Graph Theoretical Properties of the Brain's Structural Network

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Introduction

Understanding the intricate structure of the human brain and its dynamic changes across the lifespan is a fundamental aspect of neuroscience. Recent advances in neuroimaging and graph theory have provided unique insights into how the brain's structural network is organized and functions at different stages of life. Graph-theoretical analysis, in particular, has emerged as a powerful tool to describe and quantify the topological characteristics of brain networks, shedding light on the underlying principles of brain organization, development, and deterioration due to aging or disease.

The structural connectivity of the brain, representing the physical or anatomical pathways between different regions, can be effectively modeled using graph theory. This approach considers brain regions as nodes and the connections between them as edges, allowing for the application of various metrics such as degree distribution, clustering coefficients, and centrality measures. These metrics serve to illustrate the efficiency and resilience of the brain network, providing correlations with cognitive functions and potential implications for neurological and psychiatric conditions.

This study focuses on exploring the evolution of graph-theoretical properties in the brain's structural network across different age groups. We hypothesize that significant changes in these properties occur due to neuroplastic processes such as synaptic pruning in youth and potential neurodegenerative patterns in older age. By analyzing connectivity matrices for 88 individuals aged 18 to 48, we aim to capture a snapshot of how these networks vary with age and potentially correlate these variations with cognitive and functional implications.

Background

Human brain imaging, especially using magnetic resonance imaging (MRI), has transformed our understanding of the brain (Ogawa et al. 1990). Currently, the application of network science is revolutionizing brain imaging by providing new perspectives on brain organization and insights into complex brain functions (Bullmore and Sporns 2009; Simpson, Bahrami, and Laurienti 2019). Structural brain network analysis has become a prominent sub-field of structural connectivity analysis, where structural associations between brain regions are quantified to create a brain network represented by an $n \times n$ connection matrix. In this context, graph theory has emerged as a powerful framework for analyzing the intricate architecture of the brain's structural networks. By representing the brain as a network, where nodes correspond to distinct anatomical regions and edges denote the white matter tracts connecting them, we can observe the complex interplay underlying brain function and structure. This application of graph theoretical principles in neuroscience allows for the quantification and visualization of brain connectivity patterns. This approach provides a means to explore how different brain regions interact, how information flows through the network, and how the overall structure supports cognitive functions and behaviors (Bullmore and Sporns 2009; Reijneveld et al. 2007).

Recent research has discovered that Brain networks exhibit distinct topological features that align with small-world (He, Chen, and Evans 2007) and scale-free network models (Eguíluz et al. 2005). Small-world networks are characterized by a high clustering coefficient and short path lengths, facilitating efficient information transfer with minimal wiring costs. This configuration supports both local specialization and global integration, which are crucial for cognitive functions. Scale-free networks, on the other hand, feature a few highly connected hub nodes that play a pivotal role in maintaining network robustness and facilitating widespread communication. These properties have been consistently observed in both functional and structural brain networks, underscoring their significance in maintaining neural efficiency and resilience (Reijneveld et al. 2007). The small-world architecture of the brain ensures that any two regions can be connected through a relatively short path, which is essential for rapid information processing. At the same time, the presence of highly connected hubs in scale-free networks provides robustness against random failures, as the network's overall connectivity is preserved even if some connections are lost. These topological features are believed to be fundamental to the brain's ability to adapt to new situations and recover from injuries (Reijneveld et al. 2007).

The topology of brain networks is intricately linked to their functional capabilities and vulnerabilities. In healthy brains, the optimal small-world configuration supports efficient information processing and cognitive flexibility. However, deviations from this optimal structure are often associated with neurological disorders. For instance, conditions like Alzheimer's disease, schizophrenia, and epilepsy have been shown to disrupt normal connectivity patterns, leading to impaired cognitive functions and increased susceptibility to pathological activities (Stam et al. 2006; Breakspear et al. 2003; Percha et al. 2005; Reijneveld et al. 2007). Graph-theoretical analyses thus offer valuable biomarkers for diagnosing and understanding the progression of these diseases. In Alzheimer's disease, the loss of connectivity between key regions, particularly hubs, correlates with cognitive decline and memory impairments. Schizophrenia is associated with altered connectivity patterns that affect the integration of information across the brain, leading to symptoms such as hallucinations and delusions. Epilepsy involves abnormal connectivity that predisposes the brain to seizures. By examining these deviations from normal network topology, we can gain insights into the underlying mechanisms of these disorders and develop more effective interventions.

