

## Measuring Spectral Power to Potentially Measure Correlations in the MMSE Test

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### Abstract:

Alzheimer's disease and frontotemporal dementia are two types of neurological diseases claiming victims across the world. EEG offers a unique solution to this problem. This paper will explore the correlation between patient's power density spectral values within frequency bands and MMSE scores to possibly determine a correlation regarding cognitive decline to predict neurological diseases within patients. A statistical analysis was performed on an EEG dataset from an MDPI article containing three patient samples (Alzheimer's, frontotemporal dementia, and healthy controls). The data was processed into Google Sheets, where a two-sample unequal variance test was performed to measure the statistical difference between Alzheimer's patients vs. healthy controls and frontotemporal dementia patients vs. healthy controls. The results show an interesting potential for EEG metrics in the potential prediction of neurological diseases.

### Introduction:

Alzheimer's disease (AD) and frontotemporal dementia (FTD) are two progressive neurological diseases that, in total, affect over 7 million Americans. Alzheimer's disease, the most common form of dementia accounting for 60-80% of cases, is commonly characterized by overall cognitive decline and memory loss. Recent reports suggest that patients with AD exhibit strong negative emotions such as depression, apathy, and anxiety before cognitive decline. Patients with AD may also exhibit behavioral symptoms such as sleep deprivation, increased irritability, or depression. Behavioral symptoms for FTD, specifically, account for 5-10% of cases. There is a common overlap between FTD and AD regarding cognitive decline. However, there are key differences in behavior symptoms regarding the following: disinhibition, apathy, hyperorality, dietary changes, psychotic symptoms such as delusions and hallucinations, schizophrenia, and bipolar disorder. Diagnosis for neurological diseases such as AD and FTD requires clinical evaluation, neurological testing, neuropsychological testing, and imaging tests such as positron emission tomography (PET) or magnetic resonance imaging (MRI). The overall effectiveness of these diagnostic approaches makes it hard to diagnose AD or FTD, specifically, in the face of other neurological diseases with similar behavioral and psychological symptoms. This leads to the main problem with the current state of diagnosis, which is the slow and delayed process of diagnosing AD or FTD. As Alzheimer's disease and FTD are progressive neurological diseases, behavioral and psychological symptoms worsen increasing cost and decreasing quality of life. Thus, a speedier diagnosis of neurological diseases is urgently needed, thus providing a gateway for the use of Electroencephalography (EEG) technology.

The idea of using EEG technology as a means of early diagnosis has been linked as an intriguing, up-and-coming option. EEG is a low-cost, non-invasive, and portable technology that records the electrical activity of a patient's brain to observe neuronal activity by recording brain signals from electrodes placed on the scalp. Machine learning technology then can be used to detect abnormalities within these signals to detect certain neurological disorders. Caution

regarding the accuracy of EEG still needs to be considered, requiring further testing. Two main metrics regarding EEG analysis include spectral power, an EEG metric that looks at underlying brain activity, and spectral phase, another feature of brainwave oscillations that indexes the timing of neuronal oscillations. Fell and Axmacher (2011) describes how phase synchronization between oscillatory phases can support memory by “facilitating neural communication and by promoting neural plasticity”, further detailing the connection between spectral phase and communication between brain regions. This paper focuses on one of these EEG metrics, spectral power. Spectral power demonstrates the distribution of signal power over the frequency components of the signal. This metric is extremely useful in revealing the distribution of energy in the signal’s frequencies, helping to understand the frequencies that are most powerful in a patient’s brains. This provides invaluable information of overall brain activity observed, which can be compared across populations to determine cognitive decline in different frequencies.

Miltiadous and colleagues (2023) collected EEG recordings of three groups of patients AD, FTD, and healthy controls (HC), where they found that the AD group of individuals exhibited increased broadband spectral power on average relative to FTD and HC through observing the correlation between spectral power and cognitive decline. The Mini-Mental State Examination (MMSE) was specifically used as a bench-mark for observing cognitive decline. Regarding the results of the test, it was explained that “MMSE score ranges from 0 to 30, with a lower MMSE indicating more severe cognitive decline.” It was found that “the average MMSE for the AD group was 17.75 ( $SD = 4.5$ ), for the FTD group it was 22.17 ( $SD = 8.22$ ), and for the CN group it was 30.” This suggests that spectral power may have an impact on the scores of the MMSE test and thus, cognitive decline. The results of this paper may illustrate the potential importance of spectral power as a diagnostic marker for neurodegenerative diseases. It’s unknown whether the findings of Miltiadous and colleagues were significantly different between groups (AD/FTD/HC), what the effects of various neurodegenerative disorders are on established EEG metrics such as spectral power, or how these metrics would compare/contrast between AD/FTD/HCs.

