

Exploring Brain Connectivity Patterns and Cognitive Resilience in Aging: A Study with the LEMON Dataset

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Abstract—Investigating how brain connectivity and cognitive resilience evolve throughout life in healthy individuals is crucial to understanding the underpinnings of cognitive aging. This study uses the Leipzig Mind-Brain-Body (LEMON) dataset to explore the evolution of brain connectivity and cognitive resilience, focusing on differences in connectivity metrics among young (20–30 years) and old adults (70–80 years) and their correlation with cognitive performance measured by the California Verbal Learning Test (CVLT). Despite observable declines in connectivity with age, the data suggest a maintained network stability, potentially aiding in cognitive preservation. However, the weak correlations between connectivity metrics and cognitive performance suggest that cognitive resilience in aging could involve mechanisms beyond traditional connectivity measures, underscoring the importance of further exploring the complex interactions between brain networks and cognitive functions in healthy aging.

I. INTRODUCTION

Aging is associated with numerous physiological, cognitive, and neural changes, often leading to declines in memory, attention, and executive function, along with structural and functional alterations in neural circuits and connectivity [1]. Understanding these changes is crucial for developing effective strategies to promote healthy aging and mitigate cognitive decline. One promising avenue of research involves cognitive resilience, which refers to the ability of an individual to maintain cognitive function despite age-related neural changes. Cognitive resilience plays a key role in supporting healthy aging, allowing individuals to maintain independence and quality of life.

Research has shown that brain connectivity—the interactions and communication between brain regions is fundamental to understanding the processes that support cognitive function and resilience [2]. Connectivity within specific frequency bands, such as alpha, beta, and gamma, provides insight into how efficiently different regions of the brain communicate, which is crucial for maintaining cognitive abilities. Declines in connectivity efficiency, especially in higher-frequency bands like beta and gamma, are often associated with impairments in cognitive functions. On the other hand, alpha band connectivity is suggested to be more stable with age, which makes it a particularly interesting target for understanding resilience[3][4].

Existing studies on age-related changes in brain connectivity have often reported decreased connectivity and efficiency in older adults[5]. This reduction suggests a diminished capacity of the aging brain to integrate information across widespread networks, impacting overall cognitive performance. However, much remains unknown about the specific changes in connectivity measures and how they relate to cognitive resilience, especially when comparing young and old adults[6].

This research effort is crucial because early identification of connectivity patterns associated with cognitive decline can enable targeted interventions to maintain cognitive health [7][8]. By understanding how connectivity changes across the lifespan, we can better determine who might be at risk for cognitive impairments and intervene early to slow or even prevent further decline [9]. Research indicates that interventions such as cognitive training, physical exercise, and lifestyle modifications can positively impact brain connectivity and cognitive function, particularly if implemented during early or middle stages of aging [10][11]. Additionally, findings from this study can contribute to enhancing current practices in healthcare settings by providing objective markers for cognitive resilience, helping clinicians design personalized treatment plans aimed at improving quality of life in older adults [12].

This study aims to address these gaps by analyzing brain connectivity and cognitive resilience across the lifespan using the LEMON dataset. Specifically, we examine changes in brain connectivity metrics, such as connection counts, connection strengths, and global efficiency, to determine their association with cognitive resilience, measured by the California Verbal Learning Test (CVLT)[13]. In this study, we focus on two distinct age groups: younger adults (20–30 years) and older adults (70–80 years), comprising 124 and 22 subjects, respectively. By using Phase Locking Value (PLV) and Coherence (COH) matrices to quantify connectivity, we explore how differences in connectivity are linked to cognitive resilience across age groups.

Our study distinguishes itself from existing research by combining multiple connectivity measures (PLV, COH, global efficiency) with a cognitive performance assessment (CVLT), providing a more comprehensive understanding of cognitive

resilience and aging[14]. Additionally, we focus on specific frequency bands (alpha, beta, and gamma) to discern how different aspects of connectivity may change with age and impact cognitive function[15].

Identifying differences in brain connectivity and cognitive resilience between age groups is essential for understanding the underlying mechanisms of aging and for designing strategies that promote healthy aging[16][17]. Our study aims to enhance the understanding of how aging affects cognitive resilience, providing insights that may inform clinical practices and public health initiatives aimed at improving brain health across the lifespan.