The substantial body of research on brain structural networks highlights the immense potential of integrating graph theory with neuroimaging data to enhance our understanding of the brain's structural and functional organization. By utilizing publicly available datasets, we aim to investigate the evolution of graph-theoretical properties in the brain's structural network across various age groups and determine if significant changes are observable.

Data

Studying the human brain with magnetic resonance imaging (MRI) has become a cornerstone of modern neuroscience. MRI offers several tools to estimate interactions between brain regions. For instance, using functional MRI (fMRI), researchers can analyze brain activity time series to estimate functional connectivity, which refers to the statistical dependence between distant regions' activities. They can also attempt to estimate effective connectivity, which measures the direct influence one brain region has on another. In this context, structural connectivity can help us identifying the physical connections that carry information between neural populations, usually represented by white matter tracts linking predefined gray matter regions.

Structural connectivity is typically derived from diffusion-weighted MRI data (DW-MRI or DWI). This method involves acquiring multiple images of each volume element (voxel), each sensitive to diffusion along a specific spatial axis. This information is then spatially connected to simulate white matter tracts throughout the brain. The resulting tractogram offers a detailed visualization of the brain's structural connections and provides quantitative data on the presence and extent of these connections between specific gray matter regions, forming a structural connectivity matrix.

The data used in our research has been provided by the work of Škoch et al. 2022 and it is a comprehensive dataset of human brain structural connectivity matrices derived from diffusion-weighted imaging (DWI). These matrices represent the connectivity between 90 cortical regions of interest (ROIs) as defined by the Automatic Anatomical Labeling atlas. The dataset includes structural connectivity matrices of 88 healthy control individuals, who participated in the Early-Stage Schizophrenia Outcome study. The participants, comprising 48 females and 40 males with a mean age of 27.7 years, were screened to exclude any psychiatric disorders, neurological disorders, or contraindications for MRI scanning.

The data processing pipeline involved several steps to ensure quality and accuracy [Figure 1]. Initially, the DWI data underwent visual inspection to check for artifacts, and volumes with excessive image artifacts were excluded. Preprocessing of the DWI data included movement and eddy-current distortion correction using affine registration, skull stripping, and Bayesian estimation of diffusion parameters. The T1 images were also skull-stripped and registered to the MNI space using affine registration, followed by rigid-body registration between the T1 and DWI images. This two-stage process ensured accurate mapping of anatomical regions to the diffusion data space. Probabilistic tractography was performed using the voxel-wise diffusion parameters estimated by the PROBTRACKX tool. The tractography generated streamlines that represented white matter tracts connecting different brain regions. These streamlines were then used to construct the structural connectivity matrices. Each element in the matrix represents the proportion of tractography streamlines originating in one region and entering another. The connectivity matrices were normalized by the number of voxels in the seed region and the number of streamlines per voxel, resulting in a "connectivity probability" matrix. The final dataset includes the connectivity matrices, the underlying raw diffusion and structural data, as well as basic demographic information about the subjects.

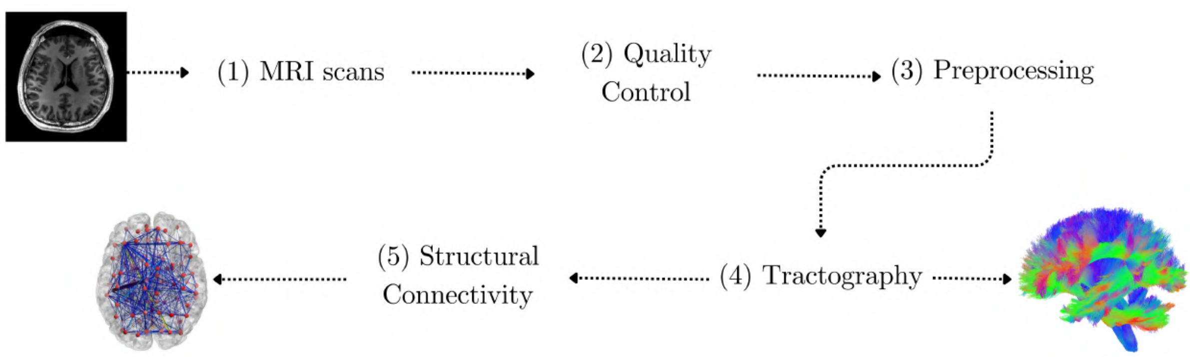


Figure 1: Data generating process (Images by Benou and Riklin Raviv 2019; Zhang et al. 2019)