To further explore this, we observed statistical differences between power spectral density (PSD) across the 3 populations, and the impact on patient’s results from the MMSE test. Recent literature suggests that there can be a potential prediction into the correlation between spectral power in different frequency bands and the MMSE test. Kwak and Tae (2006) in their paper regarding “topographical spectral power and occipital peak frequency (OPF) among elderly controls” explains that there was a “significant reduction among alpha and beta powers for elderly controls”. Additionally, Deurson and colleagues (2008) predicted an overall “lower gamma band power in AD subjects than in controls for all measured tasks”. Lastly, Miltiadous and colleagues (2023) stated that “AD patients exhibit reduced alpha power and increased theta power.” As Jeong and colleagues (2021) puts it, “on AD related to the MMSE score, the lower the score, the higher the relative power of theta waves was found in the entire hemisphere...the decrease in alpha power was greater in the posterior lead of the MCI group.”

In light of the reports above, we hypothesize that the power spectral density values in the AD population will be higher in the theta frequency band and lower in the alpha, beta, and gamma frequency bands compared to the healthy control population. Additionally, we hypothesize that the power spectral density values in the FTD population will be lower in the

alpha, beta, and gamma frequency bands compared to the healthy control population. Regarding the correlation between spectral power and cognitive decline we predict that there will be a direct correlation between power density spectral values and MMSE scores in the alpha, beta, and gamma frequency bands for the AD and FTD population, while there will be an inverse correlation for the theta frequency band in the AD population.

## Methods:

This paper uses the [dataset](#) conducted by Miltiadous and colleagues, containing 88 subjects: 36 subjects diagnosed with AD, 23 subjects diagnosed with FTD, and 29 healthy controls. Additionally, the last 4 patients of the study, all FTD patients, were not used for feasibility approaches when extracting metrics. This meant the total dataset of this study was 84 subjects: 36 subjects diagnosed with AD, 19 subjects diagnosed with FTD, and 29 healthy controls. The MNE toolbox was then used to process the data by extracting spectral power values. To do this, the "[welch method](#)" was used to extract an estimate of spectral power by dividing the data into segments, computing modified periodogram for each segment and averaging the periodogram Through the Welch method, the data could then be separated into frequency bands and ranges (Delta, Theta, Alpha, Beta, and Gamma). This was done using the Fmin and Fmax parameters in the Welch method, set to 0 and 45. Through a for-loop, the average spectral power values within each frequency band were then able to be calculated through all 19 scalp electrodes for each patient. This topographical image was then produced depicting the spectral power (in dB units) for all 5 frequency bands recorded of the three dataset groups:

The data was then exported to a CSV file, where it was processed into three tables, representing the three groups of patients: Alzheimer's, healthy controls, and FTD, on Google Sheets for statistical testing. The tables for the spectral power metrics for each of the three study populations can be found below:

participant_id	Gender	Age	Group	MMSE	delta	theta	alpha	beta	gamma
sub-001	F	57	A	16	23.56	9.98	4.11	-1.88	-5.77
sub-002	F	78	A	22	23.44	9.77	8.51	-0.93	-5.76
sub-003	M	70	A	14	22.76	11.16	9.88	-1.92	-8.36
sub-004	F	67	A	20	24.26	10.03	4.05	-0.82	-2.63
sub-005	M	70	A	22	23.76	9.69	4.66	-1.08	-4.69
sub-006	F	61	A	14	24.35	9.21	10.63	0.48	-4.90
sub-007	F	79	A	20	23.80	10.16	4.62	-1.68	-6.12
sub-008	M	62	A	16	24.86	10.44	5.17	-0.76	-4.81
sub-009	F	77	A	23	23.16	9.91	8.34	0.25	-4.58
sub-010	M	69	A	20	23.34	8.74	4.91	-1.26	-5.30
sub-011	M	71	A	22	24.32	11.18	7.89	0.18	-2.02
sub-012	M	63	A	18	24.60	10.35	6.22	-0.72	-6.08

