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Source reconstruction of electrical brain activity during attention network task performance

Abstract: Major Depressive Disorder (MDD) significantly affects mood, thought processes, and behavior. Understanding the neurophysiological mechanisms behind depression is essential for developing effective treatments. In this study, we compared source reconstruction of electroencephalography (EEG) data collected during Attention Network Task (ANT) performance from individuals with MDD, healthy controls, and those at risk of developing MDD. Our goal was to analyze the localization of alpha rhythm, particularly in relation to the P300 component. Preliminary findings revealed distinct differences in brain activation patterns among the three groups in key brain areas, particularly the Anterior Cingulate Cortex (ACC) and the Dorsolateral Prefrontal Cortex (DLPFC). Significant group effects in alpha source activity during the P300 interval were observed in response to both congruent and incongruent stimuli. One-way ANOVA results revealed notable differences in alpha activation in the Anterior Prefrontal Cortex (BA10) and ACC (BA24) between MDD and control groups, highlighting potential challenges in higher-order cognitive functions such as decision-making. Increased alpha activation in the Inferior Frontal Gyrus (BA45) in the MDD group suggests possible language processing difficulties. Furthermore, enhanced activation in the medial and dorsolateral prefrontal cortices aligns with their roles in task switching and inhibition. In the incongruent condition, significant differences were more pronounced, particularly in the Right Dorsolateral Prefrontal Cortex (BA9) and Right Anterior Prefrontal Cortex (BA10), which are vital for executive functions. The MDD group exhibited larger alpha source activation in the ACC, indicating reduced brain activation that may impair attention and task management. These preliminary findings are consistent with existing literature on altered alpha source activity in MDD, supporting the notion of cognitive and emotional processing differences in this population. Thus, our study demonstrates distinct differences in alpha source localization during the ANT, revealing significant variations in brain activation patterns related to stimulus congruence, particularly in the ACC and DLPFC across the three participant groups.
Key words: electroencephalography source localization, cognition, Attention Network Task (ANT), P300 component, Major Depressive Disorder (MDD).

Introduction

Major Depressive Disorder (MDD) is a complex mental health condition that greatly impacts mood, thinking, and behavior, as defined in the DSM-5 [1], with about 5% of adults experiencing this disorder worldwide [2,3]. The DSM-5 [1] includes cognitive dysfunction assessments as part of MDD diagnosis. Attentional impairments are prominent in MDD and may relate to impaired neuronal networks for alerting, orienting, and executive control [4]. A meta-analysis by Sinha et al. [5] shows that participants with depression exhibit differences in executive network functioning compared to healthy controls, aligning with previous studies on attention and depression. Executive control, crucial for cognitive functions such as emotion regulation and concentration, is often impaired in depressive patients [6-8]. Some studies suggest that depressed individuals tend to have a bias toward focusing on negative information [9]. However, Sinha et al. [5] agree with Mineka & Sutton's view [10] that anxiety, not depression, is linked to attentional bias for threatening stimuli. Instead, depressed individuals may struggle to disengage from negative information once attended [11-12], a difficulty related to executive control to a greater extent than to orienting.

The Attention Network Task (ANT) is a valuable tool for studying disorders involving attentional deficits including MDD [13]. The ANT is designed to be emotionally neutral, as such findings regarding executive control deficits do not pertain to emotional

content perceived or remembered. The ANT is used to assess three main attention networks: the Executive Control Network, the Alerting Network, and the Orienting Network. The Executive Control Network is crucial in detecting targets and resolving conflicts, mainly involving the medial frontal and anterior cingulate cortices [14]. The efficiency of the Executive Control Network is measured by looking at response times (RTs) for congruent versus incongruent stimuli, often using a flanker task [15]. The Alerting Network is connected to arousal and involves several brain areas, including the brainstem (especially the locus coeruleus), thalamus, and various frontal and parietal lobe regions [16]. Its efficiency is evaluated by comparing RTs in cued versus uncued situations [17]. The Orienting Network helps select stimuli based on their location or modality, relying on structures such as the pulvinar and superior colliculus [18]. Its efficiency is assessed by examining RT differences between spatial and central cues [19].