Network Analysis

Given the extensive dataset available for our study, comprising 88 matrices, we will proceed through several methodical steps. Initially, we will analyze the structural connectivity of a single individual to establish a baseline understanding of a single brain network's structure. Subsequently, we will examine three individuals, each representing a different age group, to assess potential age-related differences. Finally, we will categorize the individuals into three age groups: Group 1 (ages 18-25), Group 2 (ages 25-35), and Group 3 (ages 35-45). We will average the structural connectivity matrices within each group and analyze the resulting average networks to identify any structural evolution across these age groups. The analysis will primarily utilize visual representations and key graph-theoretical metrics, such as node and edge centralities.

Analysis on a single network

For the initial part of our analysis, we will focus on a single structural connectivity matrix from a 19-year-old subject. A preliminary understanding of the brain's structural network can be gained by examining the graphical representations and heatmaps presented in Figures 2 and 3.

Figure 2 presents three structural connectivity matrices heatmaps visualizations: (a) includes all possible connections as defined by the structural connectivity matrix, (b) employs network backboning to simplify the structure, and (c) refines the connections by including only those above the threshold of 0.01. The Original Adjacency Matrix presents a densely connected network with a wide range of connection strengths, underscoring the inherent complexity of the brain's structural connectivity. The Network Thresholding Adjacency Matrix, with a threshold of 0.01, significantly reduces the number of connections, emphasizing only the strongest links, which are more concentrated within specific regions, often within the same hemisphere. The thresholded matrix, in particular, suggests a prevalence of strong intra-hemispheric connections, which may have functional implications for neural processing and integration. Unfortuately, the Network Backboning Adjacency Matrix fails to retain edges with the highest connection proportions and it will not be considered for further analysis.

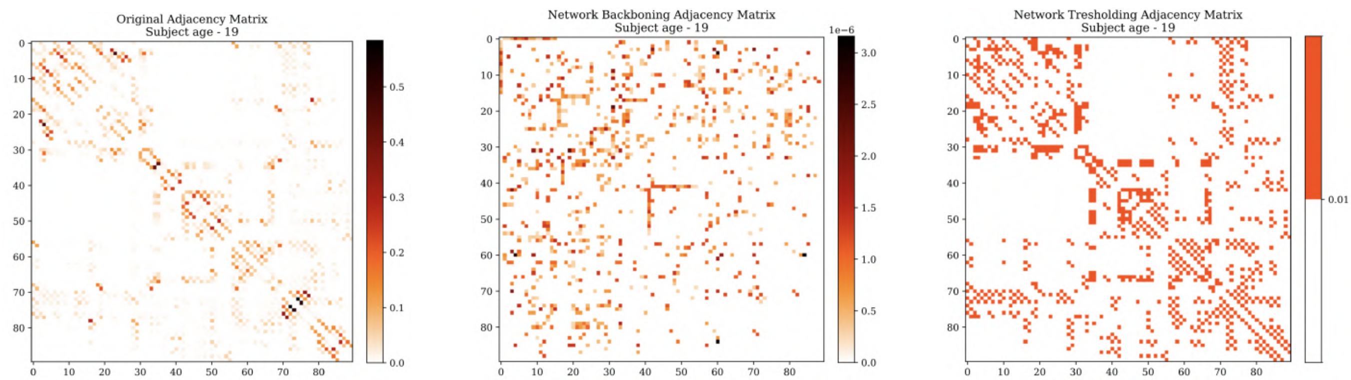
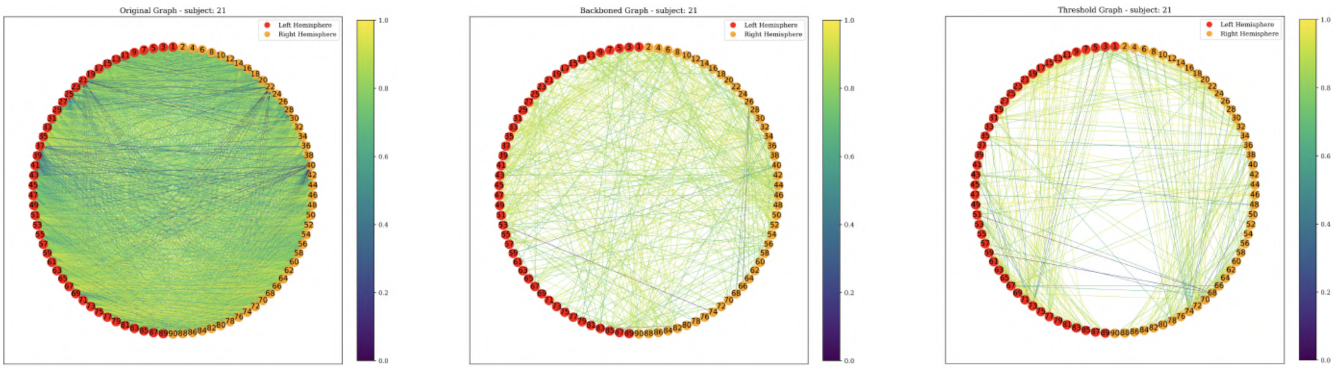


