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Neural Correlates of Self-Referential Thinking and the Influence of Mindfulness Meditation and Positive Fantasizing

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Master's Thesis

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Contents

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Abstract

With the global prevalence of Major Depressive Disorder (MDD), it becomes imperative to explore effective therapeutic interventions and identify reliable objective measures for detecting depressive symptoms. A key feature of MDD is an increase in self-focused thoughts, often manifesting as ruminations on negative experiences and self-blame. These maladaptive thoughts can exacerbate depression and pose a relapse risk for those with remitted Major Depressive Disorder (rMDD), who, despite not currently experiencing depression, remain vulnerable. It remains unclear whether the neural patterns of self-referential thinking in rMDD return to a healthy state or remain altered due to their depressive history.

Research exploring self-referential thinking has found it to be closely linked to the brain's default network, with altered patterns of brain oscillations, particularly in the theta and alpha bands, during self-focused thought. More recently, heartbeat-evoked potentials (HEPs) have emerged as another measure for assessing these self-referential neural patterns. This thesis therefore examines whether HEPs and brain oscillations extracted from EEG data over the default network can distinguish between self-focused and non-self-focused thoughts in individuals with rMDD and healthy controls (HCs). It also evaluates the impact of mindfulness meditation and positive fantasizing interventions on these neural patterns and explores the potential of machine learning (ML) classifiers to differentiate between the two types of thought.

Results showed that HEPs did not significantly differentiate thought types, while brain oscillations in the theta, alpha, and beta bands showed distinct patterns, particularly in frontal and parietal regions. However, only theta oscillatory power in the parietal region (Pz and P4 electrodes) at 180-350 ms provided strong evidence for differences between thought types. There was no strong evidence for group differences in HEPs, and while some differences in beta oscillatory power were observed, they were not consistently supported by Bayes Factor analyses. Neither mindfulness meditation nor positive fantasizing produced significant changes in HEPs or brain oscillatory power which we theorize may be due to the brief participant engagement period with the interventions. Moreover, the interaction effects of these interventions with the groups were similarly inconclusive.

To evaluate whether these differences captured by brain oscillatory power could be used to accurately differentiate between self-focused and non-self-focused thoughts we trained several ML classifiers. Our classifiers demonstrated moderate success in distinguishing between the two types of thought, achieving a maximum cross-validation score of 65%. However, the high misclassification rates underscore the need for better feature selection and further refinement before these classifiers can be applied in clinical settings.

1 Introduction

Major Depressive Disorder (MDD) remains a prevalent issue in our modern world, affecting upwards of 3.4% (approximately 264 million individuals) of the global population [1]. Those diagnosed with MDD are marked by a variety of debilitating behavioural, emotional, and cognitive symptoms including persistent negative feelings of sadness and hopelessness as well as cognitive impairments in attention, working memory, and executive function [2]. Among the cognitive symptoms, research has shown that there is a notable relationship between MDD and self-focused thoughts. Those diagnosed with MDD are reported to have a heightened focus on themselves, marked by increased ruminations, self-blame, and other forms of self-focused thought [3, 4, 5]. Rumination especially can be a particularly harmful form of self-focused thought, as this process involves a repetitive, intrusive, and unproductive focus on one's negative emotions and problems, leading to a vicious cycle that perpetuates depressive states [6, 7]. Moreover, based on patient responses to self-report questionnaires, the severity of their depression seems to be directly correlated with how frequently patients engage in rumination [8].

One approach to better understand the effects of MDD on patient behaviour and cognition is by examining their spontaneous thought patterns. Spontaneous thoughts are defined as a sequence of mental states arising relatively freely due to an absence of constraints on content and transitions between mental states [9]. It encompasses a range of mental activities including mind-wandering and daydreaming, where thoughts are primarily characterized by a decoupling of attention from external stimuli and a focus on internally generated information [10]. Importantly, spontaneous thoughts are not inherently negative and can lead to positive outcomes such as the facilitation of creative problem-solving and future planning [11, 12]. However, in the context of MDD, spontaneous thoughts often take on a maladaptive form, characterized by repetitive negative self-focused content [7, 13]. These maladaptive thoughts can impair the individual's ability to engage in effective problem-solving which only exacerbates feelings of hopelessness and contributes to the maintenance of MDD [7, 13]. By studying spontaneous thoughts, researchers can observe how the disorder manifests and impacts mental states outside of structured tasks or self-report measures.

These cognitive patterns can not only be observed in patients presently diagnosed with MDD but also in those with remitted Major Depressive Disorder (rMDD). Individuals with rMDD are those who have been previously diagnosed with MDD but are not currently experiencing depressive symptoms. Nonetheless, these individuals remain vulnerable and at risk for relapse [6, 14] which has been theorised to stem from enduring neurobiological changes, even after symptoms appear to be in remission. Research has shown that those with rMDD share several structural and functional brain abnormalities with those currently experiencing MDD [15, 16]. Although the normalization of connectivity between brain regions is observed during remission, it often does not fully return to levels seen in healthy controls, indicating residual abnormalities that leave these individuals at risk for relapse. As such those with rMDD present a unique opportunity to study how the effects of depression can persist and whether these cognitive changes are different from those with no prior depressive history.

Nonetheless, by recognising the persistent brain abnormalities and thinking patterns associated with depression, it becomes evident that targeted interventions are crucial for mitigating the risk of relapse. Given the role of negative spontaneous thought in both active and remitted MDD, a wide variety of positive interventions that target these thought patterns have been developed to treat and prevent depressive episodes. However, all interventions vary in terms of their methodologies and focal points. Cognitive-behavioural therapy (CBT) for example, is a goal-oriented and structured form of therapy that actively challenges and disputes irrational or negative thoughts and beliefs in an effort to replace them with more balanced and constructive alternatives [17].

In contrast to CBT's direct approach of attempting to change the content of one's thoughts, mindfulness meditation encourages individuals to adopt a non-judgmental, present-focused awareness, which can help in disengaging from maladaptive rumination and other forms of negative self-focused thought [18, 19, 20]. By encouraging individuals to observe their thoughts and emotions without attachment or judgment, mindfulness meditation encourages the development of an ongoing practice that can be integrated into daily life, which has been shown to reduce the risk of relapsing into depressive episodes as well as lead to changes in brain activity patterns associated with self-referential processing [18, 19, 21].

In the same vein, positive fantasizing serves as another method for modulating one's thoughts. Positive fantasizing refers to the act of envisioning favourable, idealized outcomes or scenarios in one's mind. Unlike other interventions that focus on altering existing negative thoughts or cultivating present-moment awareness, positive fantasizing actively redirects attention toward creating and engaging with positive mental imagery. By immersing themselves in these optimistic scenarios, individuals build a habit of directing their thoughts towards more hopeful and uplifting possibilities, making it harder to fall into cycles of negative ruminations which in turn enhance their overall emotional well-being [22, 23, 24].

Additionally, aside from mindfulness meditation and positive fantasizing targeting the persistent negative cognitive patterns associated with MDD, a key advantage of these practices is their adaptability and potential for integration into daily life, allowing individuals to continue benefiting from them long after initial treatment. Mindfulness meditation, for instance, can become a lifelong practice, helping individuals maintain a balanced and non-reactive approach to their thoughts and emotions. Similarly, positive fantasizing can also be cultivated as a long-term habit, gradually reinforcing positive cognitive patterns that counterbalance the habitual negativity often seen in MDD.

The present study aims to explore whether there are discernable differences between self-focused versus non-self-focused thought as well as the efficacy of these interventions – mindfulness meditation and positive fantasizing – in altering self-focused spontaneous thoughts, particularly in individuals with rMDD and healthy controls. Given how those with rMDD remain vulnerable to relapse, understanding the impact of these interventions on their thought patterns can provide valuable insights into preventive strategies and long-term management of depression. To explore these thought patterns, Heartbeat-Evoked Potentials (HEPs), which represent neural responses to the perception of one's heartbeat, and brain oscillations will be utilized. Previous research has demonstrated that HEPs are closely linked to self-focused cognition and bodily state monitoring [25, 26], making HEPs an ideal measurement for assessing the effectiveness of interventions aimed at altering these cognitive processes in patients. The same can said for brain oscillations given that research has shown that different frequency bands of brain oscillations are associated with self-referential cognition/processing [27, 28, 29, 30].

While self-report measures such as questionnaires or interviews can also be used to measure how effective interventions are at altering self-focused thought patterns, these methods come with inherent limitations. Self-report measures rely on individuals accurately recognising and reporting their cognitive processes, as such if the patient has limited introspective awareness they can provide inaccurate information. Additionally, self-report measures can result in patients consciously or subconsciously distorting their experiences based on subjective expectations or beliefs about the intervention.

In contrast, HEPs as well as brain oscillations offer objective and quantifiable measures of neural activity associated with self-related processing and cognition. These objective assessments can enhance the validity and reliability of findings and provide a clearer understanding of how effective these interventions are in altering self-focused thought patterns.

Furthermore, an additional component of this study will be the development of a machine learning (ML) classifier. This classifier aims to distinguish between self-focused and non-self-focused thoughts based on the patterns observed in HEPs and brain oscillations. The rationale behind this approach is grounded in the hypothesis that if there are discernible neural differences between self-focused and non-self-focused thoughts, then a classifier should be able to use these neural correlates to accurately classify the type of thought a person is experiencing. This would not only corroborate the findings that these two types of thought are neurally distinct, but it could also show potential for use in the medical field. By having a classifier that can detect when a patient is engaging in self-focused thoughts, clinicians could gain objective insights into the rate at which these thoughts occur and use this to tailor treatment strategies that specifically target these thought processes.

1.1 Research Questions

This project aims to explore whether there are significant differences between self-focused versus non-self-focused thought that can be identified through HEPs and brain oscillations. By identifying which of these neural correlates best captures differences, we aim to develop an ML classifier that can distinguish between the two types of thought. We strive to create an accurate classifier as this would corroborate the findings that there are discernable neural differences between the two groups of thought.

Moreover, we aim to extend our analysis to explore whether these neural correlates differ between individuals with rMDD and healthy controls, as well as explore whether mindfulness meditation and/or positive fantasizing interventions modify the patterns observed in self-focused thoughts.

As such, this thesis will focus on the following questions:

- Q1. Are there significant differences in HEPs and brain oscillatory power between self-focused and non-self-focused thoughts?
- Q2. How do these self-focused and non-self-focused thoughts differ between individuals with rMDD and healthy controls?
- Q3. To what extent do mindfulness meditation and positive fantasizing interventions influence self-focused spontaneous thoughts and their neural correlates, in individuals with rMDD compared to healthy controls?
- Q4. Given the differences in self-focused spontaneous thoughts, can a ML classifier accurately differentiate between the two types of thought?

2 Background Literature

2.1 Self-referential thinking & the default network

According to Ingram (1990), self-focused attention is defined as ”an awareness of self-referent, internally generated information” [31]. This awareness can come in the form of interoceptive awareness (ability to sense and interpret internal bodily signals), or awareness of thoughts and emotions. Neuroimaging studies have shown that the brain's default network has increased activity during periods of rest and is involved in self-referential processing, including spontaneous thought and self-focused attention [32, 33]. Within the default network, brain regions that are strongly associated with an increase of activity during self-focused attention include the regions active during interoceptive awareness such as the medial prefrontal cortex (mPFC) and the insular cortex, as well as another region known as the posterior cingulate cortex (PCC)[34, 33, 35, 36]. Notably, the mPFC shows varying levels of activity depending on the nature of the self-referential task. For instance, when individuals engage in tasks that require them to focus on their internal states or emotions, there is an increase in activity along the dorsal mPFC. Conversely, when the task is more externally focused, such as distinguishing between images that show the indoors vs. the outdoors, there is a relative decrease in activity in the mPFC [33]. Additionally, when processing traits that could either reference the self or a close friend, self-referential processing activated the mPFC significantly more than other-referential processing [37].

Studies exploring event-related potentials (ERPs) of self-referential thinking have also provided insights regarding where and when these processes occur in the brain. Research by Walla et al. (2007) utilized magnetoencephalography (MEG) to investigate the subconscious effects of personal pronouns on word encoding. They showed that nouns paired with personal pronouns like ”my” or ”his” elicited distinct neural activation patterns compared to neutral pronouns like ”a.” Significant effects were observed between 200-400 ms over occipito-parietal electrodes and between 500-800 ms over left frontal electrodes. These findings suggest that early-stage processing distinguishes between personal and neutral information, while later processing differentiates between self-related and other-related information [38]. Another study that focused on the relationship between self-referential processing and depressive rumination found that specific brain regions are differentially activated during self-referential tasks in individuals with MDD compared to healthy controls. According to Hsu et al. (2021), task-based EEG recordings revealed that MDD patients exhibited distinct differences in late ERPs (800ms to 2200ms) across fronto-central electrodes when engaging in self-referential versus non-self-referential tasks. This difference was not observed in the control group, indicating an altered neural processing pattern in individuals with depression [39].

These findings map well onto the neuroimaging results regarding the brain's default network. The frontocentral electrodes showing differential ERP patterns in self-referential tasks are located over regions that include the mPFC and PCC, both components of the default network. This convergence of ERP and fMRI data highlights the critical role these regions play in processing self-referential information and underscores their involvement in the altered neural dynamics observed in depression.

Activity in the default network, specifically the mPFC, has also been observed in spontaneous thoughts such as when participants are engaging in mind-wandering [40, 41]. While spontaneous thoughts can be considered a form of self-focused attention, they differ in that these thoughts are generated without any intentionality or direction. Forms of spontaneous thought such as mind-wandering and daydreaming are characterized as being decoupled from ongoing perceptual input and are internally rather than externally focused [40]. Moreover, these types of spontaneous thought can be supported by self-related processing, for example, during mind-wandering highly self-related internal information has been shown to dominate over low self-related external task-relevant stimuli [12]. Given the similarities in the behaviour of self-focused attention and spontaneous thought, it's unsurprising that both involve the default network.

2.2 Spontaneous thought & MDD/rMDD

The nature and content of our spontaneous thoughts are also heavily influenced by our emotions, especially for mind-wandering thoughts with studies finding that the the unhappiness of participants caused wind-wandering episodes. Smallwood et al. (2009) conducted a study where they induced a positive, neutral, or negative mood in participants prior to them participating in a sustained-attention-to-response task (SART) where researchers would record and measure their mind-wandering episodes. Their results showed that inducing a negative mood led to participants making more errors on the SART and having more attentional lapses (mind-wandering episodes). Additionally, a negative mood resulted in the participants being less inclined to adjust their behaviour and reengage following an attentional lapse. In contrast, the induction of a positive mood resulted in participants better re-engaging and adjusting after a lapse [42]. These findings demonstrate that individuals with a prior negative mood are more likely to engage in mind-wandering, suggesting that a negative mood might lead to or exacerbate mind-wandering.