sub-013	F	64	A	20	24.41	10.53	5.19	-1.26	-5.78
sub-014	M	77	A	14	24.53	10.38	4.65	0.25	-1.74
sub-015	M	61	A	18	24.03	9.68	7.74	-1.33	-5.98
sub-016	F	68	A	14	24.42	10.09	4.02	-2.45	-7.77
sub-017	F	61	A	6	24.57	11.23	5.56	-1.17	-6.41
sub-018	F	73	A	23	24.29	11.92	8.05	1.43	-4.87
sub-019	F	62	A	14	24.02	9.44	4.77	-0.66	-3.03
sub-020	M	71	A	4	24.83	9.87	4.36	-1.69	-5.38
sub-021	M	79	A	22	24.22	10.01	4.99	0.06	-2.43
sub-022	F	68	A	20	24.43	11.51	7.23	0.88	-2.55
sub-023	M	60	A	16	24.06	10.33	6.38	-0.02	-3.48
sub-024	F	69	A	20	24.03	11.39	5.59	-1.40	-7.86
sub-025	F	79	A	20	23.96	10.07	9.93	0.90	-0.02
sub-026	F	61	A	18	24.27	10.77	5.30	3.35	4.44
sub-027	F	67	A	16	24.62	13.33	5.72	1.28	-0.20
sub-028	M	49	A	20	23.88	10.76	5.01	-1.59	-7.29
sub-029	F	53	A	16	23.79	11.56	5.30	-0.81	-5.02
sub-030	F	56	A	20	25.42	14.04	7.99	1.68	-0.83
sub-031	F	67	A	22	24.33	9.94	7.29	-0.25	-3.50
sub-032	F	59	A	20	24.12	13.13	8.64	2.52	-2.97
sub-033	F	72	A	20	23.77	9.64	6.29	0.98	-3.52
sub-034	F	75	A	18	24.03	10.00	4.23	-1.69	-7.52
sub-035	F	57	A	22	23.74	10.08	4.76	-1.55	-5.44
sub-036	F	58	A	9	23.38	10.39	9.77	3.22	-5.64

Table 1: Extracted Spectral Power Values for the Alzheimer's Population

participa nt_id	Gender	Age	Group	MMSE	delta	theta	alpha	beta	gamma
sub-037	M	57	C	30	24.30	10.64	10.84	-0.67	-6.87
sub-038	M	62	C	30	23.53	9.34	6.58	-0.31	-6.76
sub-039	M	70	C	30	23.72	10.38	13.40	0.81	-4.99
sub-040	M	61	C	30	25.01	9.86	9.52	-0.34	-4.76
sub-041	F	77	C	30	24.06	9.29	6.79	0.34	-3.17
sub-042	M	74	C	30	24.00	9.54	8.84	0.23	-5.80
sub-043	M	72	C	30	23.82	9.50	4.93	-1.45	-6.02
sub-044	F	64	C	30	24.30	9.85	10.67	-0.19	-7.62
sub-045	F	70	C	30	24.10	10.00	5.52	-0.67	-6.49
sub-046	M	63	C	30	24.08	10.92	10.47	2.48	-4.66



sub-047	F	70	C	30	23.99	10.08	9.23	0.14	-5.49
sub-048	M	65	C	30	24.40	10.10	8.72	0.55	-2.04
sub-049	F	62	C	30	24.02	9.92	9.78	0.28	-5.39
sub-050	M	68	C	30	24.50	10.24	7.43	-0.43	-2.80
sub-051	F	75	C	30	24.59	9.69	6.69	-0.65	-4.58
sub-052	F	73	C	30	23.82	10.01	8.62	0.70	-4.55
sub-053	M	70	C	30	24.52	10.71	10.16	0.81	-2.48
sub-054	M	78	C	30	24.00	10.41	10.55	0.73	-6.00
sub-055	M	67	C	30	24.14	9.77	8.63	2.10	-6.04
sub-056	F	64	C	30	24.36	15.54	13.99	7.66	3.59
sub-057	M	64	C	30	23.95	9.63	8.15	-0.31	-6.10
sub-058	M	62	C	30	23.86	9.71	9.03	0.85	-4.23
sub-059	M	77	C	30	24.07	9.53	4.60	-1.09	-6.40
sub-060	F	71	C	30	24.36	9.62	4.31	-0.15	-6.21
sub-061	F	63	C	30	24.28	9.35	6.70	-1.94	-4.87
sub-062	M	67	C	30	24.50	9.86	10.92	-0.68	-6.56
sub-063	M	66	C	30	23.42	9.44	5.76	-0.95	-6.01
sub-064	M	66	C	30	24.51	10.57	14.51	2.68	-4.18
sub-065	F	71	C	30	24.12	9.39	5.39	-0.69	-5.21

Table 2: Extracted Spectral Power Values for the Healthy Control's Population

sub-066	M	73	F	20	24.14774 209	11.04331 802	6.900788 402	-0.92586 66636	-4.11069 1749
sub-067	M	66	F	24	23.45611 039	9.442973 001	7.176935 579	6.170911 153	5.092470 9
sub-068	M	78	F	25	23.81099 327	9.311606 871	6.252365 546	-1.72347 5601	-6.86910 703
sub-069	M	70	F	22	23.12282 062	13.89857 615	9.909374 27	0.733806 8264	-4.76177 0184
sub-070	F	67	F	22	23.43000 875	9.172616 65	4.454434 391	-0.77370 417	-4.77955 3962
sub-071	M	62	F	20	23.29541 308	9.547319 017	7.076945 335	0.752104 1546	-2.56831 203
sub-072	M	65	F	18	23.97732 846	10.86750 574	5.056675 44	-1.21730 6405	-6.19645 3323
sub-073	F	57	F	22	24.00039 33	9.471702 306	5.805955 263	-2.28363 2118	-7.48354 0579
sub-074	F	53	F	20	24.40435 903	10.64997 804	6.710669 368	-1.24277 3384	-5.18525 4692
sub-075	F	71	F	22	24.11371 921	10.13954 175	9.418118 056	2.638016 969	0.484459 442

sub-076	M	44	F	24	23.87895 62	10.28709 925	5.178378 257	0.959992 796	-2.10774 9567
sub-077	M	61	F	22	24.42659 577	9.345676 72	4.260910 774	-1.06140 1714	-3.47176 1127
sub-078	M	62	F	22	24.58945 543	9.516747 086	4.326592 923	-0.84513 92884	-5.00546 9201
sub-079	F	60	F	18	23.90105 209	9.450616 497	6.969539 884	1.652430 495	-0.80043 58647
sub-080	F	71	F	20	23.86265 358	9.752226 118	11.30617 092	0.605249 3531	-4.71015 7783
sub-081	F	61	F	18	23.94479 488	9.756725 072	4.695618 432	-2.49932 706	-8.58683 4583
sub-082	M	63	F	27	24.17141 465	9.674243 111	7.029324 007	-1.19173 046	-4.98830 0678
sub-083	F	68	F	20	24.00278 676	9.454667 747	3.854587 601	-2.09459 2227	-6.12189 5277
sub-084	F	71	F	24	22.40793 211	9.927376 755	4.253776 31	-1.33974 3065	-5.68427 8318

Table 3: Extracted Spectral Power Values for the Frontotemporal Dementia Population

The statistical testing that would be applied to the data would be a T-test comparing Alzheimer's vs. Healthy Controls, FTD vs. Healthy Controls, and Alzheimer's vs. FTD to find the most significant differences within the different frequency bands (representing parts of the brain). The results could then be used to demonstrate specific parts of the brain that correlate to the respective frequency band that show significant amounts of difference in spectral power values compared to other populations. To perform the T-test, the average and standard deviation values were taken for each frequency band of each population. Using Google Sheet T-Test application feature, the T-Test values were calculated based on the comparison of the two populations' respective frequency bands. If this value (known as p) was lower than the threshold of 0.05, it was marked as FALSE, meaning there was a significant difference that needed to be further evaluated. If not, it was marked under the TRUE label. Statistical difference would be measured for all frequency bands no matter their label. An online unpaired T-Test calculator called [GraphPad](#) was then used to determine degrees of freedom and p-value.

## Results:

Three T-Test comparisons were processed to measure the statistical difference in spectral power of the 5 frequency bands: delta, theta, alpha, beta, and gamma between AD vs. HC, FTD vs. HC, and AD vs. FTD. The takeaways found from the first statistical comparison between AD vs. HC was that theta power was found to be the strongest in the AD group ( $M = 10.58$  dB,  $SD = 1.13$ ) relative to the HC group ( $M = 10.10$  dB,  $SD = 1.14$ ) ( $t(63) = 1.68$ ,  $p < .05$ ). Additionally, alpha power was found to be the strongest in the HC group ( $M = 8.65$  dB,  $SD = 2.71$ ) relative to the AD group ( $M = 6.33$  dB,  $SD = 1.93$ ) ( $t(63) = 4.02$ ,  $p < .05$ ). There seemed to be no significant difference in gamma power between the AD group ( $M = -4.33$  dB,  $SD = 2.61$ ) compared to the HC group ( $M = -4.92$  dB,  $SD = 2.13$ ), ( $t(63)$ ,  $p = .158$ ). Furthermore, there

seemed to be no significant difference in beta power between the AD group ( $M = -0.26$  dB,  $SD = 1.46$ ) compared to the HC group ( $M = 0.34$  dB,  $SD = 1.77$ ), ( $t(63)$ ,  $p = .073$ ). Lastly, there seemed to be no significant difference in delta power between the AD group ( $M = 24.09$  dB,  $SD = 0.52$ ) compared to the HC group ( $M = 24.15$  dB,  $SD = 0.34$ ), ( $t(63)$ ,  $p = .302$ )

The takeaways found from the next statistical comparison between FTD vs. HC was that delta power was strongest in the HC group ( $M = 24.15$  dB,  $SD = 0.34$ ) relative to FTD group ( $M = 23.839$  dB,  $SD = 0.515$ ) ( $t(46) = 2.52$ ,  $p < .05$ ). Additionally, alpha power was strongest in the HC group ( $M = 8.65$  dB,  $SD = 2.71$ ) relative to the FTD group ( $M = 6.35$  dB,  $SD = 2.08$ ) ( $t(46) = 3.13$ ,  $p < .05$ ). There seemed to be no significant difference in gamma power between the FTD group ( $M = -4.098$  dB,  $SD = 3.139$ ) compared to the HC group ( $M = -4.92$  dB,  $SD = 2.13$ ), ( $t(63)$ ,  $p = .324$ ). Furthermore, there seemed to be no significant difference in beta power between the FTD group ( $M = -0.194$  dB,  $SD = 2.079$ ) compared to the HC group ( $M = 0.34$  dB,  $SD = 1.77$ ), ( $t(63)$ ,  $p = .362$ ). Lastly, there seemed to be no significant difference in theta power between the FTD group ( $M = 10.037$  dB,  $SD = 1.080$ ) compared to the HC group ( $M = 10.10$  dB,  $SD = 1.14$ ), ( $t(63)$ ,  $p = .851$ )

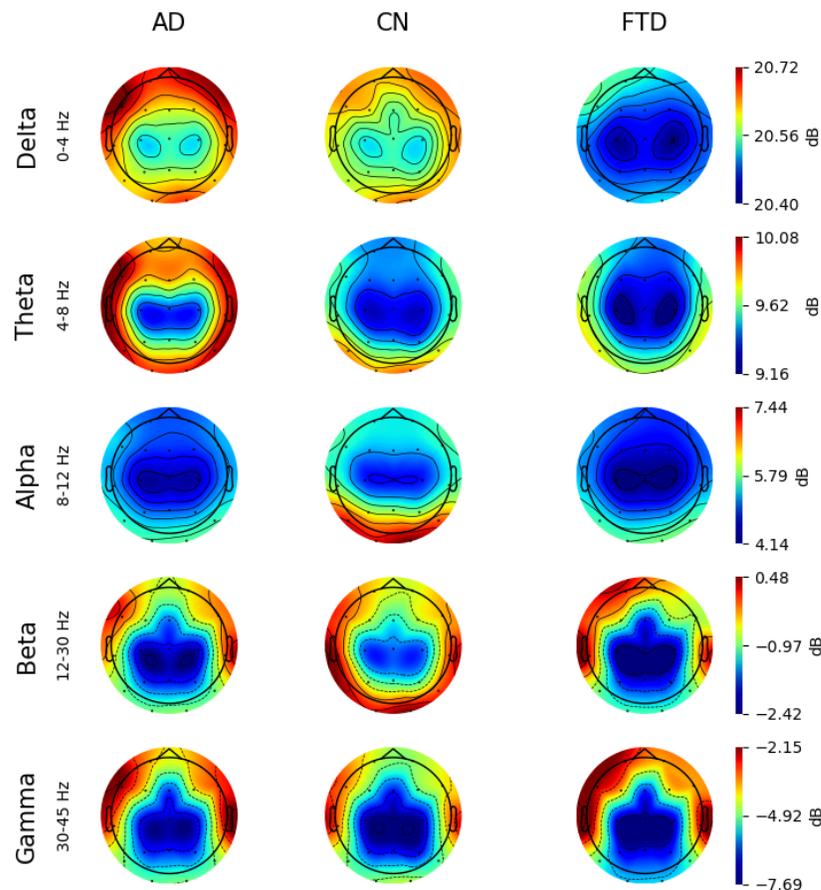


Figure 1: Topography of Spectral Power across the 3 Populations over 5 frequency bands

## Discussion:

As depicted in the results section of the paper, there were two statistical tests: AD vs. HC and FTD vs. HC, in order to observe statistical differences in power spectral density within the 5 frequency bands observed. Referring back to the initial prediction, it was hypothesized that power spectral density values in the AD population will be higher in the theta frequency band and lower in the alpha, beta, and gamma frequency bands compared to the healthy control population. The results seem to support the hypothesis regarding the alpha and theta frequency band as theta power was on average larger compared to the control population, meanwhile alpha power was on average lower compared to the control population. Spectral power in the beta, gamma, and delta frequency bands in the AD population however showed no substantial statistical difference compared to the control population, contrasting with the hypothesis. While, for the power spectral density values in the FTD population, it was hypothesized that spectral power would be lower in the alpha, beta, and gamma frequency bands compared to the healthy control populations. The results seemed to support the hypothesis regarding the alpha frequency band as alpha power was on average lower in the FTD population compared to the control population. Similarly to the AD population, spectral power in the beta, gamma, and theta bands however showed no substantial statistical difference compared to the control population. However, delta power was actually weaker in the FTD population compared to the control population. Thus, spectral power metrics within alpha and theta frequency bands should be carefully monitored within AD patients, while spectral power metrics within the alpha and delta frequency bands should be carefully monitored with FTD patients.

Regarding the correlation between spectral power and MMSE scores, it was hypothesized that there would be a direct correlation between power density spectral values and MMSE scores in the alpha, beta, and gamma frequency bands of the AD and FTD population, and an inverse correlation for the theta frequency band in the AD population. The average MMSE scores for 3 populations were as follows: AD population was 17.75 ( $SD = 4.5$ ), the FTD group was 22.17 ( $SD = 8.22$ ), and the HC group was 30. Since beta and gamma power showed no difference between the disease and healthy populations, these frequency bands can be ruled out for having an impact from this sample. The results of this statistical test seems to show that in the AD population, there was an inverse correlation between theta power and MMSE scores as theta power was higher in the AD population yet the MMSE scores of these AD patients were lower than the control population. However, there was a direct correlation between alpha power and MMSE scores as alpha power was lower in the AD population, and the MMSE scores of these patients were lower compared to the control population. The results also seemed to show a direct correlation between alpha and delta power and MMSE scores as alpha and delta power was lower in the FTD population and the MMSE scores of these FTD patients were lower than the control population. Thus, the results seem to support our hypothesis regarding spectral power within the alpha and theta frequency bands.

This paper set out to measure the overall correlation between spectral power within frequency bands of patients with neurological diseases and cognitive decline in the brain through the Mini-Mental State Examination (MMSE). The findings of this paper seem to describe a direct correlation between spectral power in the alpha frequency band of patients with



Alzheimer's and Fronto temporal dementia and cognitive decline. There is an inverse correlation between spectral power in the theta frequency band with AD patients, and a direct correlation between spectral power in the delta frequency band with FTD patients. Except for delta power, this mostly aligns with the predictions that were made. This shows positive indication to the methodology and overall processing of data done in this study as the findings of this paper matches closely to findings from recent literature into a similar correlation. Although caution should be placed on the results from this correlation test, further studies regarding spectral power within the alpha, theta, and delta frequency bands should take place, in order to understand the overall significance of correlations between spectral power and other EEG metrics when determining cognitive decline and other significant changes in brain activity of patients that are diagnosed with neurological diseases such as Alzheimer's and dementia.

The interpretation of this paper has an important impact within the field of neuroscience, specifically regarding prediction on diagnosis of neurological diseases such as the ones in this study. Understanding this correlation between EEG metrics and cognitive decline can be an important stepping stone in the clinical use of EEG to diagnose neurological diseases, improving diagnosis accuracy, saving money and time, and reducing stress. Thus, further studies into this trend is invaluable to improving the quality of healthcare in the modern world.

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