Figure 2: Brain structural network - Adjacency Matrix

Figure 3 presents three visualizations: (a) includes all possible connections as defined by the structural connectivity matrix, (b) employs network backboning to simplify the structure, and (c) refines the connections by including only those above the threshold of 0.01. Nodes are positioned to separate the left and right hemispheres, and edges are colored based on their betweenness. From the first graph (a), it is evident that the brain network is highly complex, with a large edge betweenness and near-complete connectivity. The thresholded representation (c) reveals that most edges in the original network are removed, retaining primarily those that connect nodes within the same hemisphere. This suggests that the brain network is characterized by a few strong intra-hemispheric connections and a larger number of weaker inter-hemispheric connections, highlighting a potential organizational principle of neural connectivity prioritization within the brain.



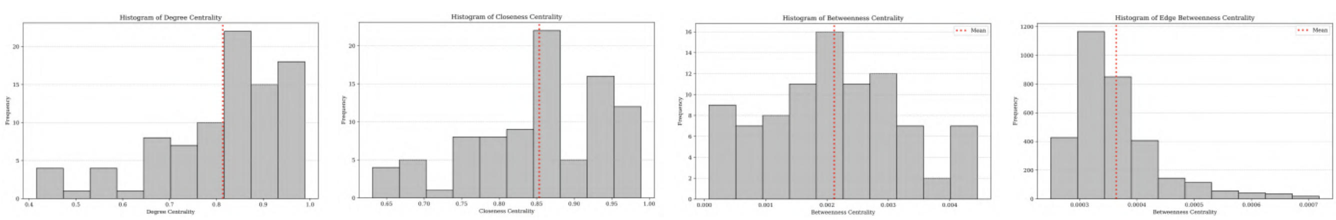
(a) Full Network (b) Backboning (c) Threshold

Figure 3: Brain structural network - Graphical Representation

Centrality Measures

This section of the analysis will focus on key node centrality measures to understand the relative structure and role distribution of nodes within the network. We will compute Degree, Closeness, and Betweenness Centrality, and identify the top five nodes according to these measures.

The distributions of these centrality measures are presented in Figure 4, while the top nodes are listed in Table 1.



(a) Degree (b) Closeness (c) Betweenness (d) Edge Betweenness

Figure 4: Distribution of Degree, Closeness and Betweenness Centrality

The histogram in figure 4(a) illustrates the distribution of degree centrality values among the nodes in the brain network. The distribution of degree centrality values is skewed towards higher values. The degree centrality values range from approximately 0.4 to 1.0. The most frequent degree centrality values fall between 0.8 and 0.9, with fewer nodes exhibiting degree centrality values below 0.7. The skew towards higher degree centrality values suggests that many nodes in the network are highly connected, indicating a well-integrated network with multiple hubs. Nodes with high degree centrality are essential for maintaining network integrity and connectivity, likely playing significant roles in various brain functions by facilitating efficient communication between different brain regions.