Additionally, research has shown that these negative moods can result in mind-wandering thoughts being skewed towards past events [43], which can be particularly devastating for those diagnosed with MDD, as having a negative emotional reactivity to mind-wandering episodes can result in a funnelling effect, where the thoughts start to predominantly focus on negative themes [44]. Having a negative affective reaction results in subsequent thoughts being the same or closely related to the contents of the previous thought, essentially locking our train of thought in a negative bubble [44]. With individuals with MDD being more likely to recall more negative information [45], the addition of this funnelling effect essentially traps them in a cycle of negative thinking, making it difficult to break free from depressive thought patterns. This cycle also results in a loop that exacerbates ruminations, and hopelessness which in turn worsens the state of one's depression [6, 7]. Such ruminative thinking can be particularly destructive for patients with rMDD, who during periods of stress or emotional upheaval are at risk of reverting to negative thinking patterns that were prevalent during episodes of active depression [6, 14].

Neuroimaging studies exploring this ruminative thinking have again highlighted the role of the default network in maintaining these maladaptive thought patterns. Specifically, research has shown that individuals with MDD exhibit hyperconnectivity within the default network, particularly involving the mPFC and PCC which was found to be associated with persistent rumination and negative self-focused thoughts [46]. The heightened connectivity between the mPFC and PCC during rest also serves as a predictor of the severity and persistence of depressive symptoms. Therefore, the researchers suggest that by reducing hyperconnectivity within the default network, it may be possible to alleviate some of the persistent negative self-focused thoughts and ruminations that characterise MDD.

This understanding extends to individuals with rMDD as well, with research finding that even during remission, individuals with a history of depression exhibit altered connectivity patterns in the default network [47]. Additionally, research has found that the mPFC in particular can encode whether an individual with a history of depression is at risk of relapse [48]. Farb et al. (2011) found that an increase in mPFC activity serves as a neural marker for the vulnerability to depressive relapse whereas the normalization of mPFC activity to the level seen in healthy controls is a marker for enduring remission.

The literature overall highlights the significant role the default network plays in mediating self-referential processing and the thought patterns observed in individuals with MDD and rMDD. While neuroimaging techniques like fMRI allow for research on the connectivity and activity patterns within the default network, research has also shown that specific neural responses, such as HEPs and brain oscillations, can serve as tools to measure default network activity and self-referential thinking.

2.3 Heartbeat-evoked potentials & self-referential processing

HEPs are neural responses to the perception of one's heartbeat and thus have been used across the literature to provide an objective correlate of interoceptive awareness [26, 49, 50, 51, 52, 53]. While HEPs are predominantly utilised to measure this form of awareness, HEPs have also been found to be associated with self-referential processing [25, 54, 55] and disorders such as MDD [56]. Park and Tallon-Baudry (2014) found that interoceptive signals, like heartbeats, can modulate activity in the insula and the anterior cingulate cortex, both of which are associated with self-referential processing. Specifically, they found that when individuals are engaged in tasks that require attention to their internal bodily states, such as counting their heartbeats, the amplitude of the HEPs in these regions is increased. This is because these regions modulate the subjective experience of one's bodily state and according to the researchers are implicated in the broader neural network responsible for maintaining a continuous sense of self [55]. Moreover, given that interoceptive awareness is often disrupted in those diagnosed with MDD [57], research has shown HEPs can capture differences in those with MDD and HCs. Terhaar et al. (2012) demonstrated that individuals with MDD exhibit significantly reduced HEP amplitudes compared to healthy controls, which they link to a diminished sensitivity in perceiving bodily signals [56].

Further exploration into HEPs and self-referential thinking found that these neural responses to heartbeats are in fact encoded in the default network during self-related spontaneous thoughts [25]. Babo-Rebelo et al. (2016) used MEG to measure neural responses evoked by heartbeats while participants engaged in free mind-wandering. Participants were interrupted at random intervals with a visual stimulus and asked to score the self-relatedness of their interrupted thought, focusing on two dimensions: the first-person perspective subject or agent in the thought ("I"), and the degree to which they were thinking about themselves ("Me") [25]. The results revealed that during these interrupted thoughts, the HEP amplitude in two regions of the default network—the ventral precuneus (vPC) and the ventromedial prefrontal cortex (vmPFC)—were closely linked with the "I" and "Me" dimensions respectively.

In subsequent research, it was shown that HEPs can differ from one another depending on whether the participant is engaging in imaginations related to themselves or to others. In a study involving 23 participants, individuals were tasked to imagine scenarios involving themselves or a friend, while their brain activity was recorded using MEG. They found that the amplitude of HEPs varied significantly depending on whether the imagination was self-focused or other-focused, with self-focused thoughts having greater HEP amplitudes. Their findings demonstrate that the brain's response to one's heartbeat is sensitive when the person is thinking of content related to self. Moreover, they found that the effect size was not influenced by their interoceptive awareness, but rather was influenced by how frequently the participants daydreamed [54]. It should be noted that research into self-focused thoughts utilising HEPs has primarily been conducted with healthy participants; therefore, there is currently a gap in the literature regarding if these same patterns can be observed in individuals with conditions like MDD and/or rMDD.

2.4 Brain oscillations & self-referential processing

Outside of HEP amplitude, another important neural correlate that can provide insights into self-focused attention and cognition is the spectrum of neural oscillatory activity. These oscillations are categorized into different frequency bands, each of which is associated with different cognitive functions and neural processes. The main frequency bands include delta (0.5-3.5 Hz), theta (4-7 Hz), alpha (8-12 Hz), beta (13-30 Hz), and gamma (>30 Hz) oscillations [58].

With the default network having strong activation during self-focused attention and introspection [34, 33, 35, 36, 46], analysis on brain oscillations within this region can offer further insights into the neural correlates of self-focused attention. Research has shown a positive correlation between alpha oscillations and the default network [27, 28], suggesting that increased alpha band activity is associated with heightened default network function. Specifically, researchers Jann et al. (2010) investigation into the topographic association of EEG spectral fluctuations found that increased activity in both alpha and beta bands was associated with increased default network activity [28].

However, not all studies have observed increases in oscillatory power across alpha and beta bands for self-focused thoughts. Bocharov et al. (2019) found that frontal alpha and theta band oscillatory power decreased while participants were experiencing spontaneous self-focused thoughts compared to non-self-focused thoughts [29]. Similarly, research by Knyazev et al. (2012) demonstrated that self-focused thoughts were best predicted by higher alpha activity within the default network followed by lower theta activity in the frontal cortex. These results suggest that increased alpha activity may signal a broader default network engagement, while decreased theta activity could reflect specific frontal processes during self-referential thought [30].

In sum, both HEPs and brain oscillations have been found to be linked to the default network, with an increase in HEP amplitude and a decrease in alpha and theta band oscillatory power reflecting engagement in self-focused compared to non-self-focused thoughts. With the default network being intricately involved in self-referential processing and spontaneous thought, any interventions aimed at altering these thoughts would in theory be reflected by corresponding changes in the neural measures across these regions. This form of research can therefore utilise neural measures to provide an objective assessment of how different interventions may affect brain activity and cognitive processes, which can then be used to develop effective therapeutic strategies.

2.5 The default network & interventions

There are a plethora of interventions that have been developed to target the persistent negative symptoms associated with psychiatric disorders such as MDD. For instance, interventions such as CBT have been found to be effective in alleviating depressive symptoms by altering connectivity within and across brain networks [59]. However, other approaches, such as mindfulness meditation and positive fantasizing also offer promising avenues for addressing the negative cognitive patterns associated with MDD with the added benefits of their long-term sustainability and ease of integration into everyday routines even after formal treatment has concluded.

2.5.1 Mindfulness meditation

Research has demonstrated that individuals with MDD are still able to experience reductions in their negative moods and experience significant mood improvements when exposed to positive events such as engaging in hobbies [60, 61]. This ”mood-brightening effect” [61] suggests that despite the tendency towards negative mind-wandering and rumination, individuals with depression can still respond positively to favourable stimuli or experiences, thus increasing how often one engages in positive experiences and activities can serve as therapeutic interventions that counteract the negative emotions seen in depression.

In practice this appears to be the case as well with several studies demonstrating over the years that mindfulness-based interventions can effectively reduce depression in both clinical and nonclinical populations [62, 63, 12, 20, 7], as well as reduce the risk of relapsing into depression [18]. Such changes happen in part due to the shifts mindfulness practices cause in cognitive patterns. Hofmann et al. (2010) analyzed 39 studies on mindfulness-based therapy with respect to depression and anxiety, where they found a medium reduction in anxiety and depression symptoms in general patient groups. Moreover, this effect was more pronounced in patients with specific anxiety or mood disorders. However, in studies with wait-list control groups or those exploring patients receiving standard treatment, the reductions were smaller, which may be more realistic as these reflect additional causal factors and are more indicative of real-world scenarios [64].

Mindfulness-based interventions overall encourage individuals to cultivate an awareness of the present moment, shifting cognitive patterns away from habitual self-focused thinking to a more present-centred awareness. This approach aligns with the concept of non-self in Buddhist psychology, which emphasizes the understanding that the self is not a fixed or permanent entity but rather a dynamic and ever-changing pattern of processes and experiences [65]. Research has shown that this shift brought upon by mindfulness can lead to significant reductions in self-referential processing. For instance, a study by Shi and He (2020) found that mindfulness meditators, compared to controls who had never practised mindfulness meditation, were worse at recalling self-related information, implying a reduction in self-referential processing and an enhanced balance between self- and other-referential processing. This shift away from a dominating self-focus to a more equitable processing of self and others suggest that mindfulness helps in cultivating a less self-centred perspective [66].

Other studies have also found similar effects where mindfulness interventions result in a more balanced and less reactive engagement with self-related and other-related information. They find that by reducing the habitual focus on the self, mindfulness interventions can decrease the intensity of negative ruminations leading to improvements in emotional regulation and symptoms of anxiety and depression.[67, 68]. This fosters a more decentered perspective allowing individuals to observe their thoughts without becoming overly identified with them which ultimately contributes to a healthier mental state.

Neuroimaging studies aiming to explore this effect have also found evidence that suggests that spontaneous thoughts and mindfulness are in an inverse relationship. For instance, Farb et al. (2012) found that mindfulness practices led to reduced activity in the mPFC. Considering how this region was found to be active during spontaneous thoughts such as mind-wandering [40, 41], a reduction in activity suggests a shift away from self-focused spontaneous thoughts towards a more present-focused mind. Moreover, the same study observed an increase in default network activity, namely, in PCC and the insula, which again suggests that participants were able to become more aware of the present moment leading to a more emotionally balanced mindset.

Outside of neuroimaging techniques, studies have also explored the effects of mindfulness meditation on brain oscillatory power offering further insights into the effectiveness of these interventions. For instance, Tang et al. (2020) discuss how mindfulness meditation enhances frontal midline theta activity, which is thought to index the control needed to maintain a meditative state [69]. Further supporting these findings, Wang et al. (2022) demonstrate that mindfulness-based cognitive therapy significantly affects resting-state theta oscillations in individuals with MDD. Their study found that an 8-week program of engaging with this intervention led to increased theta power. Moreover, they found that increased theta power specifically in the left parietal region was linked to improvements in rumination where individuals showed a decrease in maladaptive rumination and an increase in adaptive reflective rumination [70]. This form of rumination is considered beneficial as it involves a more constructive and problem-solving approach to thinking about one's problems, as opposed to the repetitive and negative focus typical of maladaptive rumination.

Studies exploring a shorter engagement period with mindfulness meditation have also shown considerable effects. For example, three days of mindfulness meditation training (20 minutes per day) was found to be effective at reducing negative mood, depression, fatigue, and confusion, as measured by the Profile of Mood States scale [71], while another examining the effects of four days of 30-minute instructor-guided mindfulness meditation training found improvements in mood, fatigue, anxiety, and mindfulness [72]. However, it is important to note that these improvements were primarily captured through self-report measures rather than direct assessments of neural changes.

Moreover, it is crucial to consider that the effectiveness of mindfulness practices can vary among individuals and that these practices can even have adverse effects. A study by Britton (2019) highlights how the increase in interoceptive awareness and/or activation of the insula cortex brought upon by mindfulness practices can also lead to an increase in emotional intensity, anxiety, panic, and traumatic flashbacks [73]. Another study found that mindfulness practices that are focused on interoceptive awareness, such as being aware of one's breath, lead resulted in the largest cortisol stress reactivity when compared to other forms of meditation [57]. Therefore it is important to recognize that one form of mindfulness meditation is not universally beneficial and may not be suitable for everyone. These practices should be attempted with care, realistic expectations, and by taking each individual's needs and history into account.

2.5.2 Positive fantasizing

One characteristic of depressive thinking is a lack of positive future-oriented thoughts and sometimes a greater affinity towards negative future-oriented thoughts [74]. One study even reported that, regardless of depression severity, patients with MDD generated fewer thoughts where future events were anticipated [75]. Given these patterns in depressive thinking, it has been hypothesized that engaging in idealized thoughts about the future, also known as positive fantasizing, could serve as a way to counteract these negative views.

Studies on positive fantasizing are often centred around the benefits of preventive cognitive therapy (PCT) as it directly integrates positive fantasizing techniques. Research on the benefits of PCT is extensive and it has been linked to lowering the recurrences of depressive episodes and preventing relapses [76, 77]. Moreover, PCT has been shown to have enduring effects on patients with rMDD. Bockting et al. (2015) found that the addition of PCT to Treatment As Usual (TAU) resulted in a significant protective effect against depressive recurrence over a 10-year period. The effectiveness of PCT was particularly pronounced in patients who had experienced multiple previous depressive episodes, demonstrating how beneficial this intervention is for those at high risk of recurrence [78].

Additionally, studies into optimism, have shown that optimism is associated with better emotional well-being and can in certain cases protect against the development of depressive symptoms [22, 23, 24]. While these studies do not directly evaluate the effects of positive future-oriented thinking, they do demonstrate how a positive outlook can have beneficial effects on one's mental health. Regardless, research on solely future fantasizing is also able to demonstrate similar results. A study by Peters et al. (2010) had participants who engaged in a brief exercise of writing about and imagining their best possible selves. The results of this exercise showed a significant increase in positive future expectancies and positive affect compared to those who wrote about and imagined a typical day, demonstrating that even brief moments of positive fantasizing can have immediate beneficial effects on mood and outlook [60]. However, it's important to note that these findings are based on self-report measures, which assess participants' perceptions of their mood rather than any objective cognitive measures that would reflect these changes.

In sum, across the literature, it has been shown that both positive fantasizing and mindfulness meditation can significantly improve mood and alter maladaptive thought patterns in individuals with MDD. If we consider how the literature shows self-referential processing predominantly takes place within the brain's default network, we can utilise neural correlates such as brain oscillations and HEP amplitude to investigate this region and explore whether there are discernible changes brought on by these interventions.

3 Methods

3.1 Experiment Design

In this study, we aim to explore whether significant differences exist in the neural correlates of HEPs and brain oscillatory power between self-focused and non-self-focused thoughts. Moreover, we wish to investigate whether these self-focused and non-self-focused HEP and brain oscillatory patterns differ between individuals with rMDD and healthy controls. Furthermore, we intended to evaluate the effects of mindfulness meditation and positive fantasizing interventions on self-focused and non-self-focused neural correlates across both groups.

