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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 across the lifespan in healthy individuals is crucial for 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 across the lifespan, focusing on changes in connectivity metrics among younger (20-30 years) and older 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 might 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 involves various physiological, cognitive, and neural changes. As individuals age, memory, attention, and executive function tend to decline, alongside structural and functional brain changes affecting neural circuits and connectivity [1] [2]. Understanding these changes is essential for developing strategies to promote healthy aging and mitigate cognitive decline.

Understanding these changes is crucial for promoting healthy aging. Cognitive aging involves gradual changes in brain function and structure. Understanding cognitive resilience the ability to maintain cognitive function despite age-related changes is key to promoting healthy aging. Research on brain connectivity, interactions between brain regions, underpins cognitive processes [3] [4].

Cognitive decline affects quality of life, daily functioning, and increases the risk of diseases like Alzheimer's. Conversely, cognitive resilience helps maintain cognitive functions despite aging, crucial for successful aging. Studying neural mechanisms of decline and resilience can identify factors and interventions for healthy cognitive aging. This study examines changes in brain connectivity and cognitive resilience across the lifespan. Using the LEMON dataset, we analyze brain connectivity and cognitive performance in young and older adults. We aim to determine age-related connectivity changes and their link to cognitive resilience measured by the CVLT [5].

A key challenge is identifying reliable indicators to differentiate between typical aging and pathological conditions. Studies show brain network connectivity and efficiency are crucial for cognitive performance, with decreased within-network and increased between-network connectivity [7]. Advanced imaging and open-source datasets enable exploration of brain connectivity metrics like connection counts, strengths, global efficiency, and resilience [8], [9].

This research is motivated by the need to detect cognitive decline early for timely interventions. Open-source datasets allow comprehensive analyses of cognitive differences between younger (20-30) and older (70-80) populations. Leveraging existing data, we can examine factors affecting cognitive performance and resilience, leading to targeted training programs and lifestyle changes his study aims to clarify brain connectivity and cognitive ability differences between age groups, contributing to healthy aging research. Identifying these differences enhances understanding of aging and supports future research on improving cognitive resilience in older adults. We aim to offer insights to inform clinical practices and public health initiatives promoting brain health across the lifespan. Advancing knowledge of the aging brain empowers individuals to protect their cognitive well-being.

II. Dataset

We utilized data from the publicly available LEMON (Leipzig Study for Mind-Body-Emotion Interactions) dataset, which consists of comprehensive neuroimaging and behavioural data from 228 healthy participants. 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 [6].

During a two-day 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 (RS-EO) and Eyes Closed (RS-EC). Additionally, participants completed various cognitive tests, including the California Verbal Learning Test (CVLT).

A. *Preprocessing*

EEG data were recorded using a 62-channel system with participants at rest. The data were bandpass filtered to isolate alpha (8-13 Hz), beta (13-30 Hz), and gamma (30-100 Hz) frequency bands for both the Eyes Closed (EC), Eyes Open (EO) datasets. Phase Locking Value (PLV) and Coherence matrices were computed for each frequency band to quantify connectivity between brain regions. Cognitive resilience was assessed using the California Verbal Learning Test (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.

III. Methods

To analyze EEG signals, we employed Phase Locking Value (PLV) and coherence 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 [11], [12]. This representation facilitates the use of network analysis techniques, including connection count, connection strength, global efficiency, and resilience measures [13], 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. [14], [15].

Connectivity patterns are essential for understanding brain activity, as they significantly affect regional activation during tasks. Connectivity is vital for shaping dynamic brain activity [14].

To explore these dynamic connectivity patterns, we employed Phase Locking Value (PLV) and coherence methods, enabling a detailed analysis of e temporal dynamics of brain function.

A. *Phase Locking Value*[15]

The Phase Locking Value (PLV) is a measure of the phase synchrony between pairs of EEG signals, indicating the consistency of phase differences across trials. Previous studies on age-related changes studied changes in phase synchrony using PLV [16]. The PLV for each electrode pair was computed as:

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

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.

B. Coherence Computation [17]

Coherence 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 coherence matrix in analysing age-related changes.[17] Coherence $C_{xy}(f)$ for each electrode pair and frequency was computed as:

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

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

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

For both PLV and Coherence Matrix, matrices were constructed for both Resting State Eyes Open (EO) and Resting State Eyes Closed (EC) conditions across all frequency bands.

C. Connection Counts and Connection Strengths

To quantify the connectivity patterns within the brain networks, we computed two primary metrics: connection counts and connection strengths [18].

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 [19].

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 [20].

D. Global Efficiency [21]

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 formula:

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

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

E. 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 [22].

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:

- Younger group: 124 participants (aged 20-30 years)
- Older 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.

Data Name	Optimal Threshold	AUC Score	T-stat	P-Value	Avg. Retain	Stat. Releveance
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 1: Optimal Threshold for PLV

A. Connection Counts and Connection Strengths

To calculate connection counts and strengths, determining the optimal threshold is essential. The ROC 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 (Area Under the Curve) 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 percentage at this threshold was calculated to provide further insights into brain network connectivity (Table 1). The analysis revealed that the average connection count and strength were consistently higher in younger subjects than in older subjects across all frequency bands and both Eyes Open (EO) and Eyes Closed (EC) conditions (Tables 2 & 3).

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 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 (Table 4). Correlation analysis between global efficiency and California Verbal Learning Test (CVLT) scores showed no significant relationship, indicating that global efficiency does not strongly correlate with cognitive ability in the participants.

	Age	**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
	Age	**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 2: Average Connection Count

	Age	**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
	Age	**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	**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 3: Average Connection Strength

		alpha		beta		gamma	
		t-test	p-val	t-test	p-val	t-test	p-val
Global Efficiency	PLV	1.64	0.1	**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	0.4	-0.91	0.37	-1.024	0.31
	COH	-0.75	0.45	-0.44	0.66	-1.85	0.065

Table 4: Global Efficiencies

C. Resilience Measures

Resilience measures were calculated to evaluate the robustness and stability of brain networks in younger and older 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 (Table 5). Correlation analysis between resilience measures and California Verbal Learning Test (CVLT) scores revealed no significant relationship, indicating that network resilience may not strongly correlate with cognitive ability in the participants.

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V. Inferences

The connection count and connection strength analysis revealed that the difference between younger and older participants are not very significant. There was a significant statistically relevant difference in the global efficiency between young and old participants only in the beta and gamma bands, whereas no statistically relevant difference in the resilience measures. Studies have shown that global efficiency also decreases 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 [11]. The decline in local efficiency is associated with impairments in cognitive functions, particularly those that rely on localized processing [24]. Some studies suggest that alpha band connectivity and power might not show as pronounced age-related declines as beta and gamma bands. This empirical evidence supports the idea that alpha rhythms are more stable with age [25].

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 older adults.

Despite reductions in connectivity metrics, correlations between these metrics and cognitive performance, as assessed by the California Verbal Learning Test (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 older adults.

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