The distribution of closeness centrality values among the nodes in the brain network [Figure 4(b)] range from approximately 0.65 to 1.0, with the most frequent values around 0.85 and several peaks indicating multiple groups of nodes with varying levels of centrality. The skew towards higher closeness centrality values suggests that many nodes are centrally located within the network, enabling them to quickly reach other nodes and thus contributing to efficient communication. The presence of many nodes with high closeness centrality, coupled with the very short average shortest path length of 1.18, indicates a highly efficient network where information can be transferred rapidly across the network.

The Node betweenness centrality values range from approximately 0.000 to 0.004, with the histogram showing a relatively even distribution and multiple peaks around 0.002 and 0.003 [Figure 4(c)]. Nodes with higher betweenness centrality values (around 0.004 to 0.004) play a significant role in facilitating communication between different parts of the network, acting as bridges or intermediaries to ensure efficient information transfer. The relatively even distribution of betweenness centrality values suggests a well-distributed network where multiple nodes contribute to maintaining efficient communication pathways, indicating robustness and resilience. This distribution indicates that the brain network does not rely excessively on a few key nodes, but rather has multiple nodes contributing significantly to connectivity and overall functionality.

The distribution of edge betweenness centrality [Figure 4(d)] is right-skewed, indicating that most edges have low betweenness centrality values, with a small number of edges exhibiting significantly higher values. The red dashed line denotes the mean betweenness centrality, with the majority of edges falling below this mean. This suggests that while most connections are not critical for the network's overall connectivity, a few edges play a pivotal role in integrating information across different brain regions. These high betweenness centrality edges are essential for maintaining the network's efficiency and robustness, making them key points for understanding the brain's structural and functional organization.

Top 5 Nodes

Nodes 36, 75, 76, 34, and 72 exhibit the highest degree, betweenness, and closeness centrality, underscoring their vital roles in maintaining the network's structural integrity and efficient information transfer [Table 1]. These nodes have numerous connections (high degree centrality), which allows them to interact with many other nodes, facilitating widespread communication and network cohesion. Their high betweenness centrality indicates that they frequently serve as intermediaries on the shortest paths between other nodes, making them critical for routing information efficiently across the network. Additionally, their elevated closeness centrality suggests that these nodes have shorter average path lengths to all other nodes, enabling them to quickly disseminate information throughout the network.

Node	Degree	Node	Closeness	Node	Betweenness
36	0.988	36	0.988	76	0.0045
75	0.988	75	0.988	36	0.0044
76	0.988	76	0.988	75	0.0043
34	0.977	34	0.978	34	0.0042
72	0.977	72	0.978	72	0.0041

Table 1: Top 5 Network nodes ranked by Degree, Closeness and Betweenness Centrality

Analysis of Networks of Three Individuals Across Different Age Groups

Next, we will extend our analysis by examining the structural networks of three randomly selected individuals of different ages. We will compare their network graphs, adjacency matrices, and centrality measures, including degree, closeness, and betweenness centrality.

The adjacency matrices for these individuals are presented in tow row of figure 5, and the corresponding binary matrices, using a threshold of 0.01, are shown the bottom row of the same figure. In the general connectivity heatmaps (top row), the 19-year-old's matrix is relatively sparse, with few regions of higher connectivity and some diagonal clusters indicating localized interactions. The 29-year-old's matrix displays more dispersed connections, suggesting widespread interactions across different brain regions, with less pronounced diagonal clusters indicating a more integrated network structure. The 45-year-old's matrix exhibits less sparse connectivity, with noticeable clusters of high connectivity, reflecting strong interactions within specific regions and a more organized network structure. In filtered connectivity heatmaps [Figure 5 (bottom row)], the 19-year-old's matrix highlights fewer but stronger interactions, with more distinct clusters indicating localized strong connectivity. The 29-year-old's matrix reveals pronounced connectivity in specific regions, showing more selective interactions and highlighting key areas of strong connectivity. The 45-year-old's filtered matrix shows distinct clusters of high connectivity, suggesting that brain networks become more specialized with age. Overall, as age increases, there appears to be a trend towards more organized and stronger connectivity within specific brain regions, providing insight into the structural changes in brain networks across different stages of adulthood.