II. DATASET

We used data from the publicly available Leipzig Study for Mind-Body-Emotion Interactions (LEMON) dataset[13], which consists of comprehensive neuroimaging and behavioural data from 228 healthy participants. A 16-min rs-EEG was recorded with a BrainAmp MR plus amplifier in an electrically shielded and sound-attenuated EEG booth using 62-channel (61 scalp electrodes plus 1 electrode recording the VEOG below the right eye) active ActiCAP electrodes (both Brain Products GmbH, Gilching, Germany) attached according to the international standard 10–20 extended localization system, also known as 10-10 system, and referenced to FCz. The dataset includes a young group (N=154, 25.1±3.1 years, range 20–35 years, 45 female) and an elderly group (N=74, 67.6±4.7 years, range 59–77 years, 37 female) acquired cross-sectionally in Leipzig, Germany, between 2013 and 2015.

During two-days assessment, participants completed a series of MRI scans at 3 Tesla and a 62-channel EEG experiment at rest. The resting-state EEG data was collected in two conditions: Eyes Open and Eyes Closed. Additionally, participants completed various cognitive tests, including the CVLT.

We did not use all the data from all the subjects in the LEMON dataset for this study. We selected only young participants aged between 20-30 years, totaling 124 subjects, and old participants aged between 70-80 years, totaling 22 subjects.

III. METHODS

To analyze EEG signals, we employed PLV and COH matrices as alternatives to raw EEG data. These methodologies are favored due to their robustness against noise and their capability to reveal meaningful functional connectivity between brain regions. PLV quantifies phase synchrony, which assesses the consistency of phase relationships across trials, thereby illuminating synchronous neural activities. On the other hand, coherence measures the linear relationships between signals in the frequency domain, providing insights into the strength and stability of frequency specific interactions. Both methods are well-established in the study of brain network interactions and offer a biologically relevant, simplified representation of complex neural dynamics[1][18]. This representation facilitates the use of network analysis techniques, including connection count, connection strength, global efficiency, and resilience

measures[19], which are crucial for understanding the efficiency and adaptability of the brain’s functional network. By utilizing PLV and coherence, our analysis robustly focuses on dynamic interactions between brain regions, yielding more robust and interpretable results[20][21].

A. Preprocessing

The data were band-pass filtered to isolate alpha (8-13 Hz), beta (13-30 Hz), and gamma (30-100 Hz) frequency bands for both the Eyes Closed, Eyes Open datasets. Phase Locking Value (PLV) and Coherence (COH) matrices were computed for each frequency band to quantify connectivity between brain regions. Cognitive resilience was assessed using the CVLT. Factor analysis was performed on CVLT scores to identify underlying cognitive factors, with the optimal number of factors determined using a scree plot, which resulted in 4 factors.

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Connectivity patterns are essential for understanding brain activity, as they significantly affect regional activation during tasks. Connectivity is vital for shaping dynamic brain activity[20]. To explore these dynamic connectivity patterns, we employed PLV and COH methods, enabling a detailed analysis of temporal dynamics of brain function.

B. PLV Computation

The PLV is a measure of the phase synchrony between pairs of EEG signals, indicating the consistency of phase differences across trials [21]. Previous studies on age-related changes studied changes in phase synchrony using PLV [22]. The PLV for each electrode pair was computed as Eq 1:

$$PLV = \left| \frac{1}{N} \sum_{t=1}^N e^{i\Delta\phi(t)} \right| \quad (\text{Eq 1})$$

where N is the number of time points, j the imaginary unit, and $\Delta\phi_{ij}(t)$ is the phase between pairs of electrodes i and j calculated for each time point t . The PLV ranges from 0 to 1, with 1 indicating perfect phase synchrony and 0 indicating no synchrony.

C. COH Computation

COH is a measure of the linear relationship between the frequencies of two EEG signals, reflecting both amplitude and phase consistency. Similarly, previous studies have shown the utility of COH matrix in analysing age-related changes

Data Name	Optimal Threshold	AUC Score	t-test	p-val	Avg. Retain	Stat. Relevance
EC_alpha	0.4	0.71	3.32	0.00114	93%	True
EC_beta	0.9	0.63	1.49	0.13788	37%	False
EC_gamma	0.9	0.77	4.08	0.00007	29%	True
EO_alpha	0.4	0.73	3.70	0.00030	90%	True
EO_beta	0.9	0.74	2.83	0.00537	38%	True
EO_gamma	0.8	0.82	4.50	0.00001	41%	True

Table I: Optimal threshold values for each dataset, along with associated AUC scores, t-test, p-val, and average connection retention percentages. The table also indicates whether the results are statistically significant. The term 'EC' refers to the Eyes Closed condition, while 'EO' denotes the Eyes Open condition.