Electroencephalography (EEG) source analysis is an effective method for investigating neural sources that influence cognitive processes in depression. EEG studies provide information about the timing and coordination of brain activity during cognitive tasks and show how different regions interact. This approach is complemented by connectivity studies, which explore the functional and structural relationships between brain areas. Together, they enhance our understanding of neural networks and how connectivity disruptions may contribute to cognitive impairments, particularly in conditions such as MDD. Wu et al. [20] conducted a systematic validation study using resting-state EEG signals and highlighted the reliability of resting-state EEG as a biomarker for detecting MDD.

Several studies have examined changes in functional connectivity within and between brain networks in individuals with depression. Specifically, Shim et al. [21] and Miljevic et al. [22] reported disrupted network connectivity, while Knyazev et al. [23] identified the impact of depression on specific brain networks, particularly the connection between task-positive and task-negative networks. EEG measures have also been utilized to explore the neurophysiological features of depression. Lee et al. [24] and Akar et al. [25] have demonstrated associations between changes in EEG power, connectivity measures, nonlinear properties, and depressive symptoms. Whitton et al. [26] examined functional connectivity using EEG in individuals with depression, finding abnormally high-frequency communication among large-scale functional networks, which provides insights into disturbances in neural communication. The findings indicate that neural activity and connectivity changes could be objective markers for assessing depression severity and treatment outcomes. Depression is significantly influenced by disruptions in functional connectivity and network-level dysregulation, which highlights the importance of investigating how different brain regions communicate and coordinate. Moreover, changes in EEG measures, such as power, connectivity, and nonlinear properties, provide valuable information about the neurophysiological basis of depressive symptoms.

We focused on the P300 component, an event-related potential (ERP) that represents cognitive resource allocation and attentional processes. The P300 is typically observed in the time window of approximately 250 to 500 milliseconds after stimulus presentation and is associated with evaluating stimulus significance and updating working memory [27-29]. Alpha frequency was chosen as a focus of our study due to its distinct psychophysiological significance and its association with behavioral measures, particularly in the context of depression. Previous research has shown that alpha peak frequency correlates with cognitive performance in various tasks, such as visual perception, while alpha peak amplitude often reflects synchronous neural discharging [30-32]. Notably, it was found that both alpha peak amplitude and frequency were related to depressive scores, exhibiting different correlation patterns influenced by factors such as gender [33, 34].

The aim of this study was to explore the specificity in alpha source activity during ANT performance in MDD patients compared to healthy participants and those at risk of MDD. Previous findings indicate individuals with MDD show reduced activation in key brain regions during conflict resolution tasks compared to controls [35]. We expected that alpha source activity in the P300 interval would show differences between groups. Alpha source activity in the P300 interval elicited by congruent and incongruent stimuli was expected to show specific brain areas related to executive control networks. This article presents preliminary results for the executive network to introduce the utility of the source reconstruction method for finding EEG biomarkers of depression.

Methods and materials

Participants. Participants were 90 adults (72 female). The average age for females was 22.62

(SD=7.26) years, and for males – 24.56 (SD=6.28) years. The study was approved by the Ethics Committee of the Faculty of Medicine and Health Care of the Al-Farabi Kazakh National University. After reading the research information purposes and instructions, all subjects signed the consent form. Based on the Inventory Depression Score [36] and an interview with a psychiatrist, participants were assigned to 3 equal groups: a control group, at risk group, and a group with Major Depressive Disorder (MDD).

EEG recording. Neuron-Spectrum-4 system (Neurosoft Ltd, Ivanovo) was used to conduct EEG recordings during Attention Network Task (ANT) performance. The recording was conducted in the following scenarios: 1) participants were instructed to keep their eyes open for 1 minute, 2) participants were instructed to keep their eyes closed for 1 minute, and 3) participants engaged in a computer task for 70 minutes. Ag/AgCl electrodes were positioned on the scalp according to the international 10-20% monopolar system. The electrodes covered the left and right frontal, central, parietal, and occipital regions, specifically F3, F4, F7, F8, C3, C4, P3, P4, O1, O2, FPz, Fz, FCz, Cz, CPz, Pz, and Oz. Two electrodes were employed to record the electrooculogram, capturing vertical and horizontal eye movements. Electrode resistance was monitored throughout the recording, ensuring it remained below 5kΩ. Data were acquired at a sampling rate of 500 Hz, and a bandpass filter ranging from 0.01 to 30 Hz was applied throughout the recording.