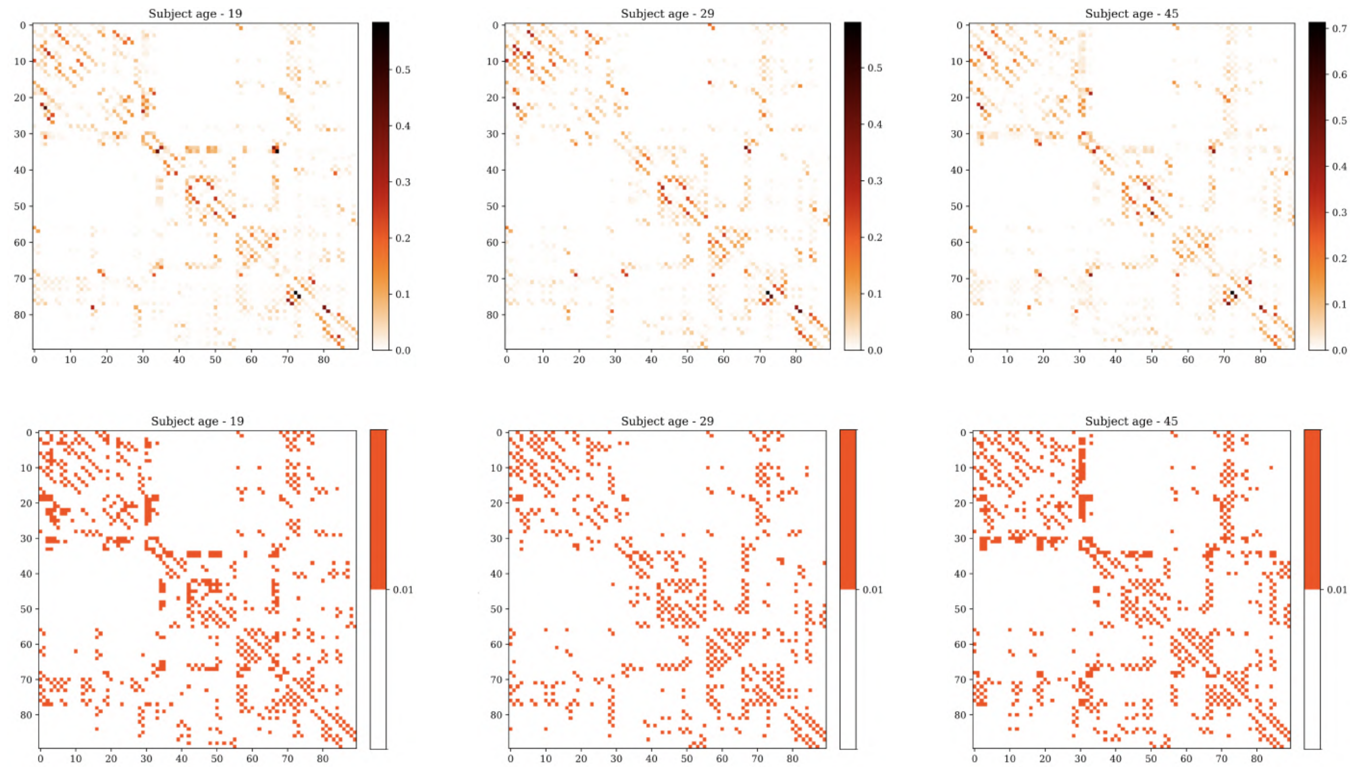


Figure 5: Adjacency Matrices of Individuals of different age groups.

Figure 6 presents structural connectivity graphs of brain networks for individuals aged 19, 29, and 45. The nodes, representing different brain regions, are colored to indicate hemispheric location (red for the left hemisphere and orange for the right hemisphere), while the edges represent connections with colors indicating edge betweenness. In the top row of figure 6, the graphs for all ages display high-density connections, with the 19-year-old showing a well-connected network with diverse edge betweenness values and balanced hemispheric distribution. The 29-year-old's network is more intricate, with more pronounced high-betweenness edges indicating critical pathways. The 45-year-old's graph, while less dense, shows a structured pattern reflecting possible age-related reorganization, with distinct high-betweenness edges highlighting key connections. In contrast, the bottom row of figure 6 emphasizes fewer, stronger connections, showing significant interactions within and between hemispheres. The 19-year-old's graph maintains robust connectivity, the 29-year-old's graph shows strong, selective connections, and the 45-year-old's graph highlights fewer but crucial pathways, suggesting increased reliance on key connections with age. Overall, these graphs illustrate a trend towards fewer but more specialized connections and the prominence of high-betweenness edges in older subjects, reflecting the evolution of brain connectivity and the emergence of key pathways that support brain function across different ages.