[23]. COH $C_{xy}(f)$ for each electrode pair and frequency was computed as Eq 2:

$$C_{xy}(f) = \frac{|S_{xy}(f)|^2}{S_{xx}(f)S_{yy}(f)} \quad (\text{Eq 2})$$

Where $S_{xy}(f)$, $S_{xx}(f)$ and $S_{yy}(f)$ are cross and power spectral densities respectively. COH values range from 0 to 1, with higher values indicating stronger linear relationships between the signals at a particular frequency.

For each frequency band, COH matrices were constructed. Each $n \times n$ matrix represents the COH between all pairs of n electrodes, where each element $C_{ij}(f)$ denotes the COH value between electrode i and j at a specific frequency.

For both PLV and COH Matrix, matrices were constructed for both Resting State Eyes Open and Resting State Eyes Closed conditions across all frequency bands.

D. Connection Counts and Connection Strengths

To quantify the connectivity patterns within brain networks, we computed two primary metrics: connection counts and connection strengths[24].

Connection counts indicate the number of connections between electrodes (nodes) and were obtained by summing the binary adjacency matrix for each electrode, reflecting the total number of significant connections[25].

Connection strengths represent the cumulative value of connections between electrodes, calculated by summing the original (non-binarized) connectivity matrix for each electrode, providing an overall measure of connection strength[26].

E. Global Efficiency

Global efficiency measures how efficiently information is exchanged across the entire network. Higher global efficiency indicates better integration of information across distant brain regions. The global efficiency E_{glob} for each subject's brain network was calculated using the following Eq 3:

$$E_{glob} = \frac{1}{N(N-1)} \sum_{i \neq j \in V} \frac{1}{d_{ij}} \quad (\text{Eq 3})$$

where N is the number of nodes (electrodes) and d_{ij} is the shortest length between nodes i and j .

F. Network Resilience Analysis

Robustness to Node Removal: Random or targeted removal of nodes (electrodes) was simulated to evaluate the network's ability to maintain connectivity. Metrics such as giant component size, network diameter, and clustering coefficient were monitored to assess changes in network structure[27].

Resilience to Edge Removal: Similarly, edges (connections between electrodes) were selectively removed to analyze the impact on network connectivity. Measures like modularity and assortative were examined to understand network stability.

IV. ANALYSIS RESULTS

We compared data from two groups:

- Young group: 124 participants (aged 20-30 years)
- Old group: 22 participants (aged 70-80 years)

Our goal was to analyze the differences between these age groups using various methods mentioned above to gain insights into cognitive abilities and brain network characteristics associated with aging.

A. Connection Counts and Connection Strengths

To calculate connection counts and strengths, determining the optimal threshold is essential. The Receiver operating characteristic (ROC) and Area Under the Curve (AUC) method was chosen for its comprehensive assessment of threshold performance across all possible thresholds, combining threshold agnosticism with statistical rigor for optimal selection. The optimal threshold was identified based on the maximum AUC score, representing the point where connectivity metrics effectively differentiated between young and old subjects. An independent t-test was conducted to compare connection counts between the age groups at the optimal threshold, assessing the statistical significance of the differences. Additionally, the average retain percent at this threshold was calculated to provide further insights into brain network connectivity, as shown in Table I. The analysis revealed that the average connection count and strength were consistently higher in young subjects than in old subjects across all frequency bands and both Eyes Open and Eyes Closed conditions, as shown in Table II and Table III.

B. Global Efficiency

Global efficiency, which measures how efficiently information is exchanged across the brain network, was computed for each subject. An independent t-test assessed the statistical

Metric	Age Group	No. Sub	EC alpha (thres=0.4)	EC beta (thres=0.9)	EC gamma (thres=0.9)	EO alpha (thres=0.4)	EO beta (thres=0.9)	EO gamma (thres=0.8)
PLV	20-30	124	1720.51	713.48	563.59	1680.4	734.71	819.04
	70-80	22	1649.27	661.04	446.0	1588.82	636.0	632.18

Metric	Age Group	No. Sub	EC alpha (thres=0.5)	EC beta (thres=0.5)	EC gamma (thres=0.6)	EO alpha (thres=0.1)	EO beta (thres=0.6)	EO gamma (thres=0.5)
COH	20-30	124	944.23	937.46	529.99	1826.2	708.85	722.48
	70-80	22	878.18	869.68	426.64	1812.5	618.4	557.27

Table II: This table described average connection retention count in PLV and COH matrices for each dataset at their optimal thresholds, comparing young and old subjects. The term 'EC' refers to the Eyes Closed condition, while 'EO' denotes the Eyes Open condition.

Metric	Age Group	No. Sub	EC alpha (thres=0.4)	EC beta (thres=0.9)	EC gamma (thres=0.9)	EO alpha (thres=0.4)	EO beta (thres=0.9)	EO gamma (thres=0.8)
PLV	20-30	124	1361.5	684.00	540.35	1347.51	705.91	759.65
	70-80	22	1296.99	635.75	427.77	1257.43	611.46	585.56

Metric	Age Group	No. Sub	EC alpha (thres=0.5)	EC beta (thres=0.5)	EC gamma (thres=0.6)	EO alpha (thres=0.1)	EO beta (thres=0.6)	EO gamma (thres=0.5)
PLV	20-30	124	688.91	672.41	405.53	960.32	549.52	514.26
	70-80	22	637.76	629.45	326.8	883.93	481.43	397.30

Table III: This table presents the average connection strength for Phase Locking Value (PLV) and Coherence (COH) matrices for each dataset at their optimal thresholds, comparing young and older subjects. The term 'EC' refers to the Eyes Closed condition, while 'EO' denotes the Eyes Open condition.

significance of differences between age groups. Significant differences in global efficiency were observed between young and old participants in the beta and gamma frequency bands, while differences in the alpha band were insignificant, shown as in Table IV. Correlation analysis between global efficiency and CVLT scores showed no significant relationship, indicating that global efficiency does not strongly correlate with cognitive ability in the participants.

		alpha		beta		gamma	
		t-test	p-val	t-test	p-val	t-test	p-val
Global Efficiency	PLV	1.64	0.10	3.16	0.002	2.53	0.012
	COH	1.85	0.07	2.63	0.009	2.37	0.018
Resilience Measures	PLV	-0.85	0.40	-0.91	0.37	-1.024	0.31
	COH	-0.75	0.45	-0.44	0.66	-1.85	0.065

Table IV: Global Efficiency and Resilience measure comparison scores between old and young subjects with t-test and p-val.

C. Resilience Measures

Resilience measures were calculated to evaluate the robustness and stability of brain networks in young and old subjects. These measures provide insights into the brain's ability to maintain functionality despite potential disruptions. Our findings suggest that overall network resilience, in terms of cognitive abilities and network integrity, did not significantly decline with age in our sample as shown in Table IV. Correlation analysis between resilience measures and CVLT scores revealed no significant relationship, indicating that network resilience may not strongly correlate with cognitive ability in the participants.

V. DISCUSSION

The connection count and connection strength analysis revealed that the differences between young and old participants

are not very significant. The constraint of our study, which involved a notably larger sample size of young participants (124 subjects) compared to old participants (22 subjects).

There was a significant statistically relevant difference in global efficiency between young and old participants only in the beta and gamma bands, whereas no statistically relevant difference was observed in the resilience measures. Previous studies have shown that global efficiency tends to decrease with age, although the extent and specific regions affected can vary. This decline indicates a reduced ability of the aging brain to integrate information across widespread networks, impacting overall cognitive performance[18].

Moreover, the decline in local efficiency is associated with impairments in cognitive functions, particularly those that rely on localized processing[28]. Some studies suggest that alpha band connectivity and power might not exhibit as pronounced age-related declines as beta and gamma bands. This empirical evidence supports the idea that alpha rhythms are more stable with age.

VI. CONCLUSION

This research systematically explored changes in brain connectivity and cognitive resilience with aging using the LEMON dataset. Our findings indicate minor declines in connectivity with age. However, the overall structural integrity and functionality of brain networks remain stable, demonstrating an intrinsic resilience that supports cognitive function in healthy old adults. Advancing knowledge of the aging brain empowers individuals to take proactive steps to protect their cognitive well-being, including adopting lifestyle changes and participating in targeted training programs[29][30].

Despite reductions in connectivity metrics, correlations between these metrics and cognitive performance, as assessed by

the CVLT, were weak. This suggests that cognitive resilience in the elderly may not be directly linked to conventional connectivity measures, potentially indicating other underlying factors or compensatory mechanisms that aid cognitive maintenance during aging. This highlights the complexity of brain connectivity and its relationship with cognitive function, which may not be fully captured by direct neural interconnections.

Our results enhance the understanding of healthy aging by emphasizing the need for further research into the interactions between brain networks and cognitive function. Future studies should integrate diverse metrics of brain function and cognitive performance to elucidate these relationships. Such efforts are essential for advancing our understanding of aging and developing targeted interventions to enhance cognitive resilience in the elderly.

This study underscores the significance of using EEG data and cognitive testing to explore brain-behavior relationships, supporting the development of strategies for healthy cognitive aging. As we continue to unravel these complex dynamics, the insights gained will enrich our understanding of the aging brain and improve the cognitive health and quality of life of old adults.

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