Behavioral task. The Attention Network Task (ANT) was implemented using E-Prime 2.0, building on the original design by Fan et al. [37]. This modified version includes 96 trials spread across 9 blocks, totaling 864 trials lasting 70 minutes. Compared to the original 15-minute task, this extension provides a more in-depth look at attentional networks. The adjusted ANT was validated in a behavioral study by Zholdassova et al. [38, 39] to ensure it aligns with the characteristics of the local population.

Task structure. Each trial started with a fixation cross, followed by a cue stimulus, and a central arrow that served as the target. Participants were asked to respond quickly and accurately using the left and right keys, depending on the direction of the arrow. The stimuli were divided into two categories: cue types and flanker types. The cue types included no cue, double cue, central cue, and spatial cue (positioned above or below the fixation). The flanker types consisted of congruent, incongruent, and neutral stimuli.

EEG analysis. *Preprocessing.* EEG data were analyzed using EEGLAB [40]. The preprocessing steps ensured quality of the EEG data and the extraction of relevant features. Preprocessing included filtering out high and low frequencies, using Independent Component Analysis (ICA) to remove artifacts [41], selecting epochs from –700 to +700 ms around the stimulus presentation, and performing pre-stimulus baseline correction. Artifact-free epochs were chosen for paired executive control stimuli across three categories: 1) incongruent and congruent stimuli, 2) cue and double-cue stimuli, and 3) central and spatial signals.

Source reconstruction. Source reconstruction was done in Statistical Parametric Mapping (SPM) (The MathWorks, Inc.) [42] and involves two main phases: forward modeling and inverse modeling, as shown in Figure 1. To ensure precise localization of the EEG data, we aligned electrode configuration with the head model. The forward problem was addressed by calculating a lead field matrix, which describes how brain activity contributes to the EEG signals registered at the scalp.

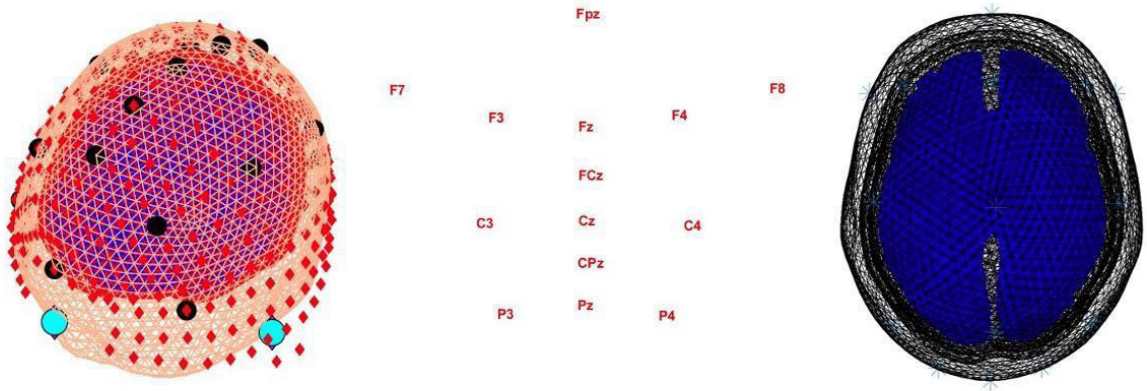
The Multiple Sparse Priors (MSP) approach assumes that only a few sources are active at any given time, allowing improved activity localization. The Greedy Search (GS) algorithm was employed to optimize the MSP method [43]. Time-frequency analysis was used to combine temporal and frequency data, which allowed localizing evoked activity within specific time-frequency windows. The P300 component, with an interval between 250 and 500 milliseconds after stimulus presentation, was the focus of the analysis.

The source reconstruction process in SPM consists of several steps (Figure 2): creation of a canonical cortical mesh that serves as a basis for projecting the EEG data; 2) the co-registration step with visualization of several key components, including MRI fiducials (in pink), sensor fiducials (in blue), sensor locations (in green), the canonical cortical mesh (in blue), the inner skull surface (in red), and the scalp surface (in light brown). This step does not require additional parameters when using the canonical mesh. However, MNI coordinates for the fiducial positions must be provided if a non-standard mesh or custom sensor positions are involved [44].

The "EEG-BEM" head model was selected for the forward model. SPM uses a Boundary Element Method (BEM) to visualize the cortical mesh and the brain, skull, and scalp surfaces, marking the electrode positions for clarity [45-46]. In the inversion process, SPM computes the lead field matrix and inverts

the forward model using the MSP algorithm. The progress is displayed in real time in the MATLAB command window. The graphical output includes a Maximum Intensity Projection (MIP) of activity in the source space and a time series of activity for each condition.

The reconstruction process estimates the cortical current sources responsible for the electrical activity detected by EEG, involving building a standard head model, co-registering it with the EEG data, and constructing a forward model to understand how brain sources appear on the EEG sensors. The inversion within a Bayesian framework using MSP was applied, focusing on a time window of [250 to 500] ms and [8 to 12] Hz, as it provides valuable insights into attentional and cognitive processing. Finally, SPM was used to generate source power images and apply cortical smoothing to enhance the analysis [47-48]. After preprocessing the EEG data and conducting source analysis, statistical analysis was performed, focusing on the P300 component within the alpha frequency range. This analysis examined the relationship and differences between EEG features and experimental conditions. A one-way analysis of variance (ANOVA) was used to assess the main effects and interactions among these factors.



a b c

Figure 1 – Source reconstruction in SPM (a) cortical mesh; (b) co-registration of electrodes; (c) "EEG-BEM" head model

Results and discussion

Demographic and clinical data. Table 1 summarizes the demographic data of the participants.

Individual source reconstruction and maximum intensity projection (MIP). In this study, source localization techniques and maximum intensity projection (MIP) were used for each of the 90 participants to explore how their brains responded to two types of stimuli: congruent and incongruent. Figures 2 and 3 show examples of individual source localizations and MIP graphs. The MIP graphs provide a clear visual representation of the maximum activation intensity across the scalp, revealing distinct brain activation patterns for each stimulus type. The MIP at 300 ms post-stimulus reveals significant activation in each participant group's frontal and parietal regions, which indicates substantial engagement during attentional processing of the stimulus.

Individual source reconstruction and MIP were computed for post-stimulus latency 0-700 ms to visualize spatial distribution. Time series data were extracted from the voxel with the largest magnitude signal within key brain regions identified from the MIP. MIP in subjects from three groups showed different latencies: control group – 464 ms, risk group – 474 ms, MDD group – 342 ms. These individual results will be used in the statistical analysis of group differences in the next steps of our study.

Table 1 – Demographic and clinical data of the participants

Group	Total Participants	Female Participants	Male Participants	Avg. Age (Female), years	SD (Female), years	Avg. Age (Male), years	SD (Male), years
Control	30	24	6	20.71	4.50	23.00	5.45
Risk	30	24	6	23.33	8.27	26.83	7.01
MDD	30	24	6	23.83	7.98	23.83	5.61
Total	90	72	18	-	-	-	-

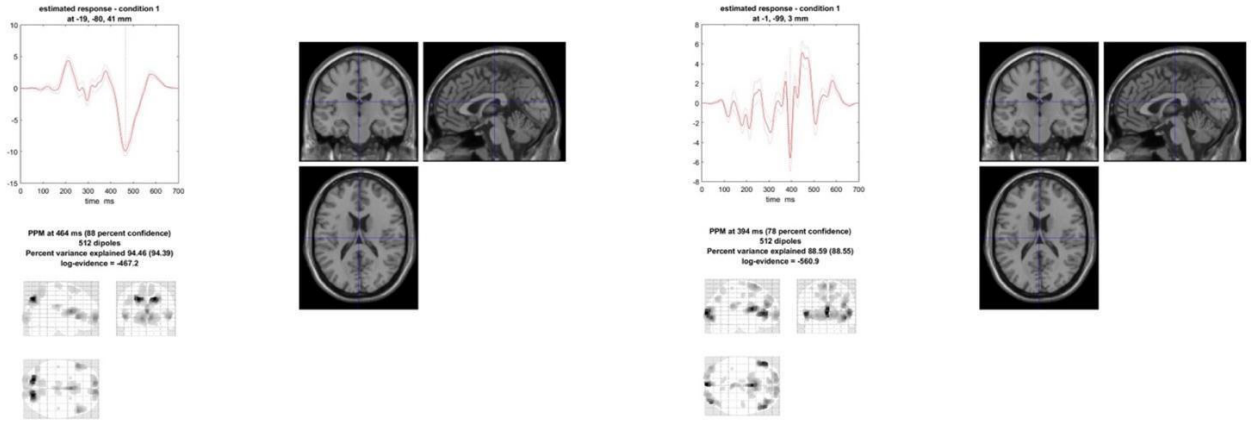


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Figure 2 – Individual source reconstruction and maximum intensity projection (MIP) for one participant from the Control group for (a,b) congruent stimulus; (c,d) incongruent stimulus