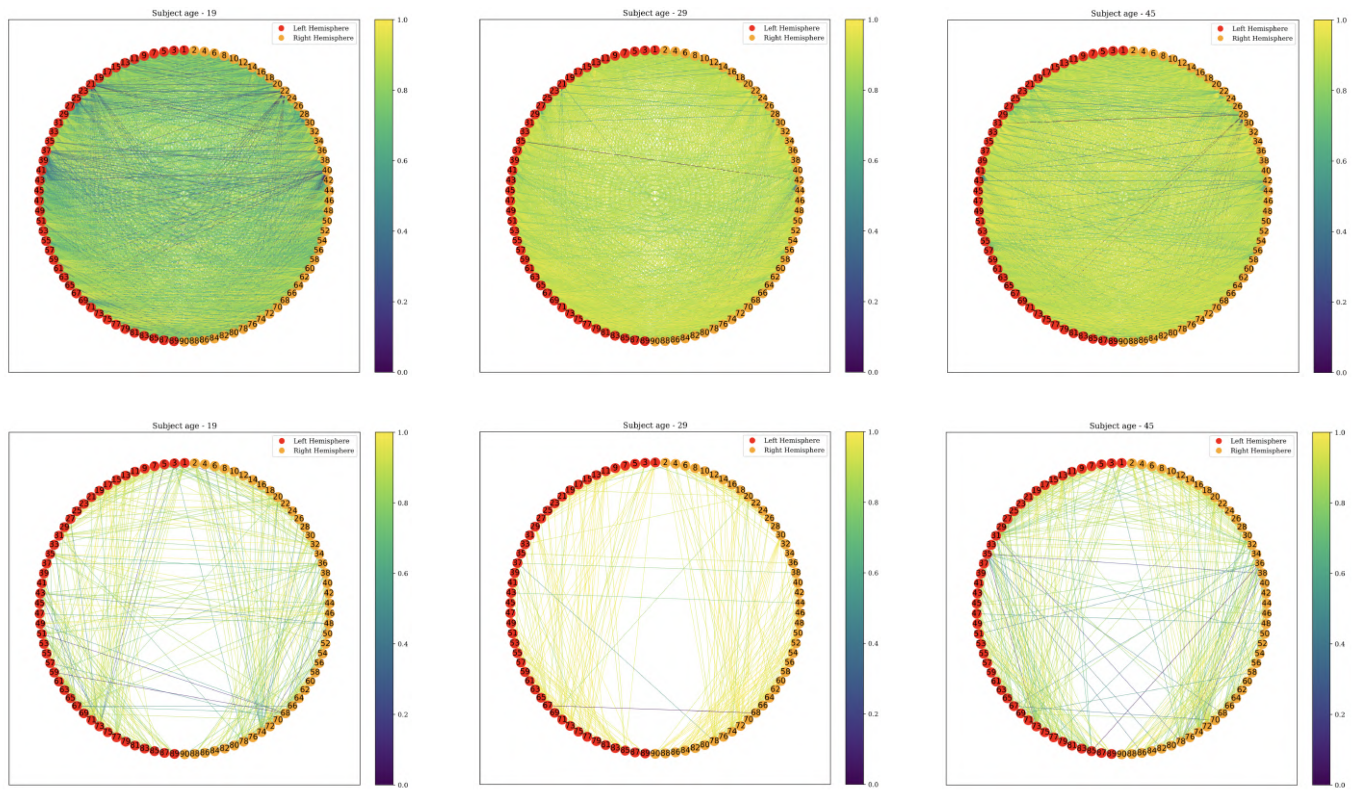


Figure 6: Structural Connectivity Network of Individuals belonging to different age groups

Centrality Measures

The histograms present the distribution of centrality measures (degree, closeness, and betweenness centrality) for individuals aged 19, 29, and 45, with the mean values indicated by red dashed lines.

The degree centrality histograms [Figure 7] show that the 19-year-old's distribution is symmetrical around the mean, indicating balanced connectivity, whereas the 29-year-old has a higher peak, suggesting more densely connected nodes, and the 45-year-old exhibits a broader, more heterogeneous distribution.

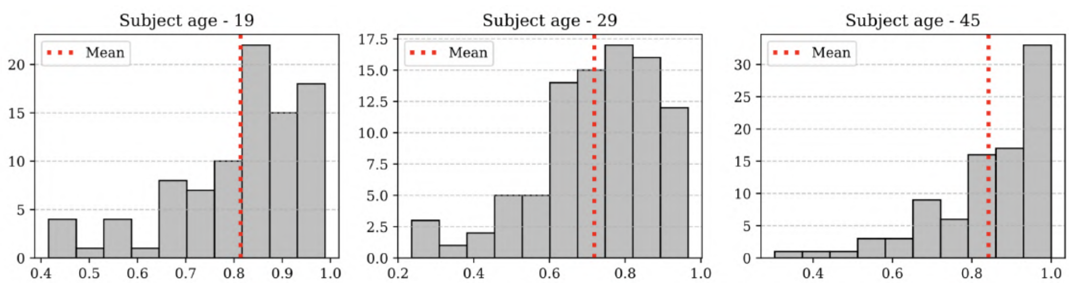


Figure 7: Distribution of Degree Centrality of Individuals belonging to different age groups

The closeness centrality histograms [Figure 8] reveal a peak around the mean for the 19-year-old, indicating similar centrality for most nodes, a slight upward shift for the 29-year-old, and a broader range with higher values for the 45-year-old, reflecting a few highly central nodes.

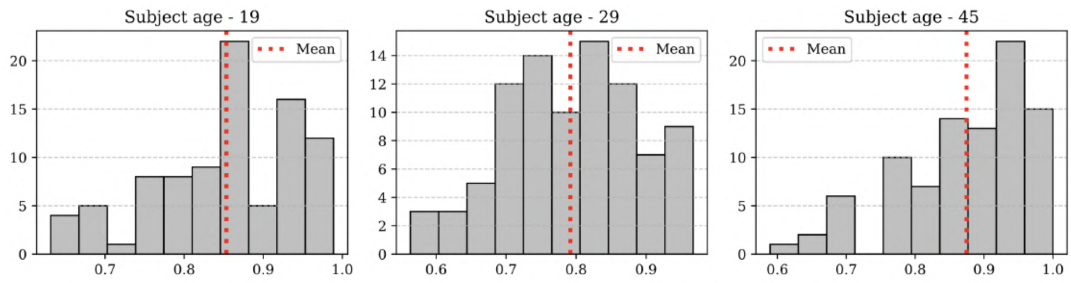


Figure 8: Distribution of Closeness Centrality of Individuals belonging to different age groups

The betweenness centrality histograms [Figure 9] indicate lower values concentrated around the mean for the 19-year-old, higher peaks for the 29-year-old, highlighting critical network connectors, and a skewed distribution for the 45-year-old.

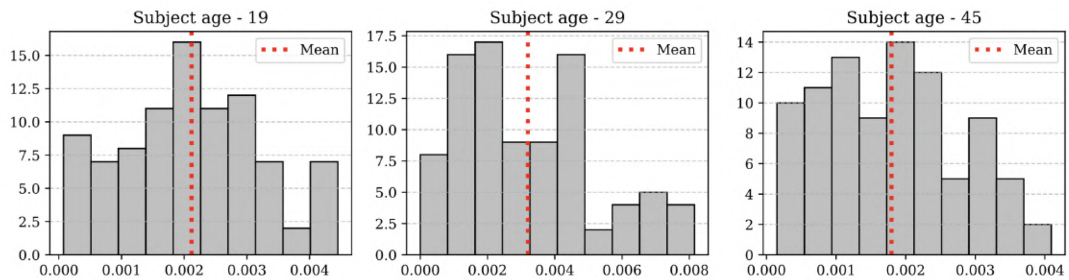


Figure 9: Distribution of Betwenness Centrality of Individuