cingulate cortex, and the dorsal lateral prefrontal cortex increased in volume within high ruminators compared to low ruminators suggesting the involvement of these structures within the rumination process [13].

Hamilton et al. (2015) published a meta-analysis summarizing the findings regarding the physiological networks involved in rumination. Earlier researchers determined that in depressive individuals, there was a functional synchronization between the default mode network and the subgenual prefrontal cortex [14]. The default mode network is a brain network that is active when the brain is in a state of wakeful rest as well as during cognitive tasks that are self-referential, as opposed to externally-driven,such as autobiographical memory retrieval, spatial planning and navigation [15 - 17]. This would include activities such as daydreaming, reminiscing, and imagination. The posterior cingulate cortex, and the medial prefrontal cortex has been shown to be associated with the default mode network [15]. Hamilton et al. hypothesized that rumination within depressive individuals impairs the connection between the subgenual prefrontal cortex and the default mode network [14]. The connection between rumination and the default mode network has been widely researched; Song et al. (2022) conducted a meta-analysis that determined that 67.5% of rumination-activated voxels within fMRI imaging were distributed within the default mode network [18]. Using their model, they were able to determine how activity between the subgenual prefrontal cortex and the default mode network can predict rumination levels in depressive individuals [14]. They were able to determine that in depressive individuals, there is only increased activity in the subgenual prefrontal cortex rather than the default mode, which was hypothesized to result in persistent, cyclic rumination [14]. This provides evidence for the role of the default mode network within depressive rumination, and the consistent cerebral circulation within the default mode network in ruminating depressive individuals [14]. It also does beg the question as to what strategies can be used to diminish the rumination cycle.

Rumination and Mindfulness

One such strategy that has been investigated to diminish ruminations within high and low ruminators is mindfulness. Given how mindfulness involves being present and having an active mind, it is antithetical to rumination and thus could have potential in reducing rumination processes among ruminators [19].

Mindfulness

Mindfulness refers to a process in which individuals maintain an open and active state of mind where they engage in conscious thinking [20]. The main premise of mindfulness is to be present and recognize concepts objectively, rather than fueled through emotions and feelings. Through this, one can better understand themselves and their own consciousness, leading to increased internal peace [20]. Evidence has shown that mindfulness results in temporary changes in activation patters of the brain through neuroplasticity, while also resulting in long-term personality changes [21].

The effect mindfulness has on the brain has been theorized and modelled throughout literature. A two-component model of mindfulness was developed that hypothesizes that mindfulness permits individuals to think comprehensively, enabling cognitive maintenance and judgement [22]. It was later proposed that the cognitive model of mindfulness in hopes of devising a generalized model describing the neural operations of mindfulness [23]. Their model focuses on the cognitive processes behind mindfulness, and how it impacts attention and working memory [23]. The researchers hypothesized that individuals that are proficient in mindfulness maintain cognitive efficiency and flexibility by suppressing extraneous cognitive processes which can include processes related to anxiety, depression and rumination [23].

In recent studies, the adoption of mindfulness training as an intervention has been used to observe differences in cognitive processes within-groups to confirm pre-developed theoretical models. Mindfulness training focuses on providing clarity to individuals regarding their thoughts and emotions [24]. Typically a mindfulness-based stress reduction (MBSR) or a mindfulness-based cognitive therapy (MBCT) program is adopted. The MBSR typically focuses on guided meditation in a large group setting to improve various cognitive and physical conditions, whereas the MBCT is typically performed individually and is usually applied to improve cognitive conditions [24]. The MBCT has been shown to effectively prevent relapse in depression participants, possibly because the MBCT focuses on navigating negative thoughts at the start of the program [24]. Given the empirical evidence supporting the effectiveness of mindfulness, specifically an MBCT program on depression, the effects of rumination on mindfulness can be questioned.

Relationship between Rumination and Mindfulness

In recent years, the relationship between rumination and mindfulness has been investigated in detail. In fact, a meta-analysis determined that mindfulness interventions potentially result in changes in one's ruminative patterns [25]. Specifically, they found that mindfulness-focused CBT resulted in a significant reduction in ruminative patterns when compared to the usual standard of care with respect to both the length of ruminations and the severity

[25]. When tested on high-ruminators and individuals with mood disorders, similar results were obtained. An MBSR program was performed on individuals with ruminative tendencies and mood disorders to determine if mindfulness training had an impact on their ruminations (Ramel et al. 2004) [26]. The researchers determined that ruminative processes decreased after the mindfulness program which aligns with the hypotheses and results from previous studies [26].

These results corresponds with a study that suggested that mindfulness training can improve one's attentional control, thereby helping in reducing maladaptive cognitive processes [27]. Teasdale et al. identified that these processes are primarily associated with ruminative processes, thus showing the potential effect mindfulness training can have on rumination [27].

Attentional control is a fundamental practice in mindfulnesss trained through focused attention [28]. It has been previously been associated with enhanced synchronicity within the frontoparietal control network, which indicates that focused attention training could lead to increased cognitive control against ruminations [28]. It is hypothesized that the frontoparietal control network develops connections with the default mode network and the salience network in order to regulate one's mental state which are further enhanced due to mindfulness training [28]. Thus, it can be inferred that the frontoparietal control network, default mode network and the salience network function together to improve cognitive control against maladaptive cognitive processes, and therefore against ruminative processes. However, there has been limited research into the specific neural structures within these networks that is impacted by mindfulness in ruminators, thus the extent of the connection between these networks have not been determined in-depth.

Biomedical Modeling

While researchers have begun to investigate the brain regions underlying rumination, mainly using fMRI which has excellent spatial resolution, there has been much less attention devoted to the neural dynamics of interacting brain regions underlying rumination. It is imperative that the neural signals are analyzed to adopt a greater understanding of the physiological dynamics and activation patterns involved. Through the use of current technology, we are able to obtain an abundance of signals that describe system and structural behaviour, biomedical signals for example allow for a true understanding of one's physiological behaviour. These signals can be modelled in order to describe the signal with respect to its structure, ultimately allowing for endless analysis and synthesis-related possibilities [29]. Analysis-focused approaches involve fitting a model to a signal to provide intricate details from which deductions can be made. This includes a Fourier analysis which provides frequency information, a Cosinor analysis which analyzes rhythmic behaviour, or a Fractal analysis to identify geometric characteristics within a signal. Conversely, synthesis-focused approaches involve original creation by reconstructing a signal using analysis data. These include but are not limited to machine learning models which are able to predict behaviour, and interface development which can use signals to transduce an output.

Modeling Brain Activity

Biomedical signals have endless possibilities given that they provide crucial insight on complex processes that occur within the human body. One important biomedical signal is brain activity which can be evaluated and and measured through an electroencephalogram (EEG). An EEG system works by obtaining electrical potentials from the brain non-invasively through an electrode cap, which typically has 64 to 256 electrodes [30]. These electrical potentials primarily originate from the cerebral cortex, which has been shown to be associated with most of one's emotions, thoughts and behaviour [30]. EEGs are commonly used in healthcare and in research to identify disruptive cognitive processes and aid professionals in understanding one's behaviour [31]. However, their application in source-imaging within healthcare has been limited.

When using an EEG, it primarily provides temporal data which can be used for to supplement biomedical model development. This is because EEGs typically have a high temporal resolution and a poor spatial resolution. Biomedical models can be modulated to use EEG signals to determine spatial characteristics, however, they are typically accompanied by an imaging modality such as an MRI or an fMRI. The size limitations of the electrodes, as well as the interacting electrical fields within the brain contribute to the EEG's low spatial resolution, thus preventing an accurate spatial representation without an imaging modality. However, using multiple electrodes in a dense electrode array, as well as a blind source separation algorithm or beamforming scheme can be used to localize the source; a process referred to as source localization.

Source Localization

Source localization is an avenue of biomedical signal processing that has been investigated recently for its ability to accurately determine the contributions of deep brain structures in cognitive processes via an EEG. Source localization using an EEG involves approximating the original source of the signal within the brain based on the recorded electrical activity. Once the signals from the electrodes are obtained, a spatial map is developed which allows for one to mathematically compute an approximate location for the underlying source. However, given the numerous concurrently active intracranial sources, there is a level of ambiguity introduced which limits the accuracy of source localization [33]. In order to overcome this challenge, a set of a priori assumptions are made in the model to approximate the density distributions and sources such that accurate dipole moments can be calculated, and their relation to an individual's cognitive process can be determined [33]. These assumptions allow the generated model to provide neurophysiological information on the signals, rather than the model simply being fitted to the data and thus limiting the generalizability of the conclusions [33]. In order to optimize the assumptions made, the integration of an EEG with an imaging modality such as an fMRI or MRI has been researched as a possible avenue to improve the a priori assumptions, and thereby improve the spatial resolution of the model [34]. Additionally, numerous algorithms have been developed with the goal of maximizing the number of dipoles fitted to the model, while minimizing the error contributed by noise and other non-deterministic signals [34].

Beamforming

Beamforming is a non-invasive technique that can be used to improve the spatial resolution of signals, and thereby improve source localization modelling predictions [35]. Beamforming works under the dipole source assumption, where electrical dipoles have three-dimensional locations and moments. Using this, a dipole map can be created and beamforming can improve the spatial resolution by amplifying the signals received from a certain area while suppressing signals received from other areas via constraints [35, 36]. Typically, a spatial filter matrix is created with weights attributed to each location; once applied, this filter indicates an estimated source based on the signals obtained from the sensors [36]. This ultimately results in improved model accuracy when determining the source of the signal.

Numerous different beamforming algorithms have been previously investigated, each with its own set of benefits and limitations. The most commonly used algorithm is the delay-and-sum beamforming algorithm which involves delaying certain signals received by a sensor, such that their Fourier transforms are in-phase with one another [37, 38]. This results in the signals received by the sensor to be possibly enhanced [37]. A similar approach can be applied to signals that the researcher intends to suppress; delaying the signals such that they are out of phase will result in destructive interference, attenuating the signal [37, 38]. Another common algorithm is the minimum variance distortionless response which involves using a spatial filter influenced by the covariance matrix of all the signals obtained by the sensor [37]. This has been determined to be effective in suppressing noise and eliminating interference, yielding an optimal signal-to-noise ratio even with the involvement of non-deterministic signals [39]. This algorithm is similar to a dynamical imaging of coherent sources beamformer where a filter based on frequency estimates is applied to the signal [40]. This allows for the amount of activity (power) to be estimated from any location within the brain [40].

Therefore, there are numerous different beamforming algorithms that can be implemented, all with unique approaches. Depending on one's signal, constraints, and a priori assumptions, a specific algorithm can be chosen to best optimize their model. Additionally, it has been commonly reported that an iterative approach may be required to optimize the performance of the model, specifically once a dipole map has been created from the signal [36].

Impact of Beamforming in Current Research

In the last few decades, beamforming has become a popular avenue of research, especially within neuroimaging. One of the first instances was by Van Veen et al. (1997), where the researchers analyzed the impact of using a weighted spatial filter to modulate brain electrical activity recorded by the sensor. This allowed the researchers to constrain their model to only pass activity from specific directions and attenuate other deterministic signals [41]. Specifically, they used a linearly constrained minimum variance beamformer which uses the covariance matrix of the noise to minimize variance from the source signal [41]. From this, a neural electrical activity map was created which estimates the source of the obtained signals, however, the researchers noted that this method requires a thorough understanding of neural schema such that directional constraints can be applied [41]. Additionally, the researchers

determined that the results of this technique are heavily dependent on assumptions, filter estimations, and references, thereby limiting this technique's efficacy [41]. However, different post-processing methods have been proposed to improve the performance of models including modifying the resolution matrix [42]. Beamforming algorithms have been thoroughly optimized to the point where they have been applied towards brain computer interfaces. Specifically, a dissertation by Mousapour et al. examines how beamforming is a potential future approach in classifying mental commands, thereby opening the possibility for more extensive brain-computer interfaces [43].

This study will investigate the effect of mindfulness on ruminative patterns in high and low ruminators via a source imaging approach. A beamforming algorithm will be applied in order to obtain a detailed understanding of the neural schema and brain networks involved in rumination. Additionally, the researchers aim to determine whether mindfulness influences the brain networks and physiological structures involved in rumination.

Methodology

Participant Recruitment

The study aimed to recruit 20 low-ruminating participants and 60 high-ruminating participants. Of the 60 high-ruminating participants, 30 of them were administered into a wait-listed control group for a duration of at least four weeks prior to participating in a mindfulness intervention. Whereas, the other 30 participants were administered the mindfulness intervention immediately. The proposed sample size was determined based on past similar intervention studies conducted by the researchers; a sample size of approximately 20 participants is required per group to account for the possibility of dropouts, and loss of data for various reasons. For the purpose of this paper, 17 participants were included: 9 from the low-ruminating group and 8 from the high-ruminating group. Data from the remaining participants will be collected and analyzed for a future publication.

Participants were recruited from McMaster University and the Hamilton area via poster advertisements on the McMaster University campus. From there, participants were navigated to enroll in the study via SONA, a participant recruitment and study management system organized by McMaster University. This system was used exclusively for participant recruitment for the study. Once recruited, the participants were enrolled into either the low-ruminating or high-ruminating group based on a pre-screening questionnaire administered through SONA. The pre-screening questionnaire consists of the following questions:

1. Thinking about your mood over the past month, how often did you feel down, sad, or depressed?

    - Participants would describe their feeling using a 4-point Likert scale consisting of the following ratings: almost never, sometimes, often, almost always.

2. People think and do many different things when they feel depressed. Please read each of the items below and indicate whether you almost never, sometimes, often, or almost always think or do each one when you feel down, sad, or depressed. Please indicate what you generally do, not what you think you should do.

    (a) I think about how only I feel this way.

    (b) I wonder why I have these problems and others don't.

    (c) I think about how sad I feel.

    (d) I think about my failures.

    (e) I try to understand my depressed feelings.

    - Similar to the previous question, participants would describe their feeling using the same 4-point Likert scale.

In addition to the aforementioned pre-screening questionnaires, participants were asked a set of general questions to determine their eligibility within the study. The inclusion criteria for the study are as follows:

1. High and Low ruminators, based on Question 2 in the SONA pre-screening questionnaire.
2. McMaster undergraduate students who have a SONA account.
3. Normal or corrected-to-normal vision

A set of exclusion criteria were also developed to ensure that the results from the study are generalizable. The exclusion criteria include characteristics that can interfere with the outcomes of the study and thereby impact the reliability of the results. For this study, the following set of exclusion criteria were developed:

1. Current or previous head injury.
2. Current or previous diagnosis of Major Depressive Disorder, Post Traumatic Stress Disorder, Generalized Anxiety Disorder, or Bipolar Disorder.
3. If participants answer "almost always" to Question 1 of the SONA pre-screening questionnaire. This indicates a risk of a mood disorder.
4. Currently engaged in more than 5 minutes a week of meditation and/or mindfulness practice.

After administering the pre-screening questionnaire, the researchers evaluated their responses prior to proceeding further with the screening process. Specifically, participants who respond "almost always" to Question 1 were excluded. Once they have been approved, the participants were emailed a brief screening questionnaire by the researchers and asked to confirm that they meet the aforementioned inclusion and exclusion criteria before further participating in the study. The questions that participants were asked are as follows:

1. Are you currently engaging in a mindfulness/meditation practice for more than 5 minutes per week?
2. Do you have a previous history of head injury/trauma, or a previous or current diagnosis of major depressive disorder, generalized anxiety disorder, bipolar disorder, or post-traumatic stress disorder?
3. Do you have a visual impairment such that you do NOT have a normal or corrected-to-normal vision?

If a participant answered no to all of the above questions, they would have be cleared to participate in the study.

Data Collection

During the first in-lab testing session, all participants were provided with a letter of information and consent form, and a COVID letter of information by one of the student investigators. Once eligibility and participation have been confirmed, the participant was placed into either a low-ruminating or high-ruminating group based on their pre-screening responses. Participants with low rumination scores completed one in-lab testing session and a task-home questionnaire, whereas the participants with high-ruminating scores completed two in-person sessions with a four-week interval between them, and have two sets of take-home questionnaires after each session. The high-ruminating participants assigned to the intervention group completed meditation sessions during the four-week interval between testing sessions, while the wait-listed control group completed the meditation sessions after their second in-lab testing session. The first in-lab testing session lasted approximately 2 hours, and the second testing session lasted approximately 1 hour in duration.

First In-Lab Testing Session

Prior to recording the participant's brain activity, they were required to complete 2 computerized questionnaires that assess mindfulness and rumination, and 1 computerized cognitive test (Stroop color naming task). The first questionnaire used is the Five Facet Mindfulness Questionnaire (FFMQ) which measures trait mindfulness by asking participants how a mindfulness-related phrase aligns with their experiences. The second questionnaire is the Rumination Response Scale (RRS) which measures trait rumination by asking participants if they have experienced rumination-related thoughts. The score obtained through the RRS would determine which group the participant would be classified in. For this study, a median split of the RRS scores was used to classify participants. Essentially, the median was calculated and if an individual had an RRS score above the median, they would be classified as a part of the high-ruminating group, otherwise, they would be classified as a part of the low-ruminating group. Both questionnaires will be completed digitally via the McMaster secure LimeSurvey interface to ensure that the data is secure. After the questionnaires, the participants completed a Stroop test to assess their inhibitory control. The Stroop test requires participants to name the ink colors of words where the word and the ink color do not match. This creates interference which can help indicate attentional and inhibitory control within participants. This task was completed using an interface developed by the researchers. Once those were completed, the participant was asked to describe past ruminations and autobiographical memories that they have had in detail. These were recorded by the participants on a secure interface and was to be used during the data collection tasks.

Within this study, brain activity was measured and transduced into an electrical signal via an electroencephalogram (EEG). As mentioned, it is the standard method for measuring brain activity in neuroscience research [28]. EEGs operate by non-invasively recording the electrical activity within the brain attributed to post-synaptic potentials, and thus inform one of the activity and activation of structures within the brain. These signals are recorded via electrodes attached to an electrode cap in a systemic array.

Within this study, 128 electrodes were used in a 10-20 system to standardize the placement of the electrodes, ensuring replicability. Once the electrode cap was applied to the

participant, a water-based conductive gel was inserted at each electrode site to reduce noise and improve signal quality. In order to accurately represent the neural activity through an electrical signal, a feedback loop exists between the Common Mode Sense (CMS) electrode and the Driven Right Leg (DRL) electrode. The CMS electrode serves as a reference for the common mode voltage collected through the measuring electrodes, resulting in a partially pre-processed signal file. Specifically, the signals from the measuring electrode and the CMS electrode are compared and subtracted, thereby aiding in the removal of non-deterministic noise such as power line frequency, and electrode irregularities. The DRL electrode simply reduces the impedance of the circuit, resulting in an increased common mode rejection ratio, thereby increasing the signal-to-noise ratio of the system, and yielding improved signal quality.

Initially, a measure of resting-state brain activity was measured for 5 minutes; the resting-state brain activity was the primary data used for this thesis. During the resting-state data collection, the participants were asked to close their eyes and relax; this was to minimize the effects of blink artifacts and lateral eye movements within the data. The participants were asked to do this until they heard an auditory tone indicating that 5 minutes has passed. This was followed by a task-switching paradigm; the participant was presented with 10 blocks of cued rumination (CR), autobiographical memory (AM) and working memory (WM) trials. During the CR and AM trials, the participant was then presented with cue words based on their self-reported ruminations and autobiographical memories and asked to imagine the rumination or memory they represent. For the WM block, a "2-word-back" task was implemented. The participant will be presented with a series of neutral words and will be asked to identify the word shown two words before.

Once the task-switching paradigm is complete, high-ruminating participants were given a brief tutorial of a FitBit device and the Calm mindfulness app, both of which was provided to them and used to deliver the mindfulness intervention. The data was accessible to the researchers and was secured safely on a McMaster research data server.

Take-Home Questionnaire #1

After completing the first in-lab testing session, the participant was emailed a link to a McMaster-hosted LimeSurvey. The Limesurvey consisted of several questionnaires that assess depression/stress/anxiety, interoceptive awareness, sleep quality, handedness, dissociation, and emotional regulation. The included questionnaires are as follows:

- Depression Anxiety Stress Scales (DASS) - Measures three interrelated emotional states: depression, anxiety and tension/stress
- Multidimensional Assessment of Interoceptive Awareness (MAIA) - Measures interoceptive awareness
- Sleep Quality Scale (SQS) - Measures sleep quality
- Edinburgh Handedness Inventory (EHI) - Measures handedness
- Dissociative Experiences Scale (DES) - Measures dissociation

- Difficulties in emotional regulation scale (DERS) - Measures an individual's awareness of their emotions and their self-reported ability to regulate them

Mindfulness Intervention

If participants were recruited into the high-ruminating intervention group, they were required to complete 60 minutes of mindfulness meditation per week which was tracked via the Calm mindfulness app. Their progress was monitored by the researchers on a weekly basis. Additionally, participants were asked to constantly wear their FitBit devices during the intervention such that activity and sleep data can be collected. At the end of the four-week intervention period, the second in-lab testing session was organized.

Second In-Lab Testing Session

If a participant were part of a high-ruminator group, they would be required to participate in a second session. During the second testing session, participants first repeated the rumination and mindfulness questionnaires and cognitive test performed during the first testing session. This was followed up by data collection where the participants were set up with the EEG, identically to the first testing session. The participants were administered a 10-minute resting-state EEG data collection period where participants were again asked to close their eyes and relax in order to minimize artifacts within the data.

After the EEG session, the participants in the wait-listed control group were given a brief tutorial on FitBit devices and the Calm mindfulness app that was provided to them. They were to engage in mindfulness training for 60 minutes for the next four weeks, similar to the intervention group.

At the end of the four weeks, the participants were to meet with the researchers. They were debriefed on the study and were provided with a copy of the study debriefing sheet. The FitBits were also returned to the researchers at this time.

Take-Home Questionnaire #2

Finally, participants were emailed a LimeSurvey link to the same set of online questionnaires that were previously administered after the first in-lab testing session. The results between both sets of questionnaires were compared along with the EEG data collected during the two in-lab testing sessions.

Measured Outcomes

Using the study protocol, the primary aim is to measure EEG correlates of rumination. Specifically, the EEG data during the resting-state period of the in-lab testing sessions will be used to determine the structures involved in the rumination process via visually plotted activation patterns through beamforming. However, prior to using beamforming, the EEG data must be pre-processed in order to improve the signal-to-noise ratio and yield more reliable results.

Data Pre-Processing

The EEG data that was collected during the in-lab testing sessions were through the BIOSEMI ActiveTWO system. Essentially, this system allows for the collection of high-resolution EEG signals with an increased sample rate, thereby minimizing the chance of aliasing. The collected EEG signals contain 128 channels collected from each of the electrode sites on the electrode cap. However, these signals are considered raw data as they were directly collected from the participant without any pre-processing performed as seen from Figure 1. This results in the presence of numerous artifacts and instances of noise. Some of these artifacts include blinks and lateral eye movement, all of which can impair the post-processing analyses and their results. Additionally, noise can be present due to input impedance, muscle artifacts, and other stochastic sources of noise. Thus, the data must be cleaned and modified such that the signal-to-noise ratio is improved, making it more optimal for post-processing analyses.

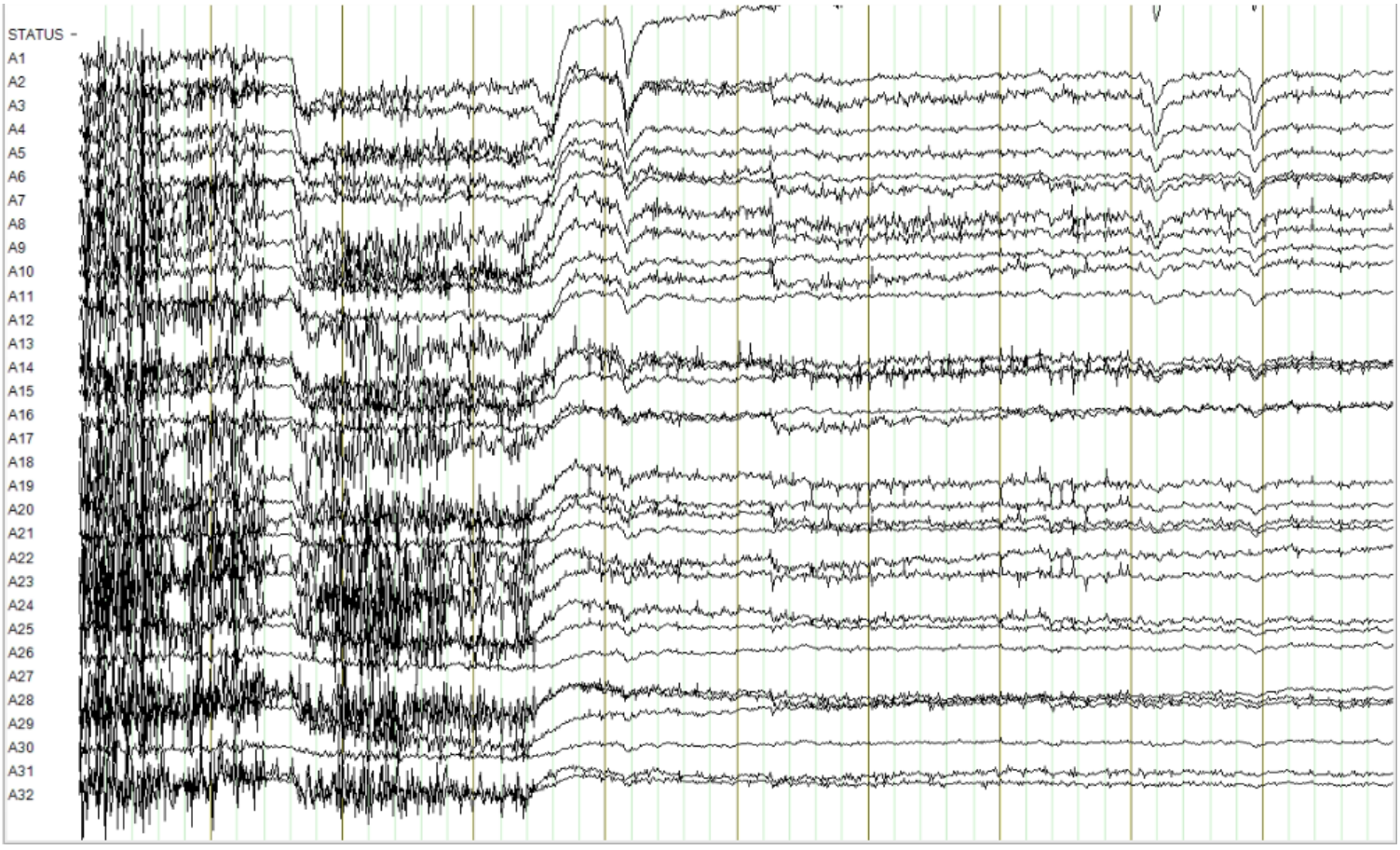


Figure 1: Raw EEG Data of channels A1 - A32

From the BIOSEMI system, the raw data is exported as a .gdf file and saved onto a secure server. Afterwards, the data is imported into EEGLAB (Figure 2) via MATLAB where the data is converted to a Brain Vision Exchange Format File which produces a .dat file.

Figure 2: EEGLAB Interface

The files were converted to a .dat file via EEGLAB so that the data could be pre-processed using the program Brain Vision Analyzer 2.1 as seen from Figure 3. Brain Vision Analyzer 2.1 is a program by Brain Products GmbH that allows EEG data to be thoroughly cleaned and primed for post-processing analyses. Within this study, the raw data was filtered and manually inspected for artifacts and noisy channels. In the event of persistent stochastic noise from a specific channel, a topographic spherical spline interpolation was performed. This method of interpolation reduces the effects of noise within a channel by approximating values based on other channels, thereby preventing the noisy channel from potentially altering the findings of the study. Following this, an Ocular Correction ICA was performed in order to identify and remove the components possessing activity related to blink artifacts and lateral eye movement. Once this was performed, the data was exported as a .dat file so that it could be imported into MATLAB and used within the post-processing analyses.

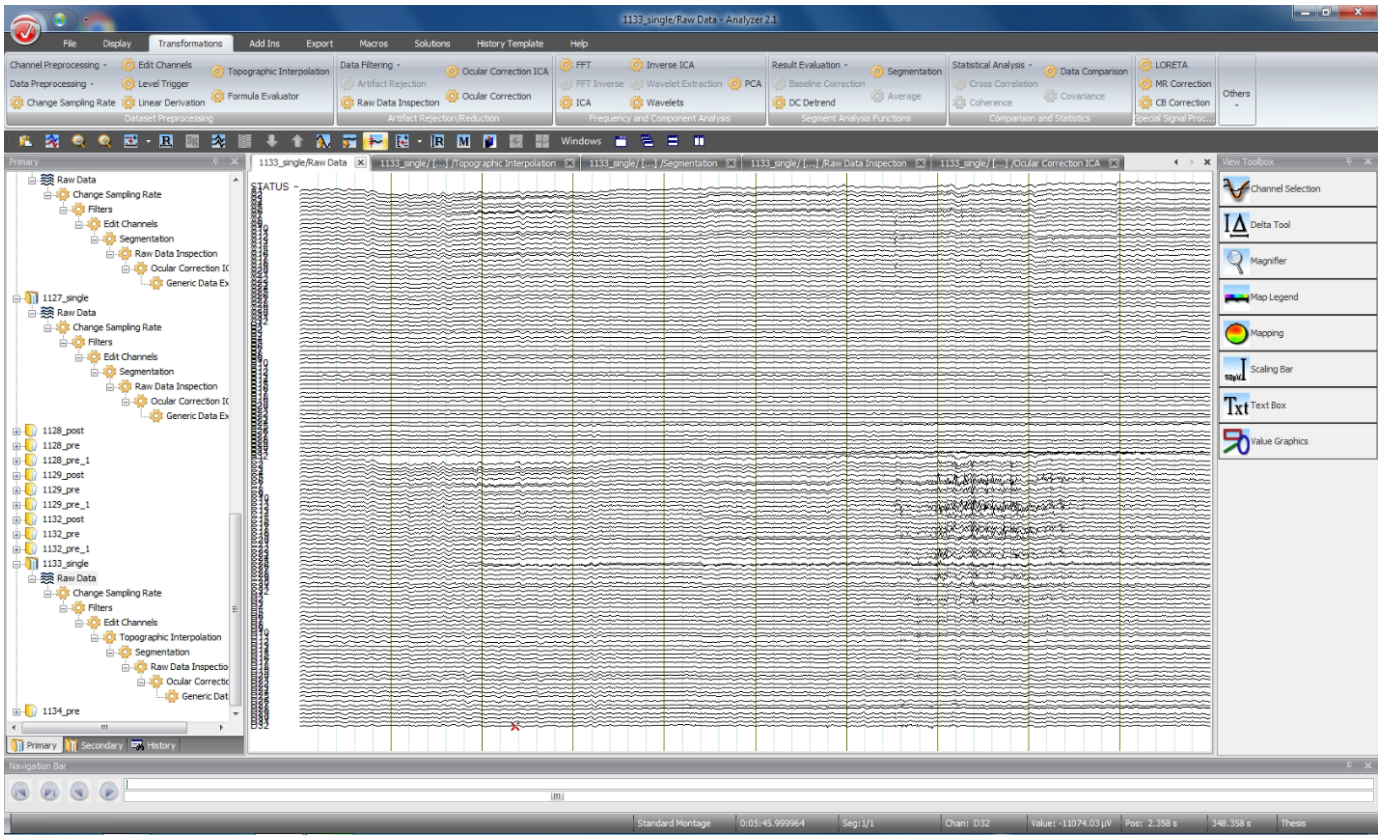


Figure 3: Brain Vision Analyzer 2.1 Interface

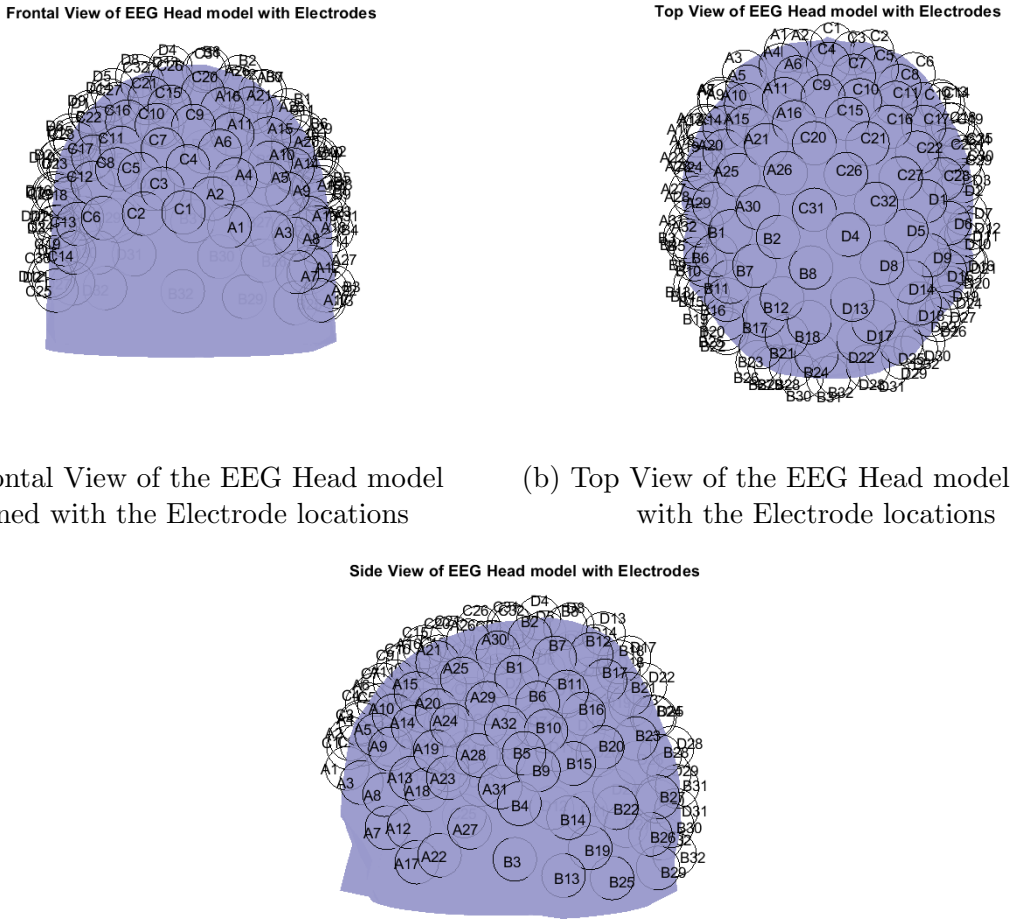
Data Post-Processing

In order to analyze the EEG data, the FieldTrip toolbox was installed and the EEG data from all of the participants were converted into a FieldTrip-suitable format. FieldTrip is a MATLAB software toolbox that is typically used for EEG analysis and was the main software involved in the analyses conducted within this paper. Firstly, the data was segmented to ensure that they are all of the same length as this ensures that the signal obtained during the task-switching paradigm or from the experimental setup was used in the analyses. As there was a slight buffer before the resting state EEG data was collected in the trials, the data was segmented from 0:45 to 5:45 minutes. The data from each participant were then concatenated into a matrix for each group (low-ruminating group and high-ruminating group). These matrices would be used when performing beamforming to identify differences in activation patterns between the two populations.

Once the data matrices were properly formatted for both populations, the electrode location file for our experimental setup was loaded into our workspace [44]. For this study, a 128-channel electrode cap was used with an ABC labeling scheme. The electrode location file allows one to associate a coordinate position with each of the 128 channels in the EEG signal and subsequently apply beamforming algorithms to it plot the spatial coordinates. It is imperative that the electrode location file is accurate and appropriately aligned as otherwise

there would be a disconnect between the activated brain regions in real life and the activated regions determined through beamforming.

Afterward, an EEG head model and an ICBM512 MRI brain model were loaded into the workspace. The EEG head model allows us to map our electrode locations to an actual human head model [45, 46]. Essentially, the electrode locations are warped from a 2D map and fitted to a 3D head model, allowing one to accurately determine where the signal was originating from on the participant's scalp. A plot with the electrodes warped on the EEG head model can be seen in Figure 4.



(a) Frontal View of the EEG Head model aligned with the Electrode locations

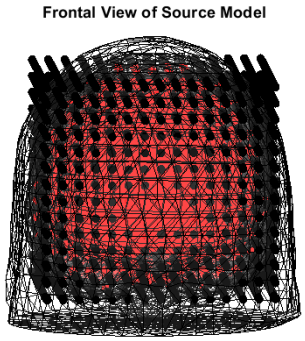
(b) Top View of the EEG Head model aligned with the Electrode locations

(c) Side View of the EEG Head model aligned with the Electrode locations

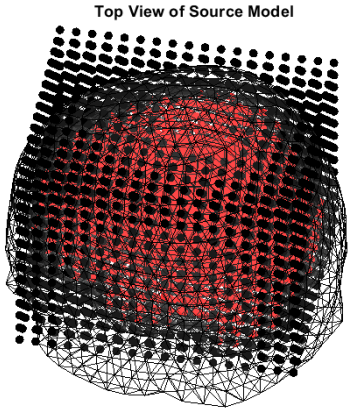
Figure 4: EEG Head Model Views with the Electrodes Aligned

The ICBM512 MRI brain model is a high-resolution template based on an average of 152 T1-weighted MRI scans created by the International Consortium for Brain Mapping [46]. The MRI model allows one to map activation patterns within the brain and visually associate them with different cranial structures. Using the EEG head model and the MRI model, a source model can be configured. This model essentially shows where the sources

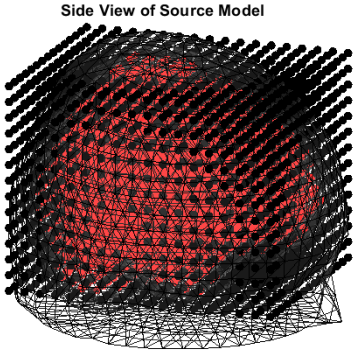
originate from as well as the entire volume matrix. Ideally, one should see that the sources should all originate from within the brain as seen in Figure 5.



(a) Frontal View of the Source Model



(b) Top View of the Source Model



(c) Side View of the Source Model

Figure 5: Source Model Views with the volume matrix in black and the source signals in red

From the figure, it can be observed that the sources in red do all in fact originate from the brain, thus the EEG head model and the electrode locations have been mapped appropriately. It is also important to notice that the volume matrix (black dots in Figure 5) covers a volume greater than the brain, this is because the EEG can measure signals within the indicated matrix and is not localized to the brain.

Additionally, a lead field can be created to show how the sources and sensors connect with one another. It is imperative to ensure that the topography of the lead field is smooth and that the lead field magnitude is appropriate for your analysis. Plots of the lead field used within this study can be seen in Figures 6, 7 along with the lead field vectors in Figure 8.

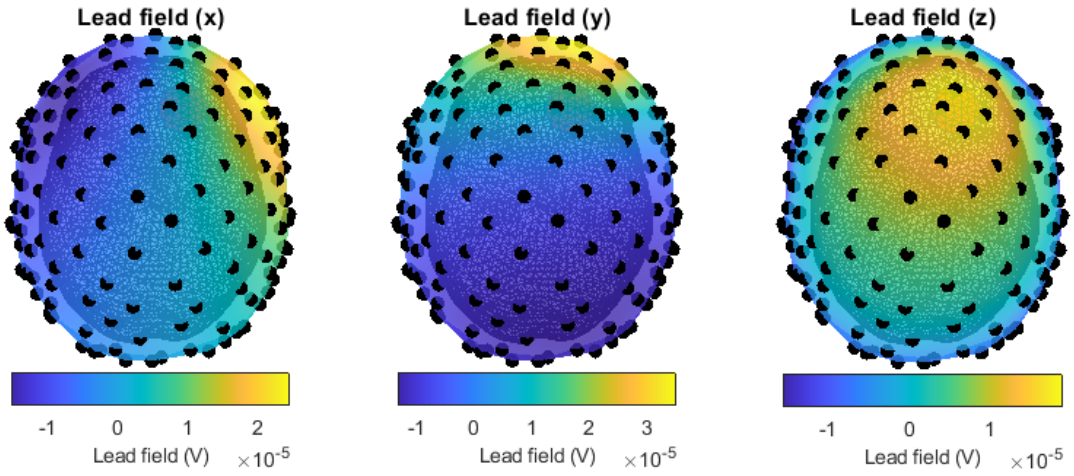


Figure 6: Lead Field Topographical Map

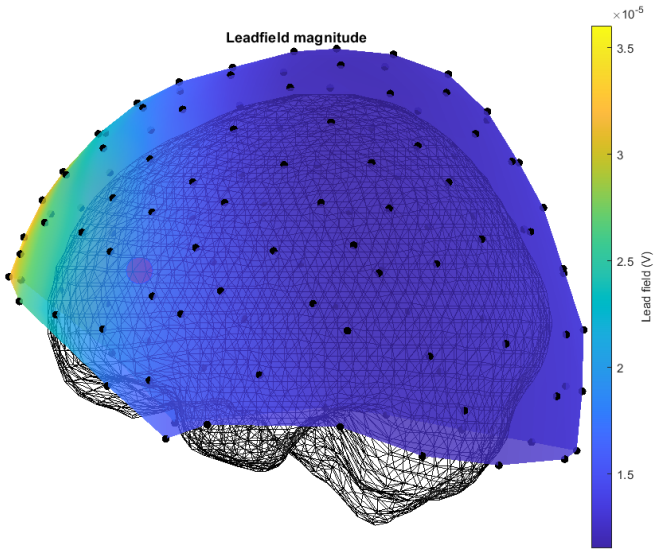


Figure 7: Lead Field Magnitude Distribution

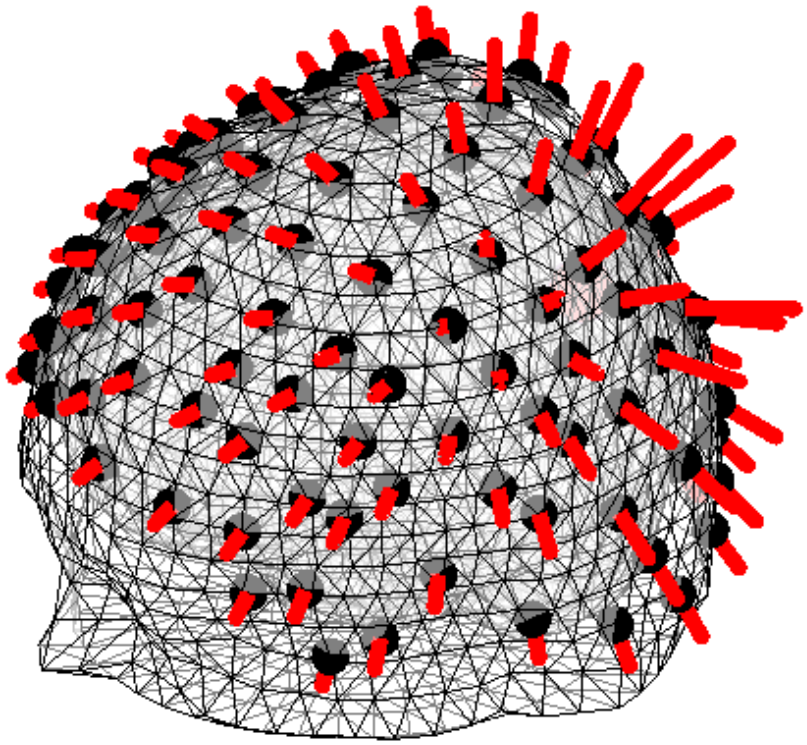


Figure 8: Lead Field Vectors; The magnitude of the vectors was increased for visual purposes

It can be seen from Figures 6 & 7 that the lead field has a smooth topography in all three planes and that the lead field magnitude is around 20 microvolts which is ideal for an EEG study. Additionally, it can be observed that the lead field vectors are normal to the scalp surface which shows that they have been configured correctly. It is important to note that the magnitude of the vectors in Figure 8 were increased to visually show the angle of the vectors.

Once the models and electrode placement have been confirmed, an LCMV (Linearly Constrained Minimum Variance) filter can be applied. The LCMV filter is a beamforming method that maps EEG power values to their sources within the brain, with the goal of minimizing the output variance. The power of an EEG signal is essentially the area under the raw signal (Figure 1 which can be determined through integration. In MATLAB, the power was calculated using Simpson's rule which allows for an approximation of definite integrals, allowing one to calculate the area under the EEG signal for each of the 128 channels. Power is essentially the magnitude of the EEG signal across a time period and helps one determine the strength of signals in different EEG channels. With the LCMV filter, the cumulative

power over the entire frequency range was obtained and used for the analyses. Using the calculated power as well as our lead field and source field model, we can estimate the power throughout each voxel of our volume matrix. It is expected that many voxels in our volume matrix are empty as many of them exist outside of the brain, however, the voxels within the brain should have power attributed to them. The power for each voxel was then averaged over the recorded time span to determine the average power from each voxel of the volume matrix.

The average power from each voxel was plotted on MRI slices using our MRI model to see activation patterns on various axial MRI slices of the brain. This was performed for both the low-ruminating group and the high-ruminating group. When comparing the regions in the low-ruminating and high-ruminating group, it is expected that there will be many areas that are active in both groups, thus a contrast plot was also created. The contrast plots essentially subtract the high-ruminating activity from the low-ruminating activity and vice versa to determine the cranial structures that are associated with each group.

Given that the rumination scores from each participant's Rumination Response Scale questionnaire vary and that an individual within the low-ruminating group could potentially still have high-ruminating activity that could alter the results, an additional comparison was performed between the highest-rated individual in the high-ruminating group and the lowest-rated individual in the low-ruminating group. Individual axial MRI plots with the LCMV beamforming filter applied were created along with the contrast plots. The results for the individual plots are hypothesized to be in agreement with the group plots.

Results

Participant Rumination Response Scale Scores

As previously mentioned, the groups that each participant was enrolled in were based on their rumination scores from the Rumination Response Scale (RRS) questionnaire. The summed scores from the seventeen participants included in this study are displayed in Table 1 below. Aside from the RRS scores, there were no notable confounding differences between the participants in each group. Thus it can be assumed that the participants in each group are similar and there are no confounding variables that need to be controlled for.

Participant ID	Score	Group
1116	44	Low
1117	64	High
1118	45	Low
1119	50	High
1120	58	High
1121	35	Low
1122	65	High
1123	38	Low
1124	42	Low
1125	49	Low
1126	41	Low
1127	62	High
1128	44	Low
1129	54	High
1132	37	Low
1133	65	High
1134	74	High

Table 1: Rumination Response Scale Scores of all of the participants included within the study.

As seen from Table 1, there are 9 participants classified as part of the low-ruminating group and 8 participants classified as part of the high-ruminating group with RRS scores ranging from 37 to 74. Based on the rumination scores compared to the median, the EEG data from the participants were separated into their respective groups vis median split.

Rumination Group MRI Plots

Once the participants were separated into their groups, an LCMV beamforming filter was applied. The filter remained constant for all participants within both groups to ensure that all comparisons made using the MRI plots were not subject to different sets of assumptions and constraints. Based on the beamforming algorithm, the MRI plots in Figures 9 & 10 were developed for the low and high-ruminating groups respectively.

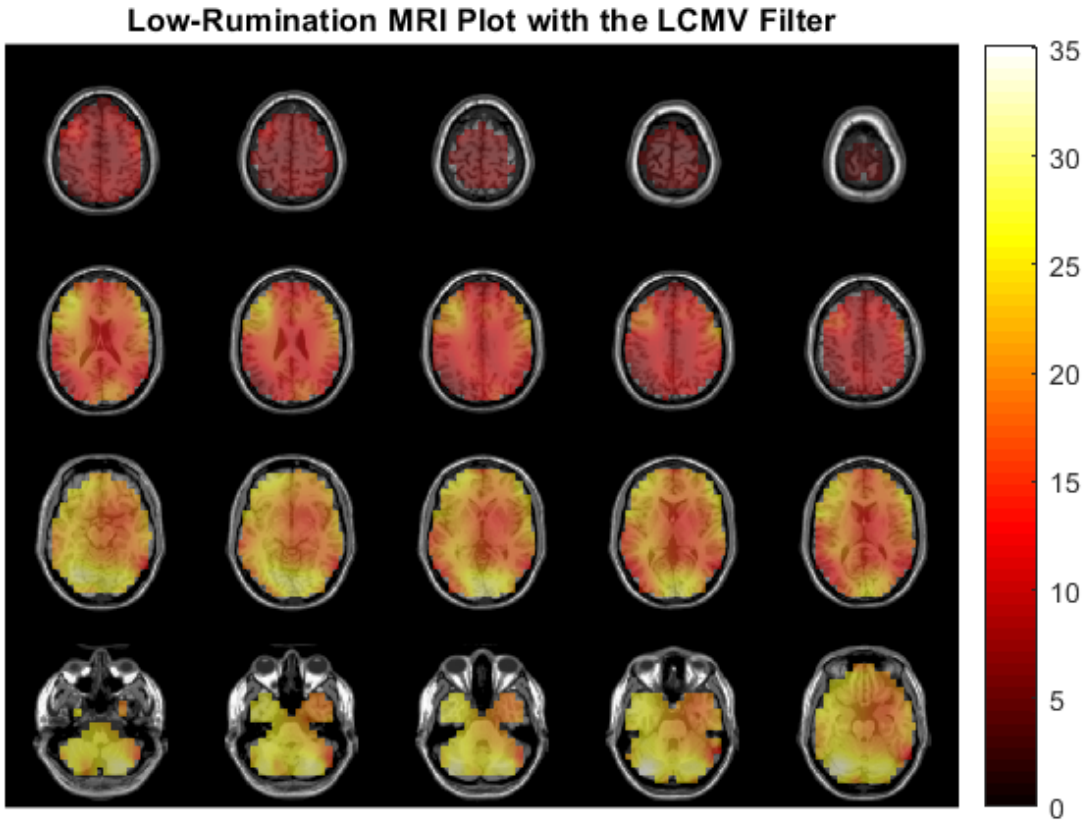


Figure 9: MRI Plot developed from the Low-Ruminator's EEG Data with an LCMV beamformer applied to map the activation of the brain in spatial coordinates. Within this plot, the areas in yellow indicate higher activation and the areas in red indicate lower activation. This plot includes 20 MRI slices of the brain taken axially to show activation patterns in a 3D space.

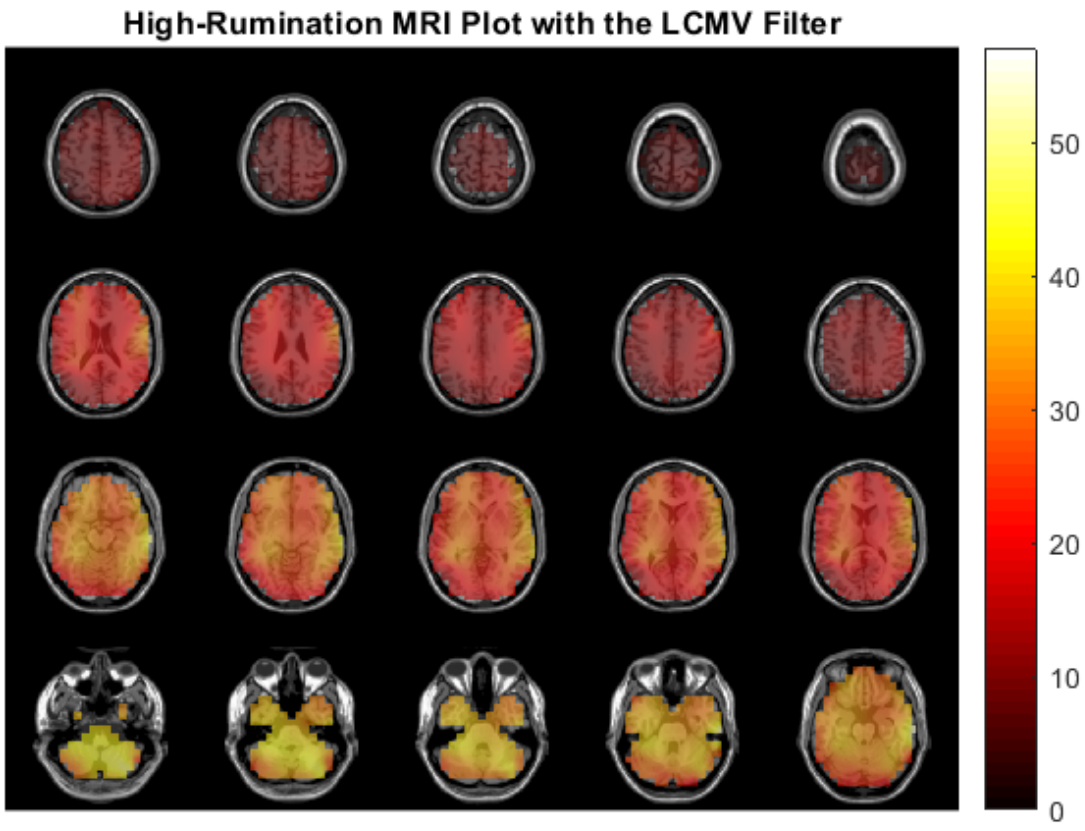


Figure 10: MRI Plot developed from the High-Ruminator's EEG Data with an LCMV beamformer applied to map the activation of the brain in spatial coordinates. Within this plot, the areas in yellow indicate higher activation and the areas in red indicate lower activation. This plot includes 20 MRI slices of the brain taken axially to show activation patterns in a 3D space.

It can be clearly seen that the signal is spread throughout the brain and there is significant overlap between the two figures. However, it can be noticed that the level of activation differs in some areas such as the left-side of the brain; the low-ruminating group seems to have higher activation in this region. It can also be observed that there is increased activation in the posterior aspect of the brain with the Low-Rumination MRI plot. This could be due to contributions from the posterior cingulate cortex or the occipital lobe; it is fairly unclear from this plot alone. Given that the comparisons are difficult to determine via this plot, a contrast plot was developed as well as seen in Figures 11 & 12.

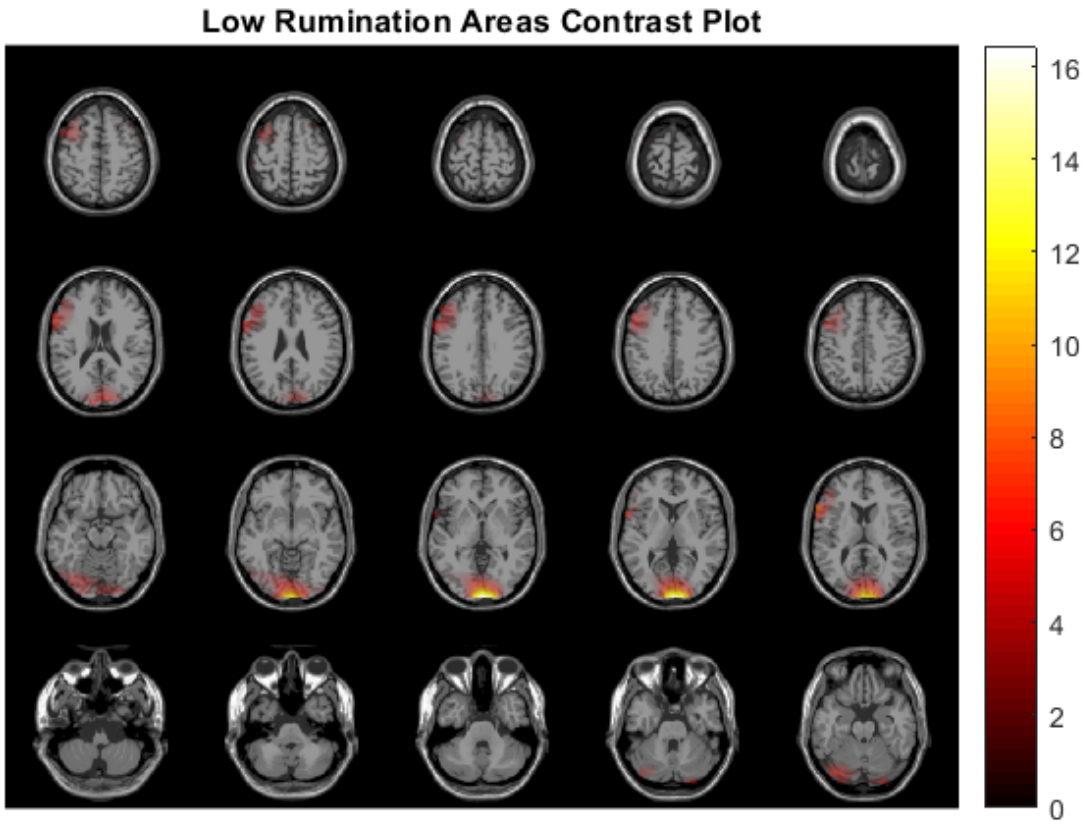


Figure 11: MRI Contrast Plot developed by subtracting the high ruminating group's average power from the low ruminating group's average power to determine the areas specific to low ruminators. Within this plot, the areas in yellow indicate higher activation and the areas in red indicate lower activation.

From the contrast plot in Figure 11, it can be determined that there are visually noticeable differences in the EEG signals between the two groups when processed through beamforming and plotted on an MRI. It can be observed that with the low ruminating group, there is some activation in the top left portion of the brain which is hypothesized to be due to the ventromedial prefrontal cortex (vmPFC) which is a part of the prefrontal cortex that has been shown to be involved in emotional processing and regulation. There also seems to be a high level of activation in the posterior of the brain. Based on Figure 9, the position of the activation indicates that the highlighted activation is most likely due to the occipital lobe.

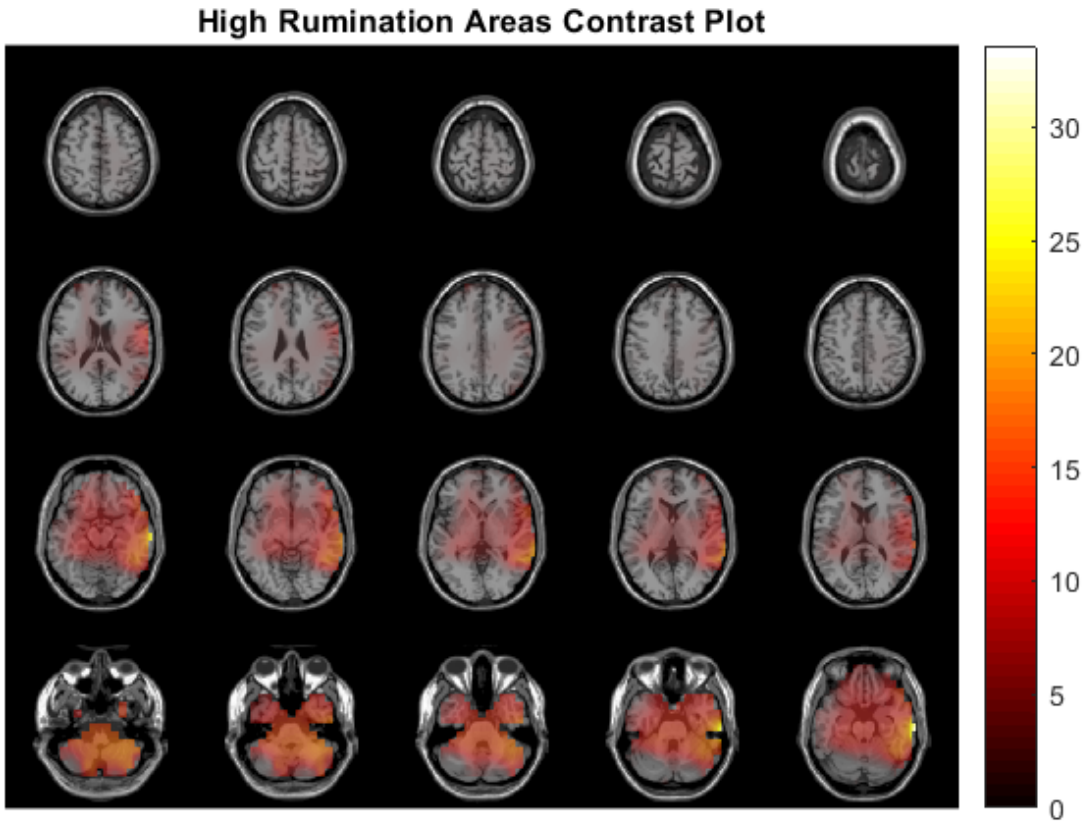


Figure 12: MRI Contrast Plot developed by subtracting the low ruminating group's average power from the high ruminating group's average power to determine the areas specific to low ruminators. Within this plot, the areas in yellow indicate higher activation and the areas in red indicate lower activation.

Similarly with the contrast plot in Figure 12, there are some visually noticeable differences. It can be observed that with the high ruminating group, there is more activation on the right side of the brain when compared with the low ruminating group. The activation pattern seems quite dispersed rather than being localized to one region. It is hypothesized that there was general activation in the limbic structures within the brain, specifically hippocampal and parahippocampal activity as those structures would be present in that area of the brain at that depth.

Individual MRI Plots of the Highest and Lowest Ruminators

In addition to observing differences between both populations, the individuals with the highest and lowest RRS scores were compared against each other to investigate whether the differences observed are consistent with the group-wise comparisons. Based on Table 1, it can be determined that Participant #1134 and Participant #1132 have the highest and lowest RRS scores respectively, thus they were used for this comparison. Participant #1134's MRI plot with the LCMV beamformer applied can be seen in Figure 13.

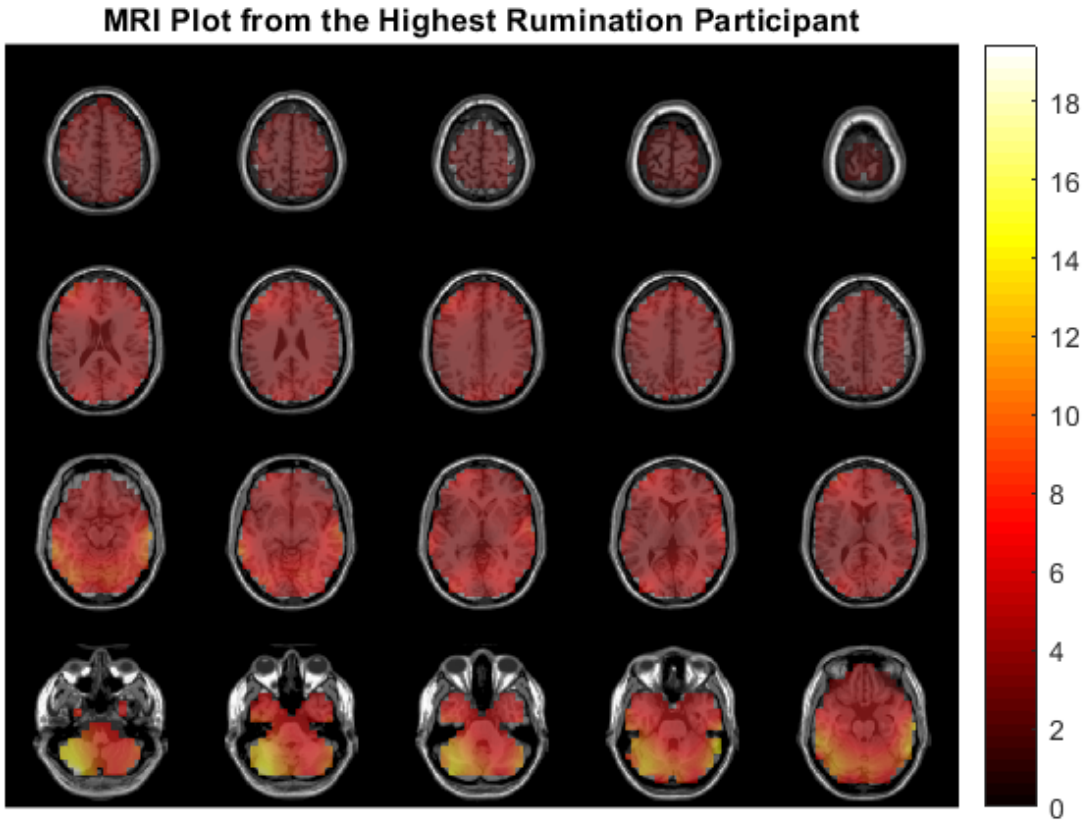


Figure 13: MRI Plot of the participant with the highest RRS Score (Participant #1134). Within this plot, the areas in yellow indicate higher activation and the areas in red indicate lower activation.

From Figure 13, it can be observed from row 4 that there is increased activation on the left-posterior aspect of the brain. This is hypothesized to be due to contributing factors from the occipital lobe and cerebellum which would be present in that area at that depth. When comparing this figure to Figure 10 & Figure 12, it can be observed that the high activation areas determined when comparing the high-ruminators group as a whole are not consistent

with the individual results of Participant #1134. Specifically in Figure 12, it was determined that an increased level of activation was present on the right side of the brain, however, the results from Figure 13 seem to only have increased activation in left-posterior portion of the brain.

The results for Participant #1132 - the individual with the lowest RRS score, can be observed in Figure 14.

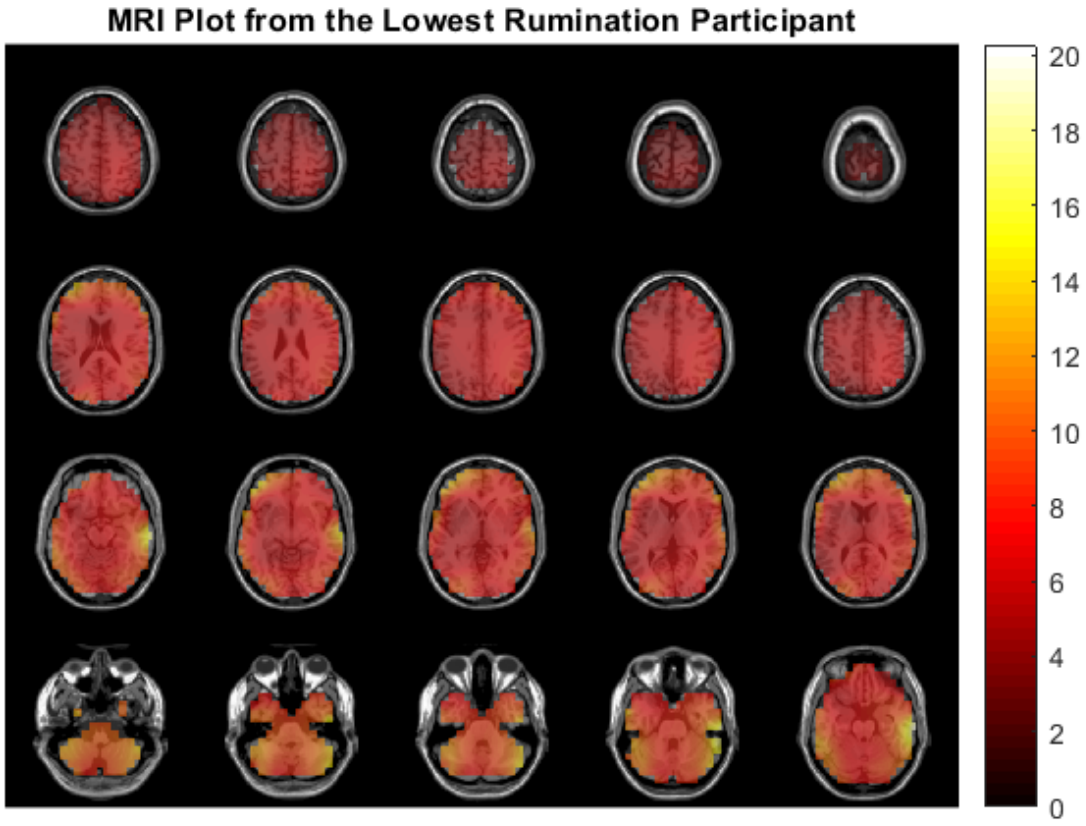


Figure 14: MRI Plot of the participant with the highest RRS Score (Participant #1132). Within this plot, the areas in yellow indicate higher activation and the areas in red indicate lower activation.

From Figure 14, it can be observed that the activation pattern is fairly dispersed and there are no specific areas in which there is an increased level of activation. When comparing this figure to Figure 9 & Figure 11, it can be observed that the high activation areas determined when comparing the low-ruminators group as a whole are consistent with the individual results of Participant #1132. Specifically with the activation of an area in the top-left portion of the brain. In Figure 14, it can be observed that this high activation is present in

the images in Row 3. As previously mentioned, this is hypothesized to be due to the vmPFC which has been shown to be critical in emotional regulation.

With both Participant #1134 and Participant #1132's results, comparisons were difficult to determine, thus a contrast plot was also developed to highlight the differences between them and to determine whether they align with the differences observed in the group-wise comparisons. The contrast plots can be seen in Figures 15 & 16.

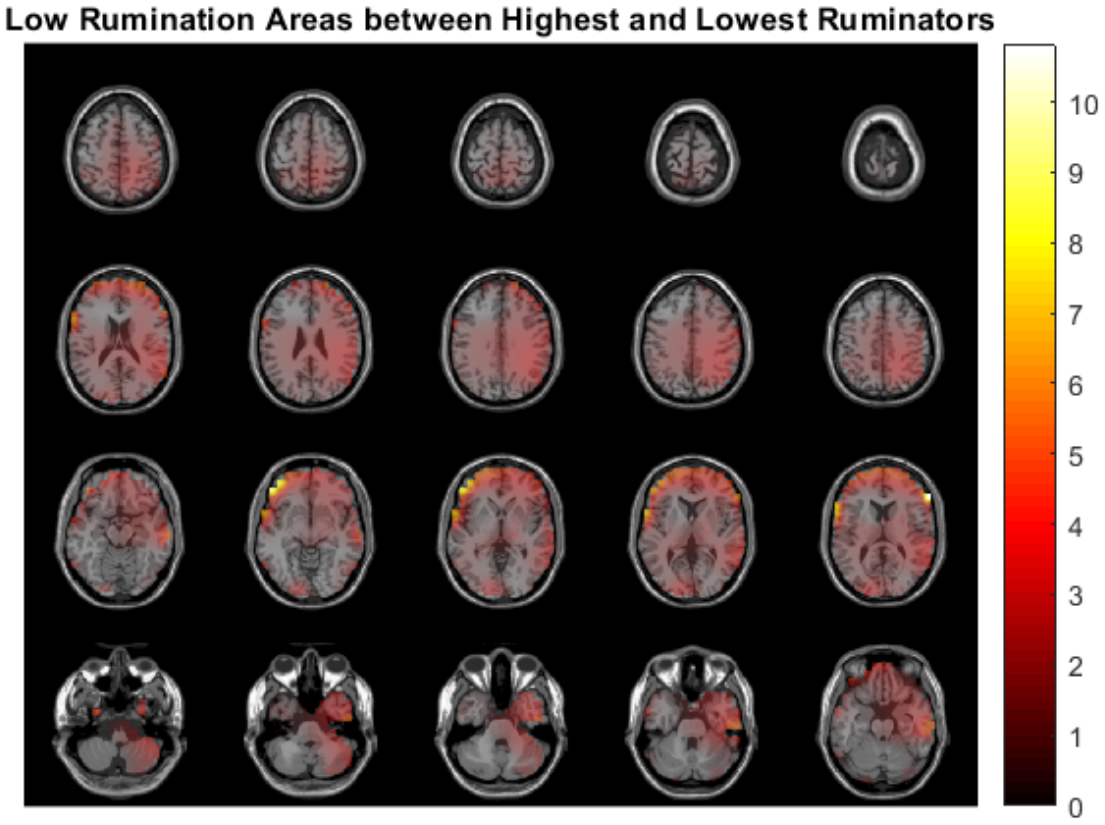


Figure 15: MRI Contrast Plot developed by subtracting the highest ruminating participant's (Participant #1134) average power from the lowest ruminating participant's (Participant #1132) average power to determine the areas specific to low ruminators. Within this plot, the areas in yellow indicate higher activation and the areas in red indicate lower activation.

From the contrast plot in figure 15, it can be seen that the areas that have increased activation in the low ruminating individual are fairly dispersed. They are spread throughout the brain, however, there is a noticeable increase in activation at the top-left portion of the brain. When comparing this nodule of activation with Figure 11, it can be seen that the position of this activation pattern is similar. Thus, it is hypothesized that this also is due to increased activity within the vmPFC.

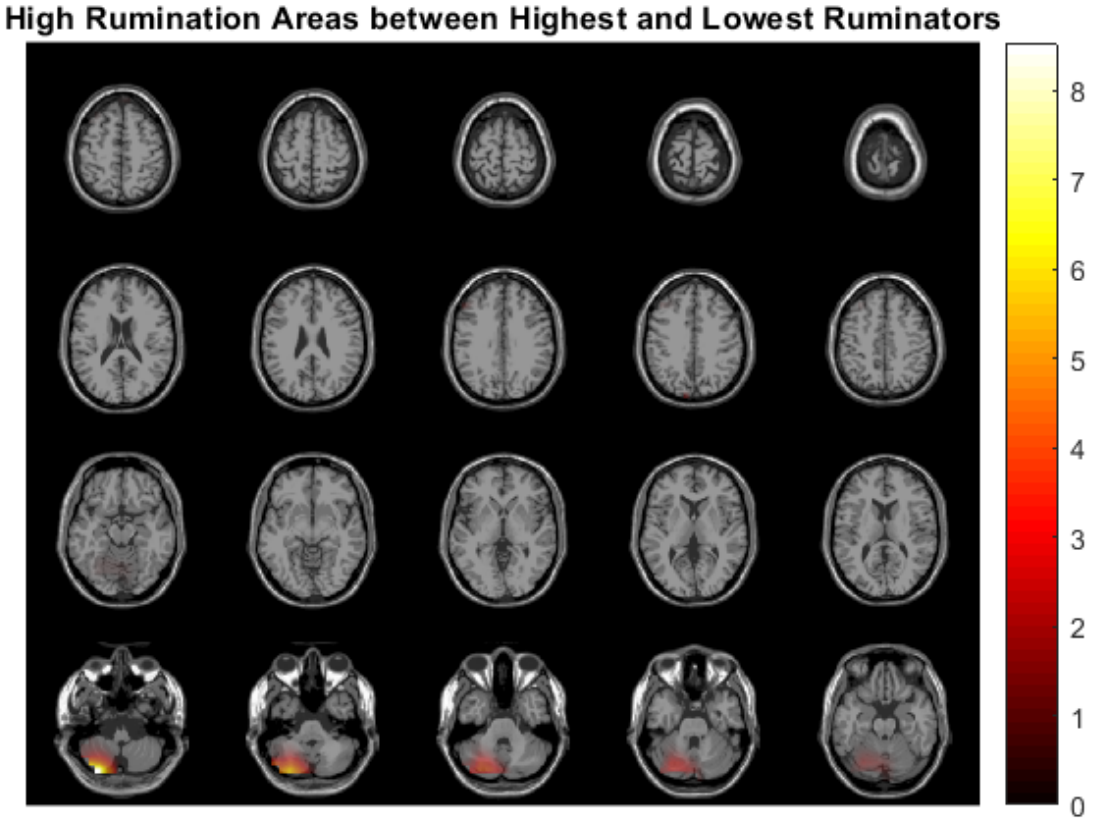


Figure 16: MRI Contrast Plot developed by subtracting the lowest ruminating participant's (Participant #1132) average power from the highest ruminating participant's (Participant #1134) average power to determine the areas specific to low ruminators. Within this plot, the areas in yellow indicate higher activation and the areas in red indicate lower activation.

From the contrast plot in figure 16, it can be seen that the areas that have increased activation in the high ruminating individual are fairly localized to the left posterior region of the brain. When comparing this area of activation with Figure 12, it can be seen that the activation patterns are in fact different. The dispersed activation pattern on the right side of the brain is not present in the contrast plot in Figure 16. Additionally, the group-wise contrast plot doesn't have any activation in the left posterior of the brain that is present in Figure 16.

Discussion

Based on the results obtained from this study, it can be determined that the low-ruminating group had higher activation in the top left portion of the brain when compared to the high-ruminating group as seen in Figure 11. As previously mentioned, this is hypothesized to be representing activity in the ventromedial prefrontal cortex (vmPFC). The vmPFC has been shown to play a significant role in emotional regulation and the modulation of ruminative patterns [47, 48]. Therefore, the higher activation of the vmPFC in the low-ruminating group coincides with the literature. The low-ruminating group is hypothesized to be better suited at regulating their emotions and controlling the level of ruminations that they experience when compared to the high-ruminating group, thus they would have increased activation in the vmPFC [49]. It is also important to note that the low-ruminating group had increased activation in the posterior portion of the brain. This was hypothesized to be due to participants engaging in visual imagery during the resting-state EEG data collection phase. Visual imagery is defined as the process of creating mental representations in the absence of sensory input [50, 51]. Individuals that engage in visual imagery have been shown to have an increased level of activation in the primary visual cortex (V1), highlighting the possible role that V1 has in generating these mental representations [50, 51]. The primary visual cortex is part of the occipital lobe which is located in the posterior region of the brain [50]. This coincides with the region of high activation depicted in Figure 11. Therefore, it is plausible to hypothesize that the high activation present in the low-ruminating group was due to the participants engaging in visual imagery. Apart from these two regions, there are no other regions of increased activation in Figure 11.

Additionally, our contrast shown in Figure 12 demonstrates that the high-ruminating group had higher activation of right hemispheric areas than the low-rumination group. As previously mentioned, this is hypothesized to be representing the general activation of the limbic structures within the brain. Specifically, the activation regions are hypothesized to be due to increased activity in the hippocampal and parahippocampal regions of the brain. Using an atlas provided by IMAIOS, a visual representation of the hippocampus labeled on an axial MRI plot can be seen in Figure 17 [52]. From the figure, it can be seen that the high activation regions present in Figure 12 coincide with the pinned region in Figure 17, thereby illustrating a possible connection between hippocampal activation and high rumination activity. Based on scientific literature from a study using an MRI, it has been shown that increased hippocampal activity has been associated with increased levels of depressive rumination which coincides with the findings of this study [53]. Thus, based on our results, we hypothesize that the regions with increased activation are due to increased activity in general limbic structures, specifically the hippocampus.

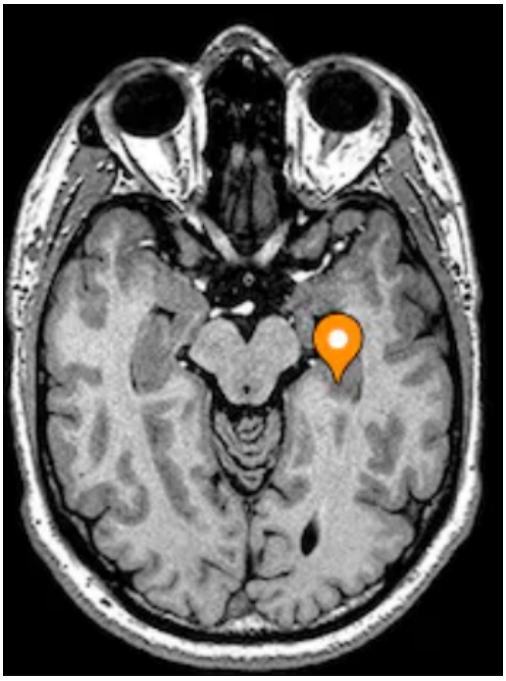


Figure 17: Axial MRI Plot with the Hippocampus Pinned. [52]

Additionally, we hypothesize that the dispersed activation in the right hemisphere of the brain present in Figure 12 is also due to emotional lateralization. This refers to the lateralization of the neural correlates of emotion, where activation within the right hemisphere of the brain is generally associated with negative mood, and activation within the left hemisphere of the brain is generally associated with positive mood [54]. This theory of emotional lateralization has been supported within scientific literature, with numerous studies supporting the assumption that the right hemisphere is more involved with negative emotional processing [55]. Thus, given that rumination involves persistent, negative emotions, it can be hypothesized that the right hemispherical activation is due to negative emotions as per the theory of emotional lateralization. This coincides with the results shown in Figure 12. Additionally, it has been well-researched that right-handed individuals possess a right hemispherical dominance for emotion [56]. Given that all of the participants in the study were right-handed, the right hemisphere of their brain would be involved in emotional processing and expression. This supports the results shown in Figure 12, as activation regions can be seen dispersed throughout the right hemisphere of the brain.

When analyzing the results from the individual with the lowest RRS score (Figure 15), it was observed that there were key differences when compared to the general trends in the low-ruminating group shown in Figure 11. Specifically, the areas with increased activation in the MRI of the individual with the lowest RRS score were fairly dispersed. There seemed to be a higher level of activation on the right side of the brain as well as within the prefrontal cortex. These findings do not coincide with the results from the low-ruminating group in Figure 11, however, this could also be due to the fact that the results from Figure 15 are only from one participant. It is important to note that there are similarities between the two figures, most notably the activation in the top-left region of the brain. This region of activation is present in both contrast plots and is hypothesized to be due to increased activation in the

vmPFC. The increased activation within this region by the individual with the lowest RRS score supports the theory that low ruminators have increased emotional regulation.

In addition, the results from the individual with the highest RRS score (Figure 16), showed differences when compared to the general trends in Figure 12 as well. Specifically, there were no regions with higher activation on the right side of the brain in the MRI plot from the individual with the highest RRS score. This begs the question as to whether the increased activation within the regions presented in Figure 12 is statistically significant. Additionally, it can be observed that Figure 16 shows high activation in the left-posterior aspect of the brain. This is fairly different when compared to Figure 12. It is hypothesized that this activation could be due to activity in the cerebellum. This could be due to the fact that the participant might have been attempting to maintain their posture or balance during the EEG recording session. This region of activation could also signify the large amounts of variability between the participants. However, more research and statistical analyses would be needed in order to determine the cause for the increased activity in the left-posterior aspect of the brain.

Limitations

Although the results obtained from this study coincide with the findings reported in scientific literature, there are limitations with the study design. EEGs are known for their high temporal resolution; they are able to accurately measure neural activity with respect to time. However, they have limited spatial resolution; EEGs are not able to visually represent neural activity sharply and accurately. Although beamforming algorithms can increase the spatial resolution of signals collected using an EEG, this approach is unmatched when compared to imaging modalities such as fMRI and MRI. The limited spatial resolution may negatively influence one's ability to determine the specific regions and structures that have increased activation between the low-ruminating and high-ruminating groups. An example is the highlighted regions in Figure 12, it is unclear as to which limbic structures are responsible for the increased activation within this plot.

The second limitation is the use of head models within the study. The adoption of a electrode digitization to map the coordinates of each electrode such as DIPFIT; a dipole fitting algorithm, would potentially result in reduced source estimation uncertainty [57]. Currently, the use of a head model template in source localization yields an accuracy of 50% in the identification of Broadmann areas, whereas using an electrode digitization method has been shown to yield an accuracy greater than 80% [57]. Thus, the adoption of electrode digitization may reduce source localization error and could potentially even improve the spatial resolution of the resultant MRI plots.

The third limitation is that the participants were split into high and low-ruminating groups based on a median split of their RRS scores. This can be unfavorable as it can limit the true contrast seen between individuals from two different groups due to how close their RRS scores are to one another. For example, Participant #1125 had an RRS score of 49, and Participant #1119 had an RRS Score of 50 yet they were both enrolled in different groups. It is hypothesized that the results between these two individuals would be fairly similar, however, the addition of their data to the group-wise comparisons can limit the differences observed. Within literature, standardized clasification cut-offs for "high" and

"low" ruminators based on RRS scores do not seem to exist, however, the use of a large meta-analysis of RRS scores would help with determining appropriate cut-offs for each group. In the future, it may be better to increase the overall number of participants as there would be in theory a better separation between the high and low-ruminating groups. This would provide more confidence that the high and low ruminators, as determined by our median split technique, come from different populations. Additionally, statistical tests could be employed to determine if there was variability within each group.

The last limitation is the relatively small sample size in both the low and high-ruminating groups. It is unclear as to whether these results can be generalized to a larger population as the limited sample size increases the margin of error with the reported findings.

Future Research

The results obtained from this study qualitatively demonstrate that there may be differences in the neural activaiton patterns of low and high-ruminating individuals, which opens avenues for future research. Firstly, the results from this study do not make any statistical comparisons between the two populations nor does it indicate if a high activation region is statistically significant. The inclusion of both of these statistical analyses would improve the validity of the findings from this paper. It would allow for quantitative, precise descriptions of the potential differences in activation patterns between the low-ruminating and high-ruminating groups. Additionally, including more participants within both the low-ruminating and high-ruminating groups would yield more generalizable results. For this study, 17 participants were used thereby limiting the validity of the results, however, a future study is in progress with the goal of 40 participants, 20 per group. Lastly, the MRI plots produced do not have comparisons between different Broadmann regions thereby relying on visual analysis and approximation to determine which structures had a higher level of activity. In the future, including power comparisons may yield increased validity within the results. Additionally, the MRI slices are solely from the axial plane. If visualization used all three dimensions, it would help in identifying areas with higher activation via visual inspection.

Conclusion

Overall, this study adopted a source-imaging approach to determine the structures involved in rumination. Using a Linearly Constrained Minimal Variance (LCMV) beamformer, the participant's EEG data was analyzed within spatial coordinates to determine regions of increased neural activation while at resting-state. The findings determine that there were visual differences between the low-ruminating and the high-ruminating group, most notably the increased activation of the ventromedial prefrontal cortex (vmPFC) in the low-ruminating group and the increased activation of limbic structures in the high-ruminating group. Although differences are shown through visual inspection, the validity of the study can be improved with the inclusion of statistical analyses comparing the high activation regions between both the low-ruminating and high-ruminating group. This study was able to provide evidence that beamforming can be used to determine the structures involved in rumination and opens avenues for future research within this field.

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