To achieve these objectives, a within-subject design was employed where the experiment incorporated two interventions: mindfulness meditation and positive fantasizing. By employing a within-subject design with repeated measures, each participant in the experimental (rMDD) and control (healthy) groups could undergo both interventions, allowing for a direct comparison of their effects on self-focused and non-self-focused thoughts.

3.2 Experiment Procedure

The experiment itself consisted of five phases: a baseline individual characteristics measurement and two pre- and two peri-intervention measurement periods [79]. During the baseline assessment, participants completed various self-report questionnaires assessing individual characteristics such as personality traits, depression sensitivity, and more. From there the experiment can be defined as being split into two blocks. In the first block, the first pre-intervention measurement was carried out. This involved one week of baseline momentary measures using Experience Sampling Methods (ESM) ten times per day, cognitive task performance two times per day, 24-hour measurements of impedance cardiography (ICG)/electrocardiogram (ECG), and one-week actigraphy measurements. Following this, the participants underwent the first peri-intervention measurement, where they practised daily with an intervention and underwent the same measurements as in the pre-intervention measurement. On the first day of this phase, participants received two hours of training on how to perform the intervention.

After this block was over, a wash-out period phase of at least one month ensued, during which participants refrained from engaging in any intervention-related activities. This was followed by the second block of the experiment, starting with the second pre-intervention measurement which included another round of the same measures as in the first pre-intervention measurement. Lastly, participants completed the second peri-intervention measurement, where they practised with the other intervention.

3.3 Data Collection

During the experiments, participant self-reports were collected using ESMs in order to obtain subjective data regarding their momentary experiences, such as their thoughts and feelings. On top of this, participants underwent a sustained-attention-to-response task (SART) in order to obtain more objective cognitive data. During a SART participants are involved in a go/no-go task, where they press a button as fast as possible for frequent non-target stimuli (go) but refrain from pressing when they observe infrequent target stimuli (no-go) [80]. The monotonous nature of this task creates an ideal environment where thoughts unrelated to the task can occur, allowing us to assess off-task thinking.

Participants performed a short version of the SART via a mobile application twice a day for seven days. The task includes four blocks with four thought probe questions per block where participants are asked about the content of their thoughts such as how self-related they were.

On the last day of the measurement week, participants visited the lab where their EEG and ECG measurements could be taken during resting state, during an implicit emotion regulation task, and during a SART. EEG and ECG data were recorded using a BioSemi Active Two system with 32 electrodes positioned at the 10–20 system and eight external electrodes. Data recording was performed using Actiview software, and sampled at a frequency of 512 Hz [79]. For this study, only the EEG and ECG data obtained during the SART will be analyzed to investigate neural correlates associated with self-focused thought.

3.4 Participants

Not all participants were able to complete all pre- and peri-intervention EEG recordings due to a variety of reasons ranging from personal to scheduling conflicts. Moreover, some of the EEG recordings that were obtained were corrupted or contained less than 30 trials for either self-focused or non-self-focused trials. As such several recordings were discarded from the analysis due to their poor quality or insufficient data for meaningful interpretation. In the end, the data from 41 participants were selected to be used in this study, with the final sample including 32 female and 3 male participants. The remaining 6 participants did not disclose their gender. 21 of these participants were in remission from clinically diagnosed MDD (rMDD), and 20 were HCs The participants' ages ranged from 18 to 58 years, with an average age of 32.66 years. The educational background of the participants was varied, with 15 participants having completed higher vocational education (HBO), 7 having completed university education (WO), 6 having completed pre-university education (VWO), 4 having completed secondary vocational education (MBO), and 2 participants with master's degrees (WO Master). The remaining 7 participants did not disclose this information. Regarding the EEG recordings, specifically, from the 41 participants, we obtained 24 pre-meditation, 31, peri-meditation, 23 pre-fantasizing, and 21 peri-fantasizing EEG recordings.

3.5 Data Preprocessing

Continuous EEG data obtained from the SART were pre-processed with the EEGLAB toolbox [81] using MATLAB. The data was visually inspected to identify any bad channels, and if said channels were detected they were replaced through the interpolation of neighbouring electrodes. Following this, the EEG signals were band-pass filtered from 0.5 Hz to 30 Hz per the established methodologies from other HEP-related studies [49].

Lastly, an independent component analysis (ICA) was conducted to remove used to remove any artefacts embedded in the data, such as the ones caused by muscle activity, eye blinks, and saccades. These artefacts can introduce unwanted noise into the EEG signals and potentially confound the analysis of the neural correlates, as such all identified artefacts were removed after manual inspection of the independent components extracted by the ICA.

3.6 HEPs

In order to obtain the HEPs, ECG data was first re-referenced and mean-centred to ensure consistency with the filtering parameters of EEG and remove any potential offset. The ECG signal then underwent band-pass filtering between 0.5 Hz and 30 Hz and was then subjected to a wavelet transform to identify QRS complexes [25]. The R-peaks, which represent the peaks corresponding to heartbeats, were detected from the wavelet-transformed signal using MATLAB's findpeaks function. R peak detection was visually verified in all subjects to ensure the accuracy of the detection process. Once verified, the latencies of these detected heartbeats were stored and added as new events to the EEG data.

These new heartbeat events lack labels regarding the self-relatedness of the participant's thoughts. To address this, a script was developed to look into a window of 15 seconds before each thought probe event. Within this timeframe, the script saves the self-relatedness label of the thought probe and assigns it to all heartbeat events within this timeframe.

Once the self-relatedness of the heartbeat events was labelled, the EEG data was epoched into trials centred around these heartbeat events, namely, from 100 milliseconds before to 600 milliseconds after R-peaks of heartbeat events. This time range was chosen based on prior research, which has consistently identified significant effects in HEPs within this window [82], with studies specifically exploring self-referential thinking observing significant effects between 100-350 ms post-R peak [25, 54]. By taking the full 100 to 600 ms post-R-peak window, we aimed to account for all potential regions of interest.

Following epoching, the trials were categorized based on the self-relatedness labels assigned to the heartbeat events. This categorization allowed for the separation of EEG data into different cognitive states, such as self-focused ST, non-self-focused ST, and 'other' (neither self-focused nor non-self-focused).

3.7 Brain oscillations

Alpha and theta band oscillations have been consistently linked to default network activity and self-referential thinking with some studies also suggesting a link between default network activity and beta oscillations [27, 28, 29, 30] We aimed to build upon this literature by investigating oscillatory power in theta (4-7 Hz), alpha (8-12 Hz), and beta (13-30 Hz) bands at the same electrode sites as the ones used in the HEPs to uncover potential differences between self-related and non-self-related thoughts across the default network. Moreover, we focused on three separate time windows: 0-180 ms, 180-350 ms, and 350-600 ms. Research on HEPs has shown that the typical time window associated with the cortical processing of heartbeats is between 200–600 ms [83], while the neural activity for self-referential is captured predominantly within the 100-350 ms window post-R-peak [25, 54]. Therefore, our selected time windows would provide insights into the brain oscillatory activity during these periods of processing as well as the early time window (0-180 ms) which could reflect brain oscillatory activity during the immediate neural response to the heartbeat leading up to the cortical processing of self-referential thoughts. Moreover, according to a quantitative systematic review on short-term heart rate variability, the average time between two subsequent heartbeats, also known as the mean RR interval, is approximately 926 milliseconds in resting adults [84]. Given this interval, the chosen time windows are all well within the span of a single cardiac cycle, ensuring no overlap between the neural responses associated with one heartbeat and the onset of the next.

The frequency analysis was performed using the Fieldtrip toolbox in MatLab [85]. Specifically, we employed a time-frequency decomposition using multitaper fast Fourier transform (FFT) with a Hanning taper. We selected a frequency range from 1 to 30 Hz and applied a sliding time window for ranges between, 0 to 180 ms, 180 to 350 ms, and 350 to 600 ms post-R-peak. For each trial, the power spectrum was computed for the previously selected electrodes.

Following frequency analysis, we computed the average oscillatory power for each self-focused and non-self-focused trial per participant. This process was repeated for each frequency band and each of the selected electrodes. This data was then saved to be used for later analysis.

3.8 Analysis

In this study, we first wanted to investigate if there were any significant differences in the HEPs and brain oscillatory power between self-focused and non-self-focused states. Previous research has shown that the default network is involved in self-related processing, including spontaneous thought and self-focused attention. Within the default network, the regions that were most strongly associated with an increase in activity during self-focused thought include the vPC, vmPFC, mPFC, the insular cortex, and the PCC [25, 34, 33, 35, 36].

Given this knowledge, we selected data from the electrodes that were positioned over these brain regions to specifically capture the neural activity related to self-focused and non-self-focused states. In the end, 17 electrodes were selected for analysis motivated by the literature on self-related processing within the default network [25, 34, 33, 35, 36, 38, 39]. These electrodes were the parietal electrodes Pz, P3, P4, the central electrode Cz, the frontal electrodes Fz, Fp1, Fp2, F3, F4, F7, F8, AF3, AF4, and the frontocentral electrodes FC1, FC2, FC5, and FC6. Analysis was to be done separately for each electrode to account for potential variations across distinct brain regions.

Lastly, we specifically chose to investigate the HEP amplitudes at a time of 180ms to 350ms post R peak. According to a meta-analysis conducted by Coll et al. (2021), attention-based HEP studies often focus on a time window ranging from 300 to 500 ms post-R peak [82]. However, when inspecting our data and observing the enlarged ERP plot for all participants, the peak latencies were not within this time window range. Instead in most channels, the peaks fell within the range of 180ms to 350ms post-R peak. Nonetheless, we explored both time windows in our analysis. For brain oscillations, we explored three separate time windows (0-180 ms, 180-350 ms, and 350-600 ms) to evaluate whether oscillatory power changes over time.

3.8.1 Cluster-based permutation test

Cluster-based permutation analysis was conducted to assess the significance of differences in HEPs between self-focused and non-self-focused thought states using the Fieldtrip toolbox [85]. This method is particularly useful for analyzing EEG data, as it accounts for the spatial and temporal correlations inherent in EEG signals whilst correcting for multiple comparisons.

A dependent-sample t-test was conducted at each time point between 180ms to 350ms post-R peak at the selected electrode sites to compare HEPs between self-focused and non-self-focused trials in order to identify clusters of time points and electrodes exhibiting significant differences. Any identified clusters would indicate regions across the brain where HEP amplitude significantly differed between self-focused and non-self-focused thoughts. While this window was chosen due to the peak latencies falling within this range, we also conducted the test on the 300 to 500 ms post-R peak window reported in [82]. The cluster-level test statistic was calculated by summing the t-values within each cluster, where the cluster-level statistics that were less than 0.05 ($p < 0.05$) were considered significant [86].

To determine the significance of observed clusters, we conducted a permutation test where the labels of self-focused and non-self-focused trials were randomly shuffled across participants, and the clustering procedure was repeated 10,000 times to generate a null distribution of cluster-level test statistics under the assumption of no difference between conditions.

3.8.2 Linear mixed-effects models

We used linear mixed-effects models to analyze the differences in HEP amplitude and brain oscillatory power between self-related and non-self-related trials for all participants. We chose linear mixed-effects models as these allow for the inclusion of continuous predictors and their interactions. In our study, we can include continuous predictors such as intervention type (pre-fantasizing, peri-fantasizing, pre-meditation, and peri-meditation) alongside categorical predictors such as self-focused vs. non-self-focused states and group (rMDD vs. healthy controls) allowing us to explore the nuanced interactions between different factors and how these interactions may influence HEP amplitude and brain oscillatory power. Additionally, the ability of these models to handle unbalanced data and incorporate random effects for participant variability is beneficial for our study [87]. Participants may have, for example, variations in baseline HEP amplitudes and in their responsiveness to interventions, thus incorporating random effects is important for obtaining accurate estimates whilst accounting for individual differences.

For the HEPs, initially, we created linear mixed-effects models to assess whether there were any significant differences in HEP amplitude between self-focused and non-self-focused trials across all participants by taking the fixed effect of Thought (self vs. non-self) and a random intercept for each participant. The model was fitted separately for each electrode to account for the variations in neural activity across different brain regions. Additionally, a Bayes Factor analysis was performed in order to assess the strength of evidence for the null hypothesis. A Bayes factor smaller than 0.33 would indicate support for the null hypothesis, suggesting there are no differences between self-focused and non-self-focused trials. In contrast, a Bayes factor greater than 3 would indicate support for the alternative hypothesis, suggesting differences between self-focused and non-self-focused trials [88]. A Bayes Factor in between 0.33 and 3 would indicate inconclusive evidence. All Bayes Factor analyses were conducted using the lmBF function from the BayesFactor package in R [89].

On top of this, post-hoc analysis using Tukey's contrasts was conducted to correct for multiple comparisons. This step is crucial as it allows us to identify the true effects and differences in HEP amplitudes between self-focused and non-self-focused trials, minimizing the risk of attributing significance to random fluctuations in the data.

Once the analysis of HEP amplitude was complete, we created linear mixed-effects models for the brain oscillation analysis. For this, instead of creating a separate model for each electrode, we created separate models for each electrode within each band to assess the differences in oscillatory power between self-focused and non-self-focused trials. Moreover, this step was repeated for each of the three separate time windows (0-180 ms, 180-350 ms, and 350-600 ms). Each linear mixed-effects model included the fixed effect of Thought, a random intercept for each participant, and the dependent variable of oscillatory power in the respective frequency band. A Bayes factors analysis and post-hoc analysis using Tukey's contrasts were also applied to these models to assess the strength of evidence for the null hypothesis and examine whether differences in power between self-focused and non-self-focused trials were significant after correcting for multiple comparisons. All linear mixed-effects models were constructed using the lmer function from the lme4 package in R [89].

3.8.3 ANOVA model comparisons

After creating these initial linear-mixed-effects models, analysis of variance (ANOVA) model comparisons were performed to evaluate the significance of including interaction terms in these models. By including additional factors we aimed to understand if they had any influence on the HEP amplitude and brain oscillatory power associated with self-focused and non-self-focused thoughts. The specific interactions investigated included Thought Type and Group which tested whether the differences in neural correlates between self/non-self-focused varied between individuals with rMDD and HCs, Thought Type and Intervention to assess the differences in neural correlates before versus after each of the interventions, and Thought Type, Group, and Intervention which explored whether the effects of interventions on the different thought types are moderated differently depending on the group.

These more complex models were then independently compared to the simple model without interactions and their results were plotted in the form of a topoplot. A significant improvement in model fit ($p < 0.05$) would suggest that the interaction term adds valuable explanatory power and that the complex model fits better to the data. For the electrodes where the complex model provided a better fit, we conducted post-hoc analysis using Tukey's contrasts to determine if the results were still significant after correcting for multiple comparisons. Moreover, for each of these complex models, we performed a Bayes Factor analysis to complement the ANOVA comparisons by evaluating the strength of evidence for the interaction effects. Specifically, the Bayes Factors for the interaction terms were calculated as the ratio of the Bayes Factor for the model including the interaction term to the Bayes Factor for the model that included only the main effects.

3.9 Machine Learning

After obtaining the features that yielded significant differences between self-focused and non-self-focused thoughts from the initial linear mixed-effects models without interactions, we wished to investigate whether a classifier could accurately distinguish between the two types of thought. We explored three classifiers namely, Random Forest, K-Nearest Neighbors (KNN), and Gradient Boosting. and conducted a grid search of hyperparameters to optimize each classifier's performance. The specific parameters of each classifier can be seen in Table 1.

These specific classifiers were selected due to their extensive literature and well-established applications, especially regarding the classification of EEG signals and data. The Random Forest classifier is known for its easy interpretability, and ability to handle high-dimensional data efficiently [90]. It utilises an ensemble learning method where multiple decision trees are constructed during training and the final prediction is made based on the majority vote of these trees. Each decision tree is built on a random subset of the data and a random selection of features, which helps to reduce variance and prevent overfitting. Additionally, this random selection process ensures that the model remains robust and can generalize well to new data [91]. While the most optimal parameters for this classifier can vary depending on the specific dataset and classification task at hand [92], key hyperparameters that significantly impact the model's performance include the number of trees, the depth of each tree, and the criterion used for splitting nodes. As such, these parameters were included in our grid search to identify the best configuration for classifying self-focused versus non-self-focused thoughts.

The Gradient Boosting classifier also utilises ensemble learning methods by creating trees sequentially, where each new tree attempts to correct the errors of its predecessor. This sequential method of training, where subsequent trees are trained on the residuals or errors of previous trees, allows

Gradient Boosting to continuously update and refine its predictions, incrementally improving model accuracy [93]. Additionally, this iterative process makes Gradient Boosting particularly effective for tasks where subtle differences in the data can have significant impacts on the outcome, such as distinguishing between self-focused and non-self-focused thoughts. The key hyperparameters that the Gradient Boosting algorithm depends on include the learning rate, the number of boosting stages (the number of trees in the ensemble), and the maximum depth of the trees [93]. In this study, we explored various settings for these parameters to ensure that the model was finely tuned to our dataset.

Lastly, the KNN classifier was chosen for its simplicity and effectiveness in handling classification tasks. KNN works by identifying the *k* nearest neighbours of a data point within the training dataset, based on a chosen distance metric, and assigning the class label most common among these neighbours to the data point [94]. This approach allows KNN to classify new, unseen data points by leveraging the similarities between the new point and its closest neighbours in the feature space. For our analysis, we implemented KNN with a range of *k* values to find the optimal number of neighbours that could best distinguish between self-focused and non-self-focused thoughts. This hyperparameter is critical as a smaller *k* value can make the model sensitive to noise in the data, a larger k value may ignore important distinctions by considering too many neighbours. The distance metric is another key hyperparameter in KNN that can significantly affect its performance. Therefore, we explored several distance metrics in an effort to optimize the KNN model's performance.

Classifier	**Parameters**	**Values**
Random Forest	Number of trees	10, 50, 100, 200
	Maximum depth of trees	None, 3, 5, 10
	Minimum samples split	2, 10, 20
	Criterion	Gini, entropy, mse
K-Nearest Neighbors	Number of neighbors	5, 20, 50, 100, 120
	Classifier weights	uniform, distance
	Distance metric	minkowski, euclidean, manhattan
Gradient Boosting	Number of boosting stages	50, 100, 150
	Learning rate	0.01, 0.1, 0.5, 1
	Maximum depth	3, 5, 10

Table 1: *Hyperparameters explored for each classifier*

Before training, features were normalized by removing the mean and scaling to unit variance to ensure that all variables contributed equally to the model's performance. From there, the whole dataset was randomly divided into train and test datasets, where 70% of the data was allocated to the training set and 30% was allocated to the testing set. To further refine the model, we utilized a 10-fold cross-validation to train the classifier [95]. Moreover, given that we had an unequal number of trials, specifically, we had more self-focused trials compared to non-self-focused trials, we implemented a random oversampling method for each cross-validation fold to ensure that the amount of data was equal for self-focused and non-self-focused trials [96]. This step was crucial as it helped to mitigate the risk of the classifier becoming biased towards the majority class, which in our case was self-focused thoughts. Once the classifiers were trained on the resampled data, we evaluated their performance on the test set to assess their generalizability and evaluate how well the classifiers can predict self-focused versus non-self-focused thoughts on unseen data.

Classifier performance was evaluated using accuracy, precision, recall, F1 score, and specificity as these metrics provide an understanding of the classifier's performance from different perspectives. Accuracy reports the ratio of correctly predicted instances to the total instances. It is given by the formula:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

where TP represents true positives, TN true negatives, FP false positives, and FN false negatives. While accuracy is a useful measure, it can also be misleading in cases of class imbalance, hence why we considered additional metrics.

Precision measures the accuracy of positive predictions and indicates the proportion of true positive observations out of the total predicted positives. In our case, precision assesses the classifier's ability to correctly identify self-focused thoughts. It is given by the formula:

$$\text{Precision} = \frac{TP}{TP+FP} \tag{2}$$

Recall measures the proportion of actual positives that are correctly identified by the classifier. This metric is crucial for understanding the classifier's ability to detect all self-focused thoughts. It is given by:

$$\text{Recall} = \frac{TP}{TP+FN} \tag{3}$$

F1 Score is the harmonic mean of precision and recall, providing a single metric that balances the trade-off between them. It is particularly useful when dealing with imbalanced datasets, as it accounts for both false positives and false negatives. The F1 Score is calculated as:

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

Lastly, specificity measures the proportion of actual negatives that are correctly identified. In our case, the negatives would be non-self-focused thoughts making this metric important for understanding the classifier's ability to correctly identify non-self-focused thoughts, which were less frequent in our dataset. Specificity is given by the formula:

$$\text{Specificity} = \frac{TN}{TN+FP} \tag{5}$$

4 Results

Each participant had an average of 305.27 trials for self-related thoughts, 157.62 trials for non-self-related thoughts, and 278.24 trials for thoughts that were neither self nor non-self-related. HCs averaged 312.41 trials for self-related thoughts and 164.8 for non-self-related thoughts, while those with rMDD had 298.28 and 150.58 trials, respectively. To determine if these differences between the groups were significant, an ANOVA was conducted which revealed there was no significant difference between the groups for self-related thoughts, $F(1,97) = 0.19$, $p = 0.67$, $BF_{10} = 0.23$, or for non-self-related thoughts, $F(1,97) = 0.26$, $p = 0.86$, $BF_{10} = 0.07$.

For self-related thoughts, HCs displayed an increase from an average of 302 trials pre-meditation to 330.13 peri-meditation, while those with rMDD displayed an increase from 285.2 to 297.93 trials. The t-tests on these trials showed that this increase was not statistically significant for HCs ($t_{(28.35)} = -0.48$, $p = 0.64$, $BF_{10} = 0.37$) or for those with rMDD ($t_{(19.16)} = -0.24$, $p = 0.81$, $BF_{10} = 0.38$). For the fantasizing intervention, HCs rose from 262.71 pre-fantasizing to 332.45 trials peri-fantasizing, whereas those with rMDD had almost no change, exhibiting a very small decrease from 304.06 to 303.11 trials. Similarly, the t-tests indicated no significant difference in the change for HCs ($t_{(15.92)} = -0.89$, $p = 0.39$, $BF_{10} = 0.52$) or rMDD ($t_{(16.49)} = 0.01$, $p = 0.99$, $BF_{10} = 0.38$).

For non-self-related thoughts, HCs had a slight increase from an average of 150.2 trials pre-meditation to 156.19 trials peri-meditation, while those with rMDD saw a decrease from 150.6 trials to 146.8 trials. However, the t-tests revealed that these changes were not statistically significant for HCs ($t_{(28.72)} = -0.18$, $p = 0.86$, $BF_{10} = 0.34$) or for those with rMDD ($t_{(22.99)} = 0.11$, $p = 0.91$, $BF_{10} = 0.37$). Regarding the fantasizing intervention, HCs initially had on average 204 trials pre-fantasizing, which decreased to 172.27 peri-fantasizing, while those with rMDD increased from 142.94 to 170.44 trials. Again, the t-tests showed no significant differences for HCs ($t_{(15.29)} = 0.82$, $p = 0.42$, $BF_{10} = 0.51$) or rMDD ($t_{(14.94)} = -0.61$, $p = 0.55$, $BF_{10} = 0.44$).

4.1 HEPs

The average HEP waveforms from -100 ms to 600 ms were plotted for self-focused and non-self-focused trials separately as shown in Figure 1. Upon initial observation, in many of these HEPs, the amplitude for both self and non-self-focused thoughts are quite similar.

4.1.1 Cluster-based permutation test

For both the latency range from 180 to 350 ms post-R peak and 300 to 500 ms post-R peak the cluster-based permutation test revealed no significant differences between self-focused and non-self-focused trials ($p > 0.05$) on the selected electrode sites.

4.1.2 Linear mix-effects models

We first created linear mixed-effects models for each electrode to assess differences in HEP amplitude between self-focused and non-self-focused trials across all participants for the 180-350 ms window. The results of these models are depicted in Figure 2a where the t-value distribution across the scalp can be observed. Immediately, it can be observed that electrode Fp2 stands out with the darkest region on the map indicating a significant negative t-value. These results demonstrate that at electrode Fp2, the HEP amplitude during self-focused trials was significantly lower than that during non-self-focused trials ($\beta = -0.248, SE = 0.077, p = 0.002$). Outside of this electrode, no other electrode sites showed any significant main effect of Thought ($p > 0.05$), suggesting no average difference in HEP amplitudes between self-focused and non-self-focused trials. Subsequent post-hoc analysis using Tukey's contrasts further confirmed these results by revealing that the HEP amplitude during self-focused trials was significantly lower than that during non-self-focused trials only in the electrode Fp2 ($adjusted p = 0.001$) after correcting for multiple comparisons.

Subsequent Bayes Factor analyses also supported these findings, where all electrodes except Fp2 ($BF = 14.92$) yielded low Bayes Factors, ranging from 0.716 to 0.15. These findings demonstrate some findings to be inconclusive while others provide strong evidence in support of the null hypothesis indicating no differences in HEP amplitudes between self-focused and non-self-focused trials. Electrode Fp2 however, yielded a Bayes Factor of 14.92, indicating strong evidence supporting the alternative hypothesis that HEP amplitude differs across self-focused and non-self-focused thoughts.

This process was repeated for the analysis on the 300-500 ms window where the results can be observed in Figure 2b. The linear mix-effects models for all electrodes showed no significant main effect of Thought ($p > 0.05$), suggesting no average difference in HEP amplitudes between self-focused and non-self-focused trials. Subsequent Bayes Factor analyses supported these findings with only electrodes FC6 ($BF = 1.45$), F3 ($BF = 1.29$), and F4 ($BF = 1.05$) yielding inconclusive results while the remaining electrodes provide strong evidence in support of the null hypothesis ($BF < 0.33$)

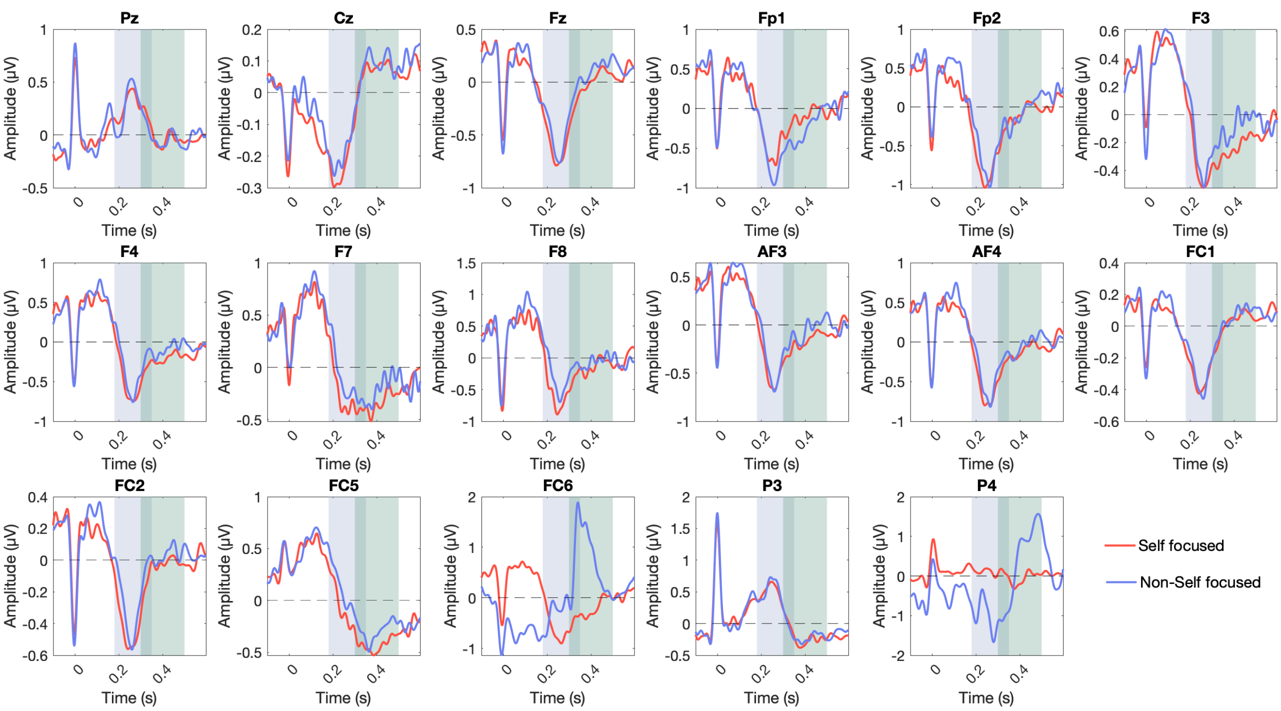
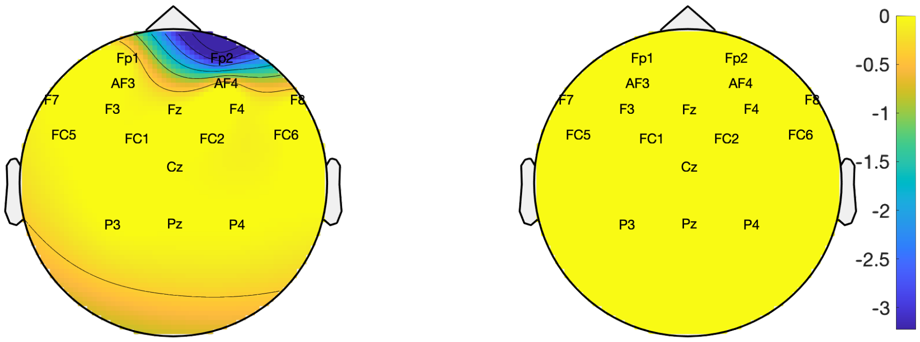


Figure 1: *Grand average HEPs in electrodes Pz, P4, P3, Cz, Fz, Fp1, Fp2, F3, F4, F7, F8, AF3, AF4, FC1, FC2, FC5, and FC6 comparing self-focused trials (red) and non-self-focused trials (blue). The time window for detecting peaks of HEP components from 180ms to 350ms post-R peak is shown in the light blue rectangle, while the time window from 300ms to 500ms post-R peak is represented by the green rectangle.*



(a) **(b)**

Figure 2: *Topographic map of t-values distinguishing HEP amplitude between self and non-self thoughts. (a) Displays the topographic map for the latency range 180 to 350 ms post-R peak and (b) displays the map for the latency range 300 to 500 ms post-R peak*

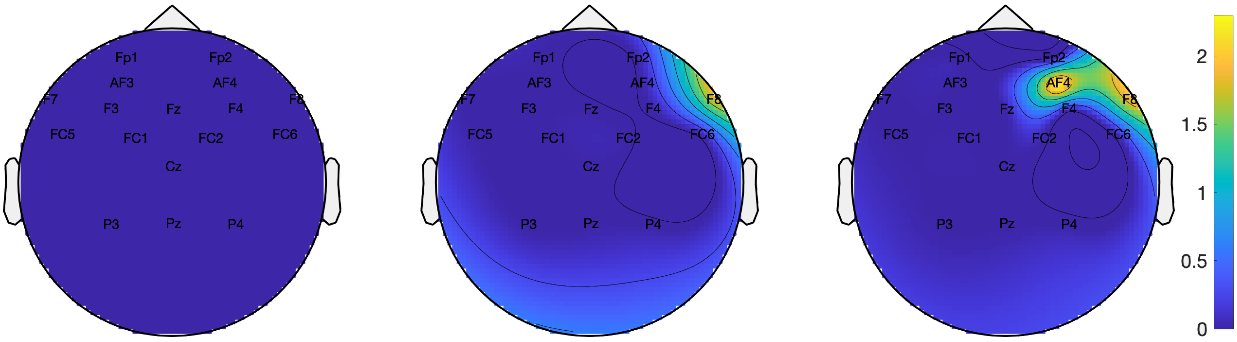
4.1.3 Effects of group & interventions - ANOVA model comparisons

We then incorporated additional interactions in our linear mixed-effects models to examine if the participant Group (rMDD vs. HC), engaging in fantasizing/meditation, or if an interaction between group, fantasizing, and meditation influenced the amplitude of thoughts differently. Following model fitting, we conducted ANOVA comparisons to determine the significance of each added interaction in improving model fit compared to the simpler preceding model depicted in Figure 2. The results of these ANOVA comparisons for the 180 to 350 ms post-R peak window can be observed in 3 where we can immediately observe that the inclusion of the group variable does not lead to significant differences across all electrode sites (see Figure 3a). This suggests that HEP amplitude for self versus non-self thoughts does not significantly differ when considering the distinction between rMDD and HC groups. Subsequent Bayes Factor analyses confirmed these findings, as Bayes Factors were consistently low across all electrodes, ranging from 0.28 to 0.04. These results support the conclusion that group differences do not significantly influence HEP amplitude in the context of self-focused versus non-self-focused thoughts.

In Figure 3b we can observe that the inclusion of interventions allows electrode F8 to better capture significant differences in HEP amplitude. This suggests that the HEP amplitudes for self-focused and non-self-focused thoughts are influenced by whether participants had engaged in mediation/fantasizing. However, the subsequent post-hoc analysis did not reveal statistically significant differences when correcting for multiple comparisons (adjusted $p > 0.05$). Subsequent Bayes Factor analyses confirmed the post-hoc results, with Bayes Factors ranging from 0.0002 to 0.015 across all electrodes, suggesting strong evidence that the inclusion of interventions did not lead to substantial differences in HEP amplitudes across self-focused and non-self-focused trials.

Lastly, in Figure 3c, we see that the interaction between group and interventions results in more distinct patterns of significant effects. The topographic map shows pronounced activity electrodes AF4 and F8, indicating these factors significantly impact HEP amplitudes across the two types of thought. However, the subsequent post-hoc analysis for these models also did not reveal statistically significant differences. Subsequent Bayes Factor analyses again confirmed the post-hoc results, with Bayes Factors ranging from 0.000002 to 0.0001. This provides very strong evidence against the likelihood that these interactions have a meaningful influence on HEP amplitudes.

This process was repeated for the analysis on the 300-500 ms window, however, none of the more complex models were shown to fit better to the data compared to the simpler model. Specifically, the inclusion of group variables, interventions, and their interactions did not lead to improved model fits or meaningful insights into HEP amplitude differences between self-focused and non-self-focused thoughts.



(a) **(b)** **(c)**

Figure 3: *Topographic map of ANOVA comparisons between models highlighting electrodes where added interactions had statistically significant effects on the HEP amplitude for self-focused and non-self-focused thoughts between 180 to 350 ms post-R peak. (a) illustrates the comparison of models with and without the group (b) shows the comparison of models with and without interventions, and (c) displays the comparison of models with and without the interaction between group and intervention. Significant transformed p-values are depicted, with non-significant values set to 0*

4.2 Brain oscillations

4.2.1 Linear mix-effects models

We then turned our attention towards linear mixed-effects models that could explore the relationship between brain oscillatory power and self-referential processing as well as other potential factors such as Group and Intervention Order. We first created a model for each band that would explore the relationship between oscillatory power and self-referential processing across all selected electrodes. Figure 4 illustrates the topographical distribution of the t-values derived from these models for theta, alpha, and beta bands across three distinct time windows (0-180 ms, 180-350 ms, 350-600 ms).

For the theta band, during the first 0-180 ms window, significant negative t-values were found in the frontocentral electrode FC6 indicating that self-focused thoughts had lower theta oscillatory power compared to non-self-focused thoughts. Subsequent post-hoc analysis for this electrode further supports these findings when correcting for multiple comparisons (adjusted $p = 0.008$). However, the Bayes Factor analysis revealed a Bayes Factor of 1.22 indicating that the observed difference in theta power between self-focused and non-self-focused thoughts is inconclusive. For the electrodes that were not significant, the Bayes Factors ranged from 0.902 to 0.15 indicating either inconclusive results or evidence for the null hypothesis where the electrodes did not capture the differences in theta oscillatory power between self-focused and non-self-focused thoughts.

In the 180-350 ms window, electrodes Pz, FC1, and P4 yielded similar trends where self-focused thoughts had lower theta oscillatory power than non-self-focused thoughts. Subsequent post-hoc analysis for these electrodes further supports these findings when correcting for multiple comparisons (adjusted $p < 0.05$). The Bayes Factor analysis revealed that evidence was substantial for electrodes Pz ($BF = 4.07$) and P4 ($BF = 5.56$), suggesting that there is evidence in favour of the alternative hypothesis that self-focused thoughts are associated with lower theta power in these regions compared to non-self-focused thoughts. However, for electrode FC1, the Bayes Factor was very low ($BF < 0.33$), indicating the evidence for the null hypothesis (no difference). For the electrodes that were not significant, the Bayes Factors provided strong evidence for the null hypothesis (all $BF < 0.33$).

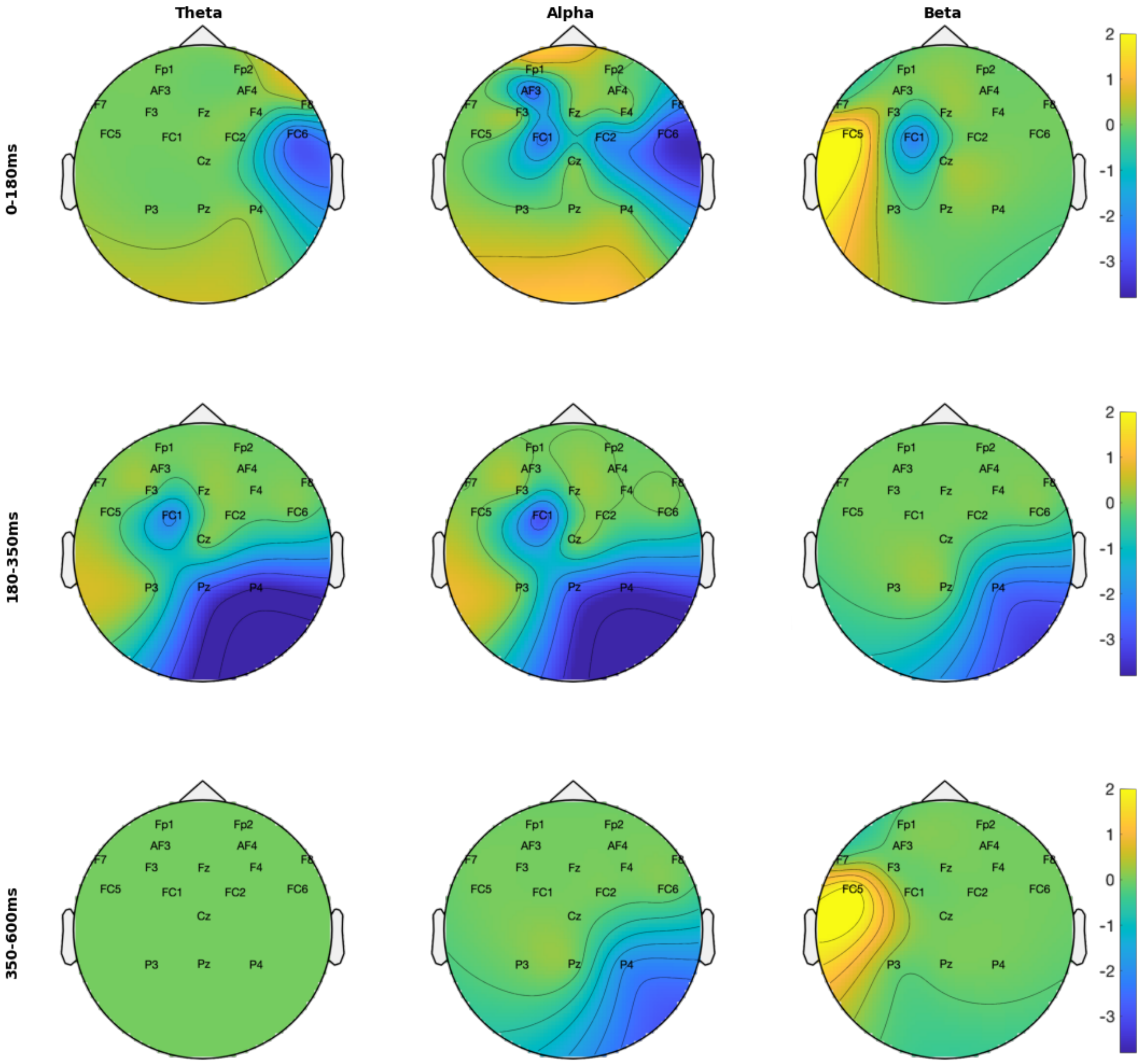


Figure 4: *Topographical distribution of t-values from linear mixed-effects models comparing oscillatory power between self-focused and non-self-focused thoughts for theta, alpha, and beta frequency bands across three time windows (0-180 ms, 180-350 ms, 350-600 ms). Non-significant electrodes are set to zero*

Lastly, for the 350-600 ms window, no electrodes were able to capture any significant differences in theta oscillatory power between self-focused and non-self-focused thoughts. This could potentially suggest that in the later stages of self-referential processing, the involvement of the theta band becomes less prominent or that the differences are too subtle to be deemed significant. The Bayes Factor analysis supports this lack of significance by providing strong evidence for the null hypothesis for all electrodes (all $BF < 0.33$).

For the alpha band, during the 0-180 ms window, the most widespread activation of electrodes can be observed across all bands and time windows. Notably, this activation takes place across the frontal and frontocentral electrodes FC2, F8, FC1, AF3, and FC6 where self-focused thoughts had lower alpha oscillatory power than non-self-focused thoughts. Subsequent post-hoc analysis for these electrodes further supports these findings when correcting for multiple comparisons (adjusted $p < 0.05$). However, the Bayes Factor analyses revealed inconclusive support for these findings. Electrodes FC1 ($BF = 1.93$), AF3 ($BF = 1.30$), FC6 ($BF = 1.26$), F8 ($BF = 0.98$), FC2 ($BF = 0.48$), and Fz ($BF = 0.39$) yielded inconclusive results while the Bayes Factors for the remaining electrodes that were not significant provided strong evidence for the null hypothesis (all $BF < 0.33$).

During the 180-350 ms window, the alpha band showed similar electrode activation as the theta band at 0-180 ms with electrodes Pz, FC1, and P4 capturing lower alpha oscillatory power for self-focused thoughts compared to non-self-focused thoughts. Post-hoc analysis for these electrodes further supports these findings when correcting for multiple comparisons (adjusted $p < 0.05$). However, subsequent Bayes Factor analyses revealed that the evidence for these findings was not as strong. For electrodes Pz ($BF = 2.26$) P4 ($BF = 2.34$), and FC1 ($BF = 0.36$) the Bayes Factors were inconclusive while for the remaining electrodes, the Bayes Factors provided strong evidence for the null hypothesis (all $BF < 0.33$).

For the 350-600 ms window, only electrode P4 captures lower alpha oscillatory power for self-focused thoughts compared to non-self-focused thoughts with post-hoc analysis further supporting these findings when correcting for multiple comparisons (adjusted $p < 0.05$). Similar to the theta band, we can observe the activation of electrodes across the default network to generally decrease during the later stages of self-referential processing. However, the Bayes Factor analyses revealed all electrodes to yield strong evidence for the null hypothesis (all $BF < 0.33$).

Lastly, for the beta band, during the 0-180 ms window, electrode FC1 indicated significantly lower oscillatory power for self-focused thoughts while electrode FC5 indicated significantly higher oscillatory power for self-focused thoughts compared to non-self-focused ones. Post-hoc analysis for these electrodes further supports these findings when correcting for multiple comparisons (adjusted $p < 0.05$). However, the Bayes Factor analyses revealed electrode FC1 to yield inconclusive results ($BF = 0.39$) while all other electrodes yielded strong evidence for the null hypothesis (all $BF < 0.33$).

In the 180-350 ms window, only electrode P4 captures lower beta oscillatory power for self-focused thoughts compared to non-self-focused thoughts with post-hoc analysis further supporting these findings when correcting for multiple comparisons (adjusted $p < 0.05$). However, the Bayes Factor analyses revealed electrode P4 to yield inconclusive results ($BF = 0.38$) while all other electrodes yielded strong evidence for the null hypothesis (all $BF < 0.33$).

Finally, for the 350-600 ms window the only electrode FC5 yielded significant results by capturing higher beta oscillatory power for self-focused thoughts compared to non-self-focused thoughts. Additionally, post-hoc analysis further supported these findings when correcting for multiple comparisons (adjusted $p < 0.05$). However, the Bayes Factor analyses revealed all electrodes to yield strong evidence for the null hypothesis (all $BF < 0.33$)

In general, the linear mixed-effects models indicated significant differences primarily in frontal and frontocentral central regions during the early stages of self-referential processing (0-180 ms), however in the later stages, especially in the middle window (180-350 ms) parietal electrodes such as Pz and P4 also began to capture these differences. Overall self-focused thoughts often demonstrated significantly lower oscillatory power in these areas with electrode FC5 in the beta band being an exception to this trend. However, the Bayes Factor analyses revealed that many of these significant findings were supported by weak or inconclusive evidence, suggesting that the observed differences in oscillatory power between self-focused and non-self-focused thoughts might not be as convincing as the linear mixed-effects models initially suggested. Notably, only electrodes Pz and P4 in the 180-350 ms theta band window exhibited moderate to strong evidence supporting the observed differences in oscillatory power, as indicated by Bayes Factors exceeding 4. Outside of these electrodes, across all bands and time windows, the Bayes Factors often supported the null hypothesis.

4.2.2 Effects of group & interventions - ANOVA model comparisons

Similarly to what was done for the HEP analysis, we then incorporated additional interactions in our linear mix-effects models to examine whether the participant Group, whether they performed fantasizing/mediation, or whether an interaction between group, fantasizing, and mindfulness meditation, moderated the relationship between self-focused thoughts and oscillatory power. Likewise, we also conducted ANOVA comparisons to determine the significance of each added interaction in improving model fit compared to the simpler preceding model depicted in Figure 4.

In Figure 5 we can observe the electrodes where the inclusion of the Group variable led to the model fitting better to the data. For the 0-180 ms window, in the theta band, only electrode F7 was shown to fit better to the model that incorporated Group, indicating that this electrode's oscillatory power for self-focused and non-self-focused thoughts significantly differed between HCs and those with rMDD. The subsequent post-hoc analysis for this electrode further supports these findings when correcting for multiple comparisons (adjusted $p = 0.03$). However, the Bayes Factor analysis revealed electrode F7 ($BF = 1.53$) yielded inconclusive evidence, while the remaining electrodes all yielded Bayes Factors ranging from 1.03 to 0.18, indicating inconclusive results and evidence suggesting that the group variable had no substantial effect on the theta band oscillatory power across the electrodes. In the alpha band, we do not observe the inclusion of Group to cause any of the electrodes to fit better to the model. These findings are corroborated by the Bayes Factors which were either inconclusive or in favour of the null hypothesis (inclusion of the group variable did not meaningfully improve the model). In the beta band, we can observe FC5, Fz, and P3 fitting better to the more complex model, however, the post-hoc analysis revealed only FC5 (adjusted $p = 0.02$) to be significant after correcting for multiple comparisons. However, the Bayes Factor analysis of these electrodes was inconclusive while the remaining electrodes either also yielded inconclusive results or Bayes Factors in favour of the null hypothesis.

For the 180-350 ms window, we can observe varying patterns across the bands. For the theta band, we can observe that the inclusion of Group only allows electrode F4 to better capture significant differences in oscillatory power across the different thought types. However, the subsequent post-hoc analysis of this electrode did not support this finding when correcting for multiple comparisons (adjusted $p = 0.08$). In the alpha band, electrodes P3 and P4 fit better to the data with the inclusion of Group in the model however, post-hoc analysis again did not support these findings when correcting for multiple comparisons (P3: adjusted $p = 0.17$, P4: adjusted $p = 0.98$). For the beta band, electrodes Pz, Cz, FC2, FC5, P3, and P4 were shown to fit better to the model that included Group, however, post-hoc analysis only supported these findings for electrodes FC2, FC1, Cz, and Fz when correcting

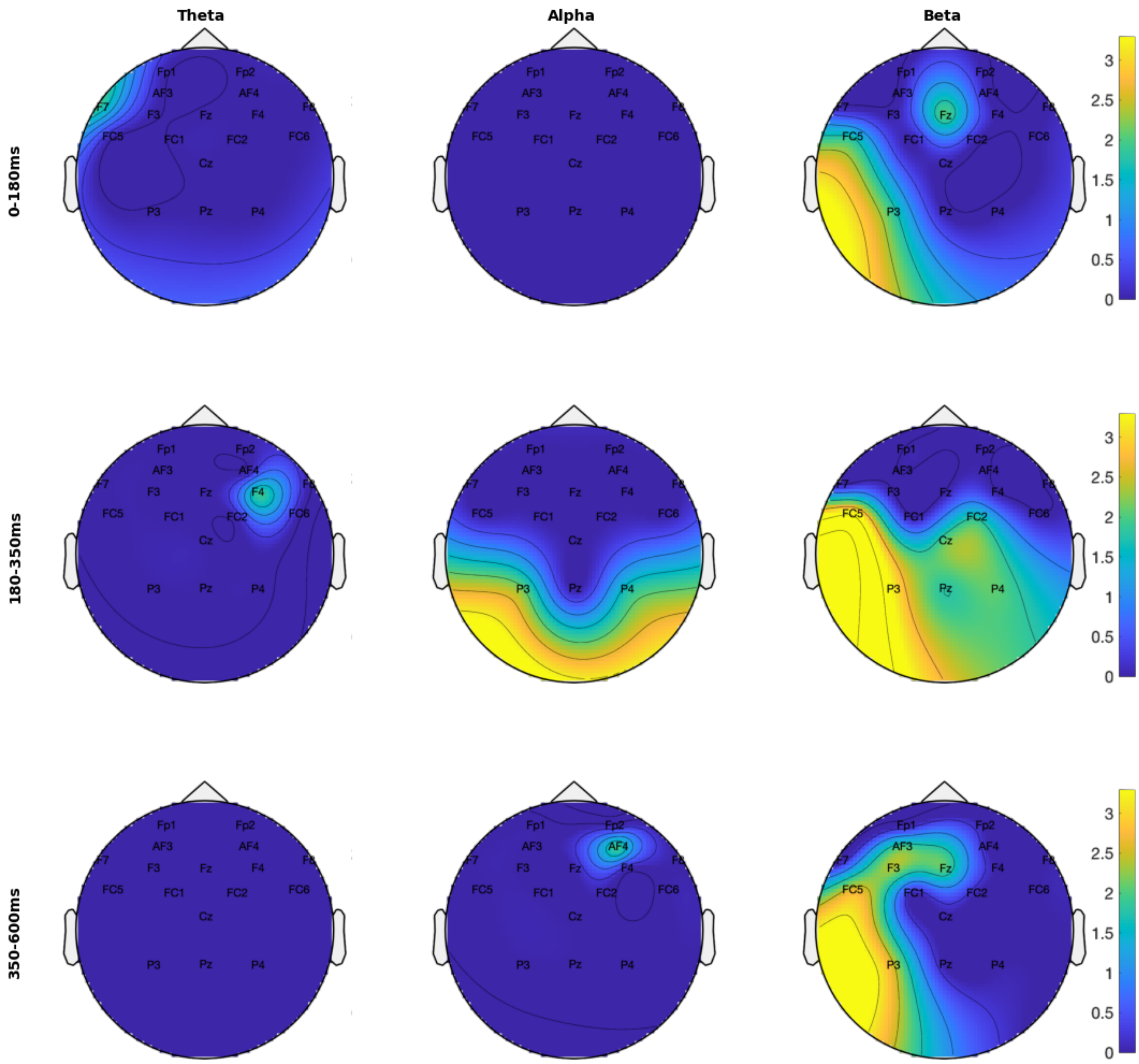


Figure 5: *Topographic map of ANOVA comparisons between the model with and without Group for brain oscillatory power. The maps highlight electrodes where the inclusion of Group had statistically significant effects on the oscillatory power of self-focused and non-self focused thoughts. The significant transformed p-values are depicted on the colour scale, with non-significant values set to 0.*

for multiple comparisons (all adjusted $p < 0.05$).

The Bayes Factor analysis revealed that from all these electrodes, only electrode FC2 in the beta band exhibited a Bayes Factor of 10.39, indicating strong evidence that the inclusion of Group in the model does meaningfully contribute to the differences in beta power across the two different types of thought. However, the electrodes P4 ($BF = 0.93$), P3 ($BF = 0.87$), Pz ($BF = 0.52$), and FC5 ($BF = 0.48$) in the beta band provided inconclusive evidence. Similarly, electrode F4 in the theta band ($BF - 0.42$), and electrodes P4 ($BF = 1.31$) and P3 ($BF = 0.59$) in the alpha band also yielded inconclusive Bayes Factors. All remaining electrodes across the bands yielded evidence in favour of the null hypothesis ($BF < 0.33$).

For the last time window (350-600 ms) no electrodes in the theta band were shown to fit better to the model that incorporated Group, while in the alpha band, only electrode AF4 was shown to fit better. However, subsequent post-hoc analysis on AF4 did not confirm these findings to be true after correcting for multiple comparisons (adjusted $p = 0.14$). Additionally, the Bayes Factors analyses revealed these findings to be inconclusive ($BF = 0.74$). For the beta band, electrodes Fz, F3, AF3, FC5, and P3 were found to fit better however, the subsequent post-hoc analysis revealed only FC5 (adjusted $p = 0.001$) and Fz (adjusted $p = 0.02$) to yield significance after adjusting for multiple comparisons, while the remaining electrodes did not (adjusted $p > 0.05$). The Bayes Factors analyses

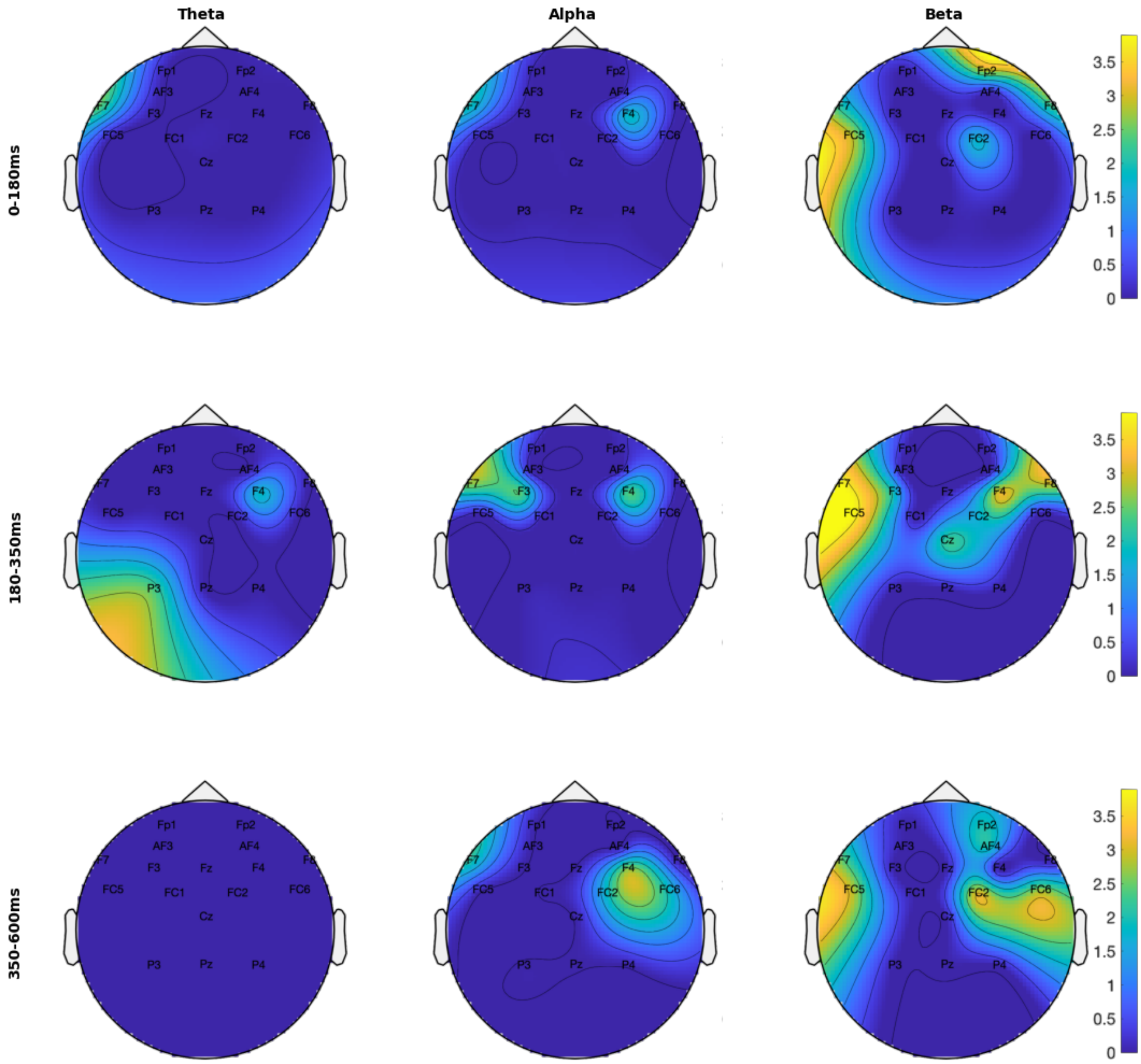


Figure 6: *Topographic map of ANOVA comparisons between the model with and without the Interventions of fantasizing and Meditation for brain oscillations. The maps highlight electrodes where the inclusion of the interventions had statistically significant effects on the oscillatory activity. The significant transformed p-values are depicted on the colour scale, with non-significant values set to 0.*

revealed that electrodes P3 ($BF = 0.64$) and FC5 ($BF = 0.45$) yielded inconclusive results while the remaining electrodes all yielded evidence in favour of the null hypothesis ($BF < 0.33$)

In Figure 6 we can observe the electrodes where the inclusion of the fantasizing and Meditation variable led to the model fitting better to the data. For the 0-180 ms window, across the theta band, only the electrode F7 showed significant differences in oscillatory power across the thoughts when incorporating the intervention variables. This suggests that there were notable differences in theta oscillatory power before and after performing the interventions. However, subsequent post-hoc analyses did not uphold these significant differences after correcting for multiple comparisons.

The Bayes Factor analysis supported these findings, demonstrating evidence in favour of there being no significant effect of the interventions ($BF = 0.2$). For the alpha band, electrodes F7 and F4 demonstrated a better fit to the model with the interventions however post-hoc analysis demonstrated none of these to be significant when correcting for multiple comparisons. Furthermore, for both electrodes, the Bayes Factor analysis yielded evidence in favour of there being no significant effects ($BF < 0.33$). For the beta band, we again see the most widespread activation of electrodes with the data in electrodes FC2, FP2, and FC5 fitting better to the model with the interventions. However, post-hoc demonstrated none of these to be significant when correcting for multiple comparisons. Similarly, for all electrodes, the Bayes Factor analysis yielded evidence in favour of there being no effects ($BF < 0.33$).

For the 180-350 ms window, across the theta band, electrodes F4 and P3 showed significant differences in oscillatory power across the thoughts when incorporating the intervention variables. However, post-hoc analysis only revealed electrode P3 to be significant when correcting for multiple comparisons (adjusted $p = 0.02$). This difference could be observed for both the fantasizing and meditation interventions. However, the Bayes Factor analysis revealed the findings for electrode F4 to be inconclusive ($BF = 0.71$) while P3 demonstrated evidence against the effects of the interventions $BF = 0.15$). For the alpha band, data from electrodes F7, F3, and F4 fit better to the model incorporating the interventions, however, the post-hoc analysis revealed none of these to be significant when correcting for multiple comparisons. Additionally, the Bayes Factor analysis for all these electrodes yielded evidence against the intervention effects ($BF < 0.33$). For the beta band, data from electrodes Cz, F3, F4, F7, F8, FC2, and FC5 all fit better to the model incorporating the interventions, however, the post-hoc analysis revealed only electrode F8 was able to capture these differences after correcting for multiple comparisons (adjusted $p = 0.003$). However, for all electrodes, the Bayes Factor analysis yielded evidence in favour of there being no effects ($BF < 0.33$).

Lastly, for the 350-600 ms window, within the theta band, we do not observe the inclusion of the interventions to cause any of the electrodes to fit better to the data. These findings are corroborated by the Bayes Factor analysis where all electrodes yielded Bayes Factors in favour of no effects ($BF < 0.33$). For the alpha band, data from electrodes F4, F7, FC2, and FC6 fit better to the model incorporating the interventions however, the post-hoc analysis revealed only FC6 (adjusted $p = 0.04$) to be significant after adjusting for multiple comparisons. Notably, these significant differences captured by FC6 could only be observed for the fantasizing intervention. However, the Bayes Factor analyses revealed inconclusive results for F4 while the remaining electrodes found none of these findings to be significant demonstrating evidence in favour of no effects ($BF < 0.33$). Finally, for the beta band, data from electrodes Fp2, F7, AF4, FC2, FC5, and FC6 fit better to the model incorporating the interventions, however, the post-hoc analysis revealed electrodes FC5, FC6, and F7 to be significant after correcting for multiple comparisons. Similarly to what was captured by the alpha band models, the significant differences captured by these beta band models could only be observed for the fantasizing intervention. However, for all electrodes, the Bayes Factor analysis yielded evidence in favour of there being no effects ($BF < 0.33$).

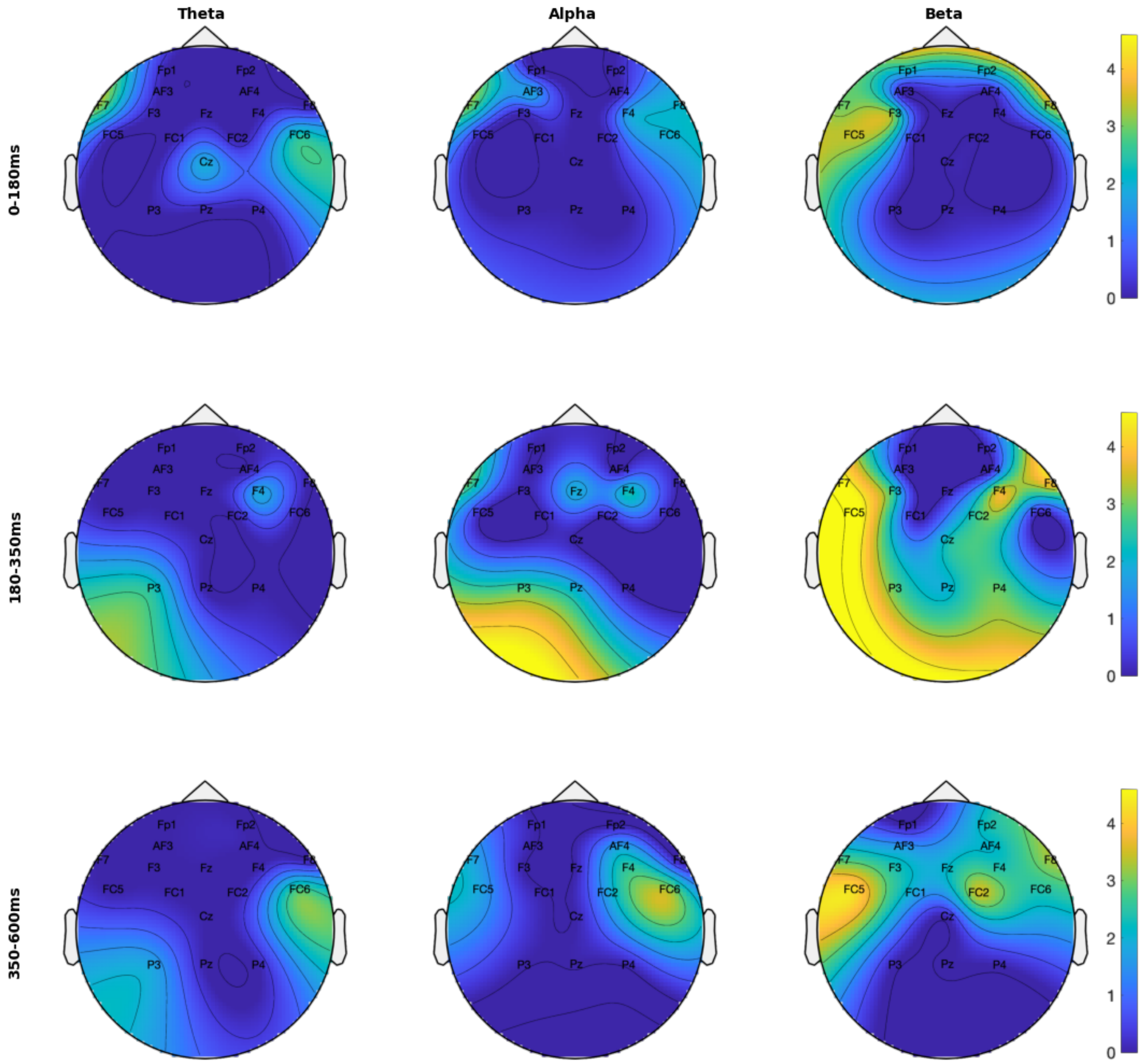


Figure 7: *Topographic map of ANOVA comparisons between the model with and without interactions between Group, fantasizing, and Meditation for brain oscillations. The maps highlight electrodes where the inclusion of the interventions had statistically significant effects on the oscillatory activity. The significant transformed p-values are depicted on the colour scale, with non-significant values set to 0.*

Finally, for the last model comparisons, we compared the initial simple model observed in Figure 4 to a model where we included interactions between the interventions and Group. This would allow us to observe if the oscillatory power of self-focused and non-self-focused were influenced by the interventions and whether these effects differed across HCs and those with rMDD. Figure 7 demonstrates which of the electrodes fits better to the more complex model and immediately we can observe the most widespread activation of electrodes compared to the previous topoplots. For 0-180 ms window, although we can see multiple electrodes across mainly the frontal region of the brain fit better to the more complex model, post-hoc analysis revealed none of these findings to be significant after correcting for multiple comparisons. The Bayes Factor analyses further supported these findings by yielding Bayes Factors in favour of there being no effects ($BF < 0.33$), suggesting that the observed differences were likely due to random variation rather than a true interaction effect between interventions and group. For the 180-350 ms window, again the post-hoc analysis revealed the majority of these findings to not be significant when correcting for multiple comparisons. However, electrode P3 in the theta band (adjusted $p = 0.04$), and electrodes P3 (adjusted $p = 0.02$) and F7 (adjusted $p = 0.04$) in the alpha band were shown to capture statistically significant changes in oscillatory power when considering the interaction between the interventions, group, and the type of thought.

Importantly, however, upon closer inspection of these models, the significance that was reported pertained to the main effect of the thought condition (i.e., self-focused versus non-self-focused) rather than the interaction between Group and interventions. These findings therefore demonstrate that while there are notable changes in brain oscillations across self-focused and non-self-focused thoughts, these changes are not modulated by the interventions or by group differences. Additionally, the Bayes Factor analyses again demonstrated evidence in favour of no interaction effects ($BF < 0.33$).

For the 350-600 ms window, the post-hoc analysis revealed only electrode F4 in the alpha band (adjusted $p = 0.04$) to yield significant differences in oscillatory power after correcting for multiple comparisons. However, these significant differences were also primarily driven by the main effect of the thought condition rather than any interaction between Group and interventions. Moreover, the Bayes Factor analyses again demonstrated evidence in favour of no interaction effects ($BF < 0.33$).

4.3 Classification of self-focused and non-self-focused thoughts

Given the lack of significant differences in HEP amplitude across self-focused and non-self-focused thoughts, we focused on the potential of using brain oscillatory power to create a classifier capable of distinguishing between the two types of thought. While the majority of the Bayes Factor analysis findings yielded inconclusive evidence or evidence in favour of the null hypothesis, we proceeded with the results of the linear mixed-effects models to see if there were still any subtle patterns in the oscillatory power data that the ML techniques could leverage in order to classify self-focused versus non-self-focused thoughts. We created multiple ML models to evaluate the performance of three different classifiers (Random Forest, KNN, and Gradient Boosting) across three frequency bands (theta, alpha, beta) and three time windows (0-180 ms, 180-350 ms, 350-600 ms). Each classifier was trained to differentiate between self-focused and non-self-focused thoughts based on significant features obtained from the initial linear-mix-effects model (Figure 4).

The classification metrics for each classifier across different bands and time windows are summarized in Table 2. Overall, the classifiers showed similar performance across different bands and time windows with slight variations in the measured metrics. All classifiers reached a maximum cross-validation accuracy of 65% and were able to achieve high precision, and F1 scores, usually capping around 0.7. In the early time windows, recall rates for the Random Forest and Gradient Boosting classifiers in the Theta and Alpha bands were notably high, reaching up to 0.78 and 0.81, respectively. This indicates that these classifiers were particularly effective at identifying self-focused thoughts in the initial phases of cognitive processing. However, this came at the cost of specificity, which remained low across both classifiers never reaching scores above 0.497. These results indicate that while the models were relatively effective at identifying true positives (self-focused thoughts), they struggled more with correctly identifying true negatives (non-self-focused thoughts).

Notably, the KNN classifier stands out as an exception to this trend, where, unlike the other two classifiers which favour recall at the expense of specificity, KNN maintains a steadier balance between the two metrics across all time windows. This consistent performance may suggest that the KNN classifier is more balanced in its approach to classifying self-focused versus non-self-focused thoughts.

5 Discussion

5.1 Self-referential thought differences

Our first research question is concerned with whether there are significant differences in HEPs and brain oscillatory power between self-focused and non-self-focused thought. Given how the literature extensively documents how self-referential processing takes place in the brain's default network [25, 34, 33, 35, 36, 38, 39], we hypothesized that HEPs and brain oscillations would be able to capture these differences if we utilised data from electrodes positioned over the default network.

Most of our findings on HEPs did not support this hypothesis. Specifically, we had expected the frontal and parietal electrodes to capture the different HEP responses to self-focused versus non-self-focused thoughts as these are positioned over the vmPFC, mPFC and vPC respectively [25, 33]. However, for both the 180-350 ms window and the 300-500 ms windows, the cluster-based permutation test did not find significant differences between the two types of thought and the linear mixed-effects models revealed that only the frontal electrode Fp2 in the 180-350 ms window captured a significant difference in HEP amplitude across thoughts when corrected for multiple comparisons. While this isolated finding could suggest frontal lobe involvement in self-focused thoughts; we found that the HEP amplitude for self-focused thoughts was lower than that for non-self-focused thoughts. This is inconsistent with what the literature has observed where self-focused thoughts have greater HEP amplitude compared to non-self-focused thoughts [54].

It's unclear as to why this opposite effect was observed in our findings. One possibility is that individual differences in cognition influenced HEP amplitude. For instance, research has shown that differences in HEP amplitude are influenced by participants' frequency of daydreaming [54], and how accurate they are at perceiving one's heartbeat [49]. Babo-Rebelo et al. (2019) specifically found that individuals who daydream more frequently showed larger differences in HEP amplitudes when imagining themselves compared to imagining others. It may be that our participants were not frequent daydreamers which could explain the lack of significant differences in HEP amplitude across the different thoughts. However, it is also possible that daydreaming frequency only affected this particular task, as actively imagining oneself may not elicit the same neural responses as having spontaneous self-focused thoughts. On the other hand, another study by Pollatos et al. (2004) found that individuals who are more accurate at perceiving their own heartbeats exhibit significantly higher HEP amplitudes. Although this study also did not directly examine spontaneous self-referential thinking, it highlighted the importance of interoceptive accuracy in influencing HEP amplitudes. Therefore, it's possible that individual differences in heartbeat perception among our participants could have contributed to the observed effects. Given that we did not consider any of these or any participant characteristics outside of their diagnosis, our study may have overlooked important variables that could have influenced HEP amplitude.

For our analysis on brain oscillations, our findings provided more nuanced insights into self-referential processing and partially aligned with our initial hypotheses. Specifically, we anticipated that differences in brain oscillatory power would be evident across theta, alpha, and beta bands, particularly in the frontal and parietal regions, which are implicated in self-referential processing. The linear mixed-effects models on brain oscillations revealed distinctive patterns across theta, alpha, and beta bands that varied over time. These oscillatory differences were particularly prominent in frontal, fronto-central, and parietal regions, aligning with the involvement of the default network in self-referential processing. Specifically, in the theta and alpha bands, these electrodes showed lower oscillatory power for self-focused thoughts across all examined time windows. These findings aligned with those reported by Bocharov et al. (2019) and Knyazev et al. (2012). Interestingly, we also observed this pattern in the beta band for electrode P4 at 180-350 ms. However, across the beta band, we also observed the opposite effect where self-focused thoughts had greater oscillatory power compared to non-self-focused thoughts. While such findings were not supported across the literature they could suggest that the beta frequency band plays a more substantial role in self-referential processing.

However, our Bayes Factor analyses frequently yielded weak or inconclusive evidence, which calls into question the validity of these findings. Only electrodes Pz and P4 in the theta band during the 180-350 ms window provided moderate to strong evidence supporting the observed differences in oscillatory power, as indicated by Bayes Factors exceeding 4. One potential reason behind this discrepancy reported by the linear mixed-effects models and the Bayes Factors is that we utilised data from each trial for each participant. Given that each participant had an average of 305.27 trials for self-related thoughts, 157.62 trials for non-self-related thoughts, and we had data from 24 pre-meditation, 31 peri-meditation, 23 pre-fantasizing, and 21 peri-fantasizing EEG recordings, the large number of observations likely contributed to the detection of statistically significant effects in the linear mixed-effects models. By providing thousands of rows of data to the models, the linear mixed-effects analysis was likely sensitive to even small variations in the data, which might not represent true underlying neural effects. The Bayes Factor analysis, despite being based on the same data, provides a different perspective by evaluating the strength of evidence for the observed effects. The consistent inconclusive Bayes Factors suggest that the statistically significant findings from the linear mixed-effects models may not be as compelling when considered in the context of evidence strength.

5.2 Group differences & intervention effects

For the 180-350 ms and 300-500 ms windows, the inclusion of group factors (rMDD vs. HC) in the HEP amplitude linear mix-effects model analysis did not result in significant differences across electrode sites. However, we did observe significant group differences in brain oscillation patterns across multiple bands and time windows. Notably, in the 180-350 ms window, significant group differences were observed in the beta band, where electrodes Pz, Cz, FC2, and FC5 demonstrated better model fit when the group factor was included. These findings suggest that the oscillatory activity in these regions may differ between individuals with rMDD and healthy controls during self-referential processing. However, only electrode FC2 in the beta band yielded Bayes Factors that suggested strong evidence for the inclusion of the group factor ($BF = 10.39$), indicating that the differences in beta oscillatory power are likely meaningful and not due to random variation. On the other hand, across all windows, electrodes in the alpha and theta bands usually had 1 or 2 electrodes that fit better with the inclusion of the Group factor, but these findings were less consistent and often not strongly supported by Bayes Factor analysis.