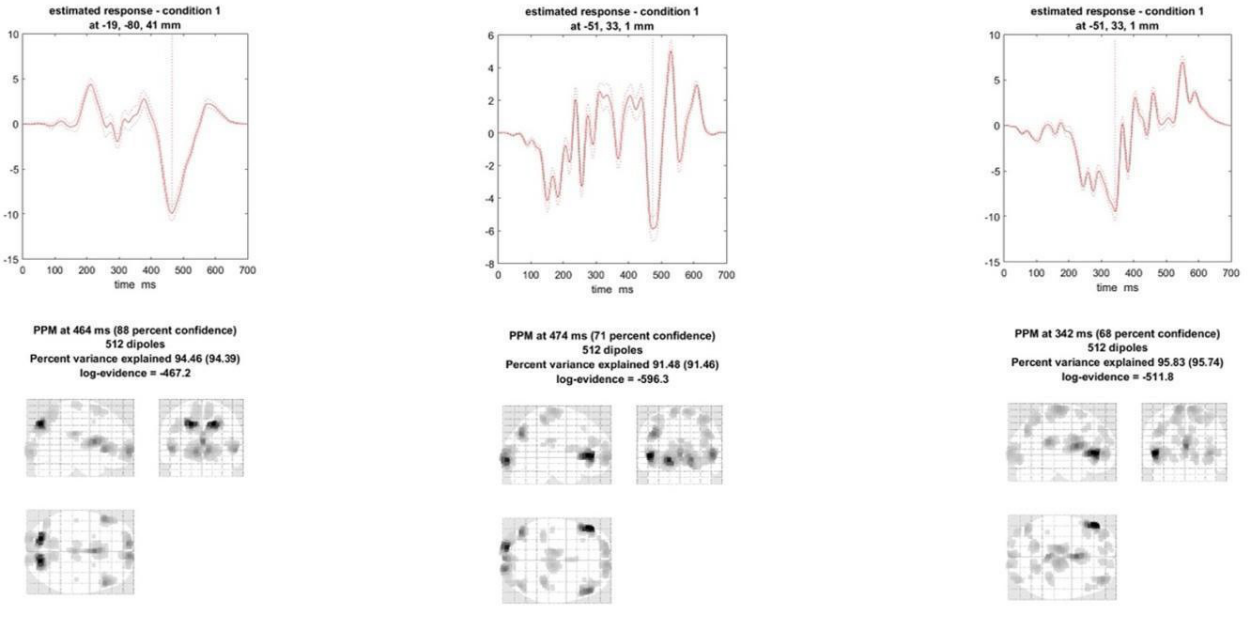

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Figure 3 – Individual source reconstruction and maximum intensity projection (MIP) for participants from the (a) Control group; (b) the Risk group; (c) the MDD group

Condition and group effects. A one-way ANOVA analysis for the congruent condition revealed significant differences in the comparison "MDD vs. Healthy" in several brain regions: the Anterior Prefrontal Cortex (BA10), the Anterior Cingulate Cortex (ACC, BA24), and the Inferior Frontal Gyrus (BA45) (Fig. 4, Table 2).

A one-way ANOVA analysis for the incongruent condition revealed significant differences in the comparison "MDD vs. Healthy" in several brain regions: the Anterior Cingulate Cortex (ACC, BA24), the Medial Prefrontal Cortex (mPFC, BA10), and the Right Angular Gyrus (BA39) (Fig. 5, Table 3).

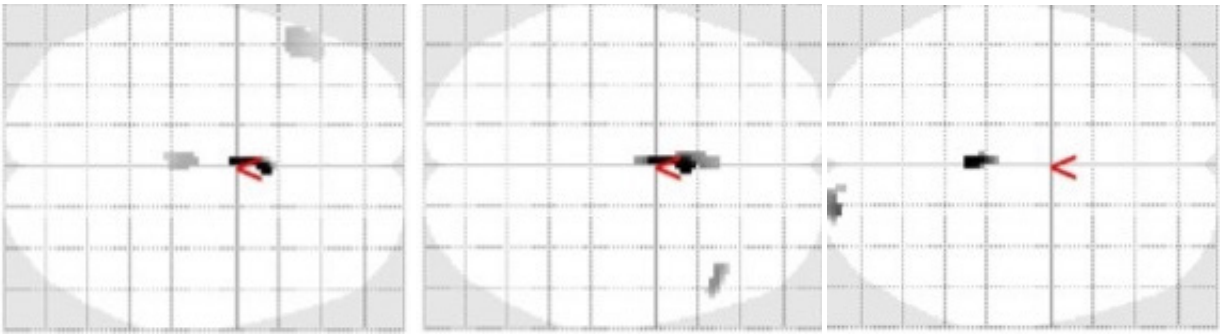

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Figure 4 – Brain areas with significant differences (a) MDD vs Healthy; (b) MDD vs Risk; (c) Risk vs Healthy

Table 2 – Brain areas with significant differences: MDD vs Healthy, MDD vs Risk, Risk vs Healthy

No.	Coordinates	Brain area	p-value
MDD vs Healthy			
1	**0 2 22**	**Anterior prefrontal cortex (BA10)**	p<0.050
2	4 10 22	Anterior prefrontal cortex (BA10)	
3	**0 -24 24**	**Anterior cingulate cortex (BA24)**	
4	**-52 20 2**	**Left Inferior Frontal Gyrus (BA45)**	
MDD vs Risk			
1	**0 2 20**	**Medial Prefrontal Cortex (BA9)**	p<0.050
2	**46 24 4**	**Dorsolateral Prefrontal Cortex (DLPFC) (Right BA46, BA45)**	
Risk vs Healthy			
1	**2 -38 20**	**Anterior Cingulate Cortex (BA24 or BA32)**	p<0.050
2	**22 94 -16**	**Right Visual (BA18)**	
3	12 -92 -8	Right Visual (BA18)	

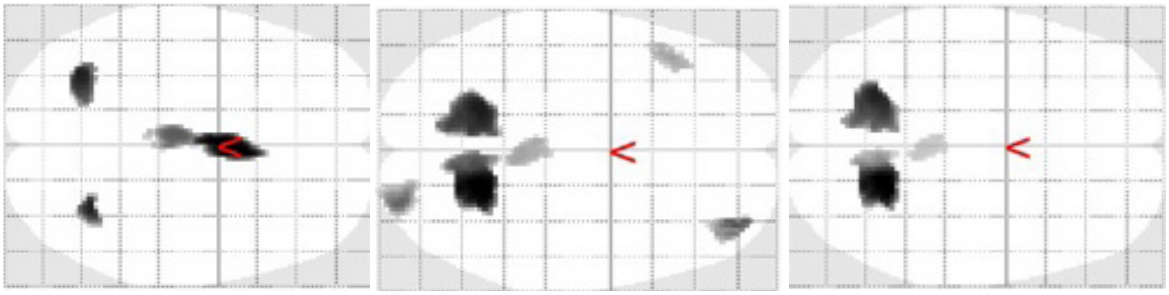

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Figure 5 – Brain areas with significant differences (a) MDD vs Healthy; (b) Risk vs MDD; (c) Risk vs Healthy

Table 3 – Brain areas with significant differences: MDD vs Healthy, Risk vs MDD, Risk vs Healthy

No.	Coordinates	Brain area	p-value
MDD vs Healthy			
1	**2 4 24**	**Anterior Cingulate Cortex (ACC) (BA24)**	p<0.012
2	-4 -22 26	Anterior Cingulate Cortex (ACC) (BA32)	
3	-4 -34 24	Medial Prefrontal Cortex (mPFC) (BA10)	
4	**-32 -66 48**	**Superior Parietal Lobule and Precuneus (BA7)**	
5	**32 -62 48**	**Right Angular Gyrus (BA39)**	
Risk vs MDD			
1	**20 -56 54**	**Right Superior Temporal Gyrus (BA22)**	p<0.003
2	8 -60 60	Superior Parietal Lobule and Precuneus (BA7)	
3	**-16 -58 62**	**Superior Parietal Lobule and Precuneus (BA7)**	
4	-18 -58 62	Superior Parietal Lobule and Precuneus (BA7)	
5	-14 -66 54	Superior Parietal Lobule and Precuneus (BA7)	
6	**38 52 0**	**Right Anterior Prefrontal Cortex (BA10)**	
7	40 52 -8	Right Anterior Prefrontal Cortex (BA10)	
8	40 42 6	Right Dorsolateral Prefrontal Cortex (BA46)	
9	**26 -92 -16**	**Right-Visual(BA18)**	
10	20 -88 -12	Right-Visual(BA18)	
11	**-42 24 36**	**Left Dorsolateral Prefrontal Cortex (BA9)**	
12	**4 -40 18**	**Medial Prefrontal Cortex (mPFC) (BA10)**	
13	-2 -34 18	Medial Prefrontal Cortex (mPFC) (BA10)	
Risk vs Healthy			
1	**22 -56 52**	**Superior Parietal Lobule and Precuneus (BA7)**	p<0.015
2	20 -66 58	Superior Parietal Lobule and Precuneus (BA7)	
3	8 -60 60	Superior Parietal Lobule and Precuneus (BA7)	
4	**-22 -62 52**	**Superior Parietal Lobule and Precuneus (BA7)**	
5	-6 -52 62	Superior Parietal Lobule and Precuneus (BA7)	
6	**2 -40 18**	**Medial Prefrontal Cortex (mPFC) (BA10)**	

The aim of this study was to explore the specificity in alpha source activity during Attention Network Task (ANT) performance in Major Depressive Disorder (MDD) patients compared to healthy participants and those at risk of MDD. The study did not address gender differences. Our results revealed significant group effects in alpha source activity in the P300 interval elicited by congruent and incongruent stimuli. The individual MIP graphs illustrate distinct brain activation patterns for each stimulus type, with significant activation in the frontal and parietal regions of all participant groups at 300 ms post-stimulus, indicating substantial engagement during attentional processing.

The one-way ANOVA results for the congruent condition between the MDD and control groups showed significant differences in the alpha source activation in the Anterior Prefrontal Cortex (BA10) and Anterior Cingulate Cortex (BA24), suggesting challenges in higher-order cognitive functions, such as decision-making and attentional switching [4, 49]. Increased alpha source activation in the Inferior Frontal Gyrus (BA45) in the MDD group may be evidence of language processing challenges [50]. Significant activation in the Medial Prefrontal Cortex (BA10) and Dorsolateral Prefrontal Cortex (BA46) in MDD align with research which showed the DLPFC is critical for functions such as task switching, inhibition, and working memory, which are important for resolving conflicts in congruent scenarios [50].

The analysis of one-way ANOVA results for the incongruent condition highlights greater significant differences between MDD and healthy control groups. The Right Dorsolateral Prefrontal Cortex (BA9) and Right Anterior Prefrontal Cortex (BA10) are crucial for executive functions, including cognitive flexibility, decision-making, and attentional control [51-52]. Furthermore, larger alpha source activation of the Anterior Cingulate Cortex (ACC) in the MDD group suggests lower brain activation, which may affect attention and task management in depression. The Medial Prefrontal Cortex (mPFC) is involved in self-referential thinking and decision-making [53], while the Superior Parietal Lobule and Precuneus (BA7) and Right Angular Gyrus (BA39) reflect visual and motor functions [54].

The results of our study are consistent with existing literature indicating altered alpha source activity in patients with MDD. Pizzagalli et al. [55] found that MDD patients exhibit higher alpha activity in certain brain regions compared to healthy controls, reflecting underlying cognitive and emotional processing differences. Additionally, patients with MDD showed distinct EEG patterns, including lower alpha band connectivity and higher gamma band connectivity, indicating altered brain activation in regions such as the ACC during attention-related tasks [56].

Limitations. There are limitations to consider in this study. First, this article focused only on the alpha wave frequency and the P300 component and presented preliminary results. Further analysis will explore other frequency bands and waves in response to other stimuli. Second, a standardized "EEG-BEM" (Boundary Element Model) head model was used for source reconstruction. The model might not capture the participants' individual differences in brain anatomy. In the next steps, personalized head models will be used.

Conclusion

Our examination of the P300 component at alpha frequency during performance of the Attention Network Task (ANT) showed distinct differences in source localization across three groups: control, individuals with Major Depressive Disorder (MDD), and those at risk of developing MDD. Our findings revealed that brain activation patterns varied significantly when comparing responses to congruent versus incongruent stimuli, particularly in areas such as the Anterior Cingulate Cortex (ACC) and the Dorsolateral Prefrontal Cortex (DLPFC).

Acknowledgments

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Conflict of interest

All authors are aware of the article's content and declare no conflict of interest.

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