These specific findings are in line with what we were expecting since those with rMDD are no longer actively experiencing depressive symptomatology we assumed their brain oscillatory activity to more closely resemble HCs. However, electrode FC2 in the beta band stands out as an exception, where the significant group difference and strong Bayes Factor suggest that beta oscillatory activity in this region may still be distinctly altered in individuals with rMDD compared to healthy controls. These results may suggest that underlying neural differences persist even after depressive symptoms have resolved. Such findings are consistent with previous research that has shown those with rMDD continue to exhibit altered functional connectivity in the central executive network, salience network, and default network, similar to those with active MDD [15]. However, while this was observed at electrode FC2 the fact that similar differences were not consistently observed across other electrodes prevents us from drawing broader conclusions about widespread neural alterations in rMDD compared to HCs. Rather, the lack of Bayes Factors in favour of the alternate hypothesis suggests that much of the brain's oscillatory activity may normalize during remission, bringing the overall pattern of neural activity closer to that of HCs. Regarding the impact of mindfulness meditation and positive fantasizing on the explored neural correlates, according to the linear mixed-effects models and the Bayes Factors analyses, the interventions did not have a significant effect on the HEP amplitude across all electrodes and both time windows.

On the other hand, while we did observe significant differences in brain oscillatory power across bands and time windows before and after the interventions, after correcting it for multiple comparisons and performing the Bayes Factors analyses the majority of these differences were not supported. The Bayes Factor analyses frequently supported the null hypothesis, indicating that the observed effects were likely due to random variation rather than meaningful changes induced by the interventions. This suggests that the neural impact of mindfulness meditation and positive fantasizing on brain oscillatory power may be minimal, or that the brain oscillations we examined were not particularly sensitive to these interventions. This was striking as research has specifically shown that engaging in mindfulness meditation leads to an increase in theta activity [69, 70], however, no such patterns could be observed in our results. One potential reason for this is that in our study, participants engaged in mindfulness meditation for only one week, at ten minutes per day, which is considerably shorter compared to the protocols used in the studies that reported significant changes in theta oscillations. For example the study by Wang et al. (2022) had participants engage in an 8-week program, which likely provided a more sustained and deeper engagement with mindfulness practices, leading to more pronounced changes.

Similarly, the absence of significant changes in brain oscillatory power following positive fantasizing might could also result from the brief and potentially insufficient exposure to the intervention. While studies have shown positive fantasizing to yield immediate beneficial effects [60], these findings are based on self-report measures and thus these effects may not directly translate to measurable changes in neural activity. However, other studies exploring PCT, which directly integrates positive fantasizing techniques, have demonstrated more substantial and long-lasting benefits [76, 77]. Comparing these findings with our results, it may be that the full therapeutic potential of positive fantasizing is best realized when it is practised over a longer period or alongside other techniques employed in PCT.

Lastly, regarding whether these interventions had differing effects on oscillatory power/HEP amplitude for those with rMDD compared to HCs, we found that after correcting multiple comparisons and performing a Bayes Factor analysis there were no significant differences. This suggests that the interventions of mindfulness meditation and positive fantasizing did not differentially affect the two groups in a statistically significant manner. Some potential reasons for this are that the interventions overall had no meaningful impact on the neural correlates we measured as indicated by previous ANOVA comparisons or that these interventions are designed to have broad cognitive and emotional benefits [63, 20, 60] therefore, regardless of the participants' diagnosis history, the effects might be similar across both groups.

Finally, if we evaluate the statistics related to the number of trials, we again can observe a lack of significant differences between the rMDD and HC groups for self-related and non-self-related thoughts. The ANOVA results indicated that neither group had more or less self-focused/non-self-focused thoughts compared to the other group. Additionally, whether participants were in the rMDD or HC group, the average number of trials for both types of thought did not significantly change following the interventions, as demonstrated by the t-test results. These findings suggest that a week of intervention engagement did not result in any significant changes regarding the frequency of self-related or non-self-related thoughts.

5.3 Classification of self-focused and non-self-focused thoughts

Our final research question was concerned with whether the differences between self-focused versus non-self-focused thoughts could be used to create a classifier capable of accurately distinguishing between the two types of thought. For this, we explored the potential of using Random Forest, KNN, and Gradient Boosting classifiers trained on the significant features obtained from the linear-mix effects model results seen in Figure 4. We found that the classifiers demonstrated moderate success, with a maximum cross-validation score of 65% across all models. This level of performance indicates that while ML techniques can create classifiers that perform better than simply guessing (accuracy above 50%), there is still room for improvement.

Firstly, we noticed that regardless of the number of features used to train the classifiers, all the classifiers demonstrated comparable performance in terms of cross-validation accuracy. For example, the beta band classifier for the last 180-350 ms window was trained with just one feature, which was the data from the P4 electrode, while the classifier for the alpha band in the 0-180 ms window was trained with data from five electrodes (AF3, FC1, FC2, F6, F8). This indicates that the addition of more features does not necessarily improve predictive accuracy.

Secondly, across all Random Forest and Gradient Boosting classifiers, we observed lower specificity and precision scores, suggesting that these classifiers were more inclined to predict self-focused thoughts. Although we employed random oversampling techniques to address the class imbalance, the classifiers still tended to favour the majority class, leading to a bias for classifying self-focused thoughts and increasing the rate at which it misclassified non-self-focused thoughts as self-focused. Overall these metrics highlight the lack of discriminative power that would otherwise be provided by additional informative features.

It's also important to note that these classifiers were trained using features that were reported as significant by the linear mixed-effects models, but which were not strongly supported by the Bayes Factor analyses. As previously mentioned, many of the significant effects identified by the linear mixed-effects models were accompanied by weak or inconclusive Bayes Factors, indicating weak evidence for the differences in oscillatory power between self-focused and non-self-focused thoughts. This would have impacted the classifiers' performance, as they were likely being trained on features that did not strongly differentiate between self-focused and non-self-focused thoughts. As such, even the classifiers trained with more features were not benefiting from any additional information that could improve their predictive accuracy. Instead, the inclusion of features with weak or inconclusive support likely introduced noise into the models, contributing to their moderate performance and high misclassification rates. Therefore, while the classification methods were not able to achieve high accuracy, this limitation is likely due to the quality of the features used rather than the inherent capability of the ML models themselves.

Overall, these results suggest that without informative features, these classifiers cannot yet be utilised in clinical trials due to the varying degrees of misclassification presented across the board. Given that the intention of these classifiers was to assess an aspect of depressive symptomatology, namely if participants are experiencing a high number of self-focused thoughts, this level of misclassification presents a significant limitation. The high rate of false positives could lead to incorrect assessments, potentially misinforming treatment plans and interventions.

5.4 Limitations

This study is not without limitations. One major limitation is the fact that we did not consider any participant characteristics in any of our analyses. For example, research has shown that participants' interoceptive accuracy and how frequently they engaged in daydreaming influenced HEP amplitudes, specifically by resulting in larger differences in amplitude across the different types of thought. [49, 54]. Therefore, had we accounted for daydreaming frequency and interoceptive accuracy, we may have observed more nuanced and significant differences in HEP amplitudes.

The same could be said about our analysis on brain oscillations. While oscillatory power was better at capturing the differences in self-referential thinking as well as the effects of group and interventions, we cannot definitely rule out the effects of individual differences that may have influenced these results. Although in our literature review, we did not find any factors that have conclusively been shown to influence brain oscillations in the context of self-referential processing, incorporating interoceptive accuracy and frequency of daydreaming could have shown whether these characteristics influence other measures of self-referential processing outside of HEP amplitude.

Another limitation of our analysis on brain oscillations is regarding the time windows we explored. Our separation of early, mid, and late processing windows was not motivated by prior literature but instead was based on our analysis on the HEP amplitude. We chose the same time window used for HEP amplitude (180-350 ms) and then created early and late processing based on this mid-range window. While there is no consensus across the literature on the precise segmentation of these windows regarding brain oscillatory power, our segmentation could have possibly limited our ability to capture specific oscillatory patterns related to self-referential thinking.

Additionally, the relatively short duration of the interventions highlights another limitation of our study. Our study involved participants engaging in mindfulness meditation and positive fantasizing for only one week, at ten minutes per day. This short duration may have been insufficient to induce measurable changes in neural activity, especially considering the effects observed in studies with longer intervention periods [69, 70, 71, 72].

Finally, another limitation is the fact that the features used for training the machine learning classifiers were selected based on their significance in the linear mixed-effects models, without sufficient support from Bayes Factor analyses. As discussed, many of these features did not strongly differentiate between self-focused and non-self-focused thoughts, as indicated by the weak or inconclusive Bayes Factors. This limitation directly impacted the performance of our classifiers, leading to moderate accuracy and issues with specificity and precision.

5.5 Future Work

Firstly, future research should seek to address the previously mentioned limitations. Researchers should incorporate individual characteristics such as frequency of daydreaming and interoceptive accuracy in their analyses, as these factors have been shown to influence HEP amplitudes and may also impact other neural measures related to self-referential processing. By considering participant characteristics, future studies can explore whether these individual differences contribute to more nuanced and significant findings. Moreover, it is important to investigate whether these characteristics have the same impact across different populations, such as those with rMDD and MDD. It may be that these characteristics only contribute to variations in healthy populations and therefore, more research is needed to determine their relevance in clinical populations.

Moreover, in the future, researchers should incorporate designs where participants engage with the intervention more frequently and/or for longer duration. Our study involved participants engaging in mindfulness meditation and positive fantasizing for only one week, at ten minutes per day. Given that we could observe no significant differences before and after these interventions, it may have been that the short duration was unable to induce measurable changes in neural activity, especially considering the effects observed in studies with longer intervention periods [69, 70]. However, studies exploring brief mindfulness meditation have shown significant mood improvements and reductions in depression involving participants practising for 20 [71] and 30 minutes [72] per day over a shorter period (3-4 days) than the one explored in this study. Although importantly, these short durations often show effects in studies that utilise self-report measures, where participants may perceive and report changes in their mood or cognitive state even after brief interventions. In contrast, task-based and biological measures, such as EEGs, often require longer intervention periods to detect significant changes. This could explain why our study did not observe significant neural differences following the short intervention period. Therefore, instead of limiting the practice to once a day for 10 minutes, future studies should explore the effects of multiple sessions per day or over longer periods as this may result in more pronounced changes in neural correlates.

5.6 Conclusions

This thesis aimed to investigate 4 research questions. The first was concerned with whether there are significant differences in self-focused and non-self-focused thoughts as measured by the neural correlates of HEPs and brain oscillations. There were no differences in HEP amplitude and our findings did not align with the literature. Our findings on brain oscillations were not as straightforward. While we observed distinct patterns of brain oscillatory power across theta, alpha, and beta bands, particularly in frontal and parietal regions associated with the brain's default network, the validity of these findings was brought into question by Bayes Factor analyses, which frequently yielded weak or inconclusive evidence. We find that only across the parietal region (electrodes Pz and P4) at 180-350 ms, theta oscillatory power demonstrated evidence supporting differences between self-focused and non-self-focused thoughts. According to our analysis, differences in self-referential thinking are not as widespread across the default network and that overall, while there are observable trends in the data, they most likely stemmed from the sensitivity of the linear mixed-effects models to detect small variations across a large dataset, rather than from robust underlying neural differences.

The second question was concerned with whether there are any significant differences in neural correlates between individuals with rMDD and HCs. No differences could be observed for the HEPs and again, while the linear mixed-effects models on brain oscillations revealed some differences between individuals with rMDD and healthy controls, particularly in the beta band during the 180-350 ms window, these observed group differences were not widespread or supported by Bayes Factor analyses.

Our third question addressed the influence of mindfulness meditation and positive fantasizing on these neural patterns. No effects could be detected for HEP amplitude and brain oscillatory power following these interventions. This lack of detectable change suggests that the short duration and time spent engaging with interventions may have been insufficient to produce measurable neural effects, however, further investigation is needed to determine whether longer or more frequent interventions might yield different results for these neural correlates.

Finally, the fourth question explored the potential of ML classifiers to differentiate between self-focused and non-self-focused thoughts based on neural correlates. The classifiers demonstrated moderate success, indicating a certain degree of effectiveness in using machine learning techniques to classify types of thoughts based on brain oscillatory power. However, given the degree of misclassifications and the fact that the classifiers were trained on features that were not strongly supported by Bayes Factor analyses, the results imply that the classifiers' performance was very limited. Further improvements are needed if we wish to utilise these tools in real-life clinical settings.

In conclusion, our findings highlight potential challenges regarding investigating neural correlates of self-referential thought. Our analysis on HEP amplitude did not align with the findings of previous studies, and although our findings from the linear-mixed effects models on brain oscillation seemed to suggest findings consistent with what was reported in the literature, the lack of strong support from Bayes Factor analyses raises questions about the validity of these findings. This discrepancy underscores the importance of integrating multiple statistical approaches to validate results, particularly in large datasets like those derived from EEG studies.

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Appendices

Time window	Band	Classifier	CV-accuracy	Precision	Recall	F1 Score	Specificity
0-180 ms	Theta	RandomForest	0.639	0.659	0.784	0.716	0.232
		KNN	0.652	0.652	0.468	0.544	0.527
		GradientBoosting	0.652	0.660	0.788	0.718	0.231
	Alpha	RandomForest	0.641	0.661	0.820	0.732	0.204
		KNN	0.651	0.670	0.509	0.578	0.526
		GradientBoosting	0.651	0.672	0.614	0.642	0.432
	Beta	RandomForest	0.605	0.659	0.701	0.680	0.315
		KNN	0.653	0.670	0.509	0.578	0.525
		GradientBoosting	0.653	0.676	0.650	0.663	0.411
180-350 ms	Theta	RandomForest	0.621	0.655	0.750	0.699	0.252
		KNN	0.652	0.666	0.491	0.565	0.535
		GradientBoosting	0.651	0.673	0.575	0.620	0.471
	Alpha	RandomForest	0.623	0.661	0.766	0.710	0.256
		KNN	0.653	0.672	0.511	0.581	0.529
		GradientBoosting	0.651	0.674	0.550	0.606	0.497
	Beta	RandomForest	0.563	0.660	0.636	0.648	0.381
		KNN	0.652	0.661	0.518	0.581	0.498
		GradientBoosting	0.652	0.670	0.614	0.641	0.427
350-600 ms	Alpha	RandomForest	0.561	0.657	0.636	0.646	0.372
		KNN	0.651	0.664	0.519	0.582	0.503
		GradientBoosting	0.651	0.667	0.665	0.666	0.372
	Beta	RandomForest	0.562	0.651	0.619	0.634	0.371
		KNN	0.652	0.666	0.487	0.563	0.539
		GradientBoosting	0.652	0.670	0.615	0.641	0.427

Table 2: *Classification metrics for different bands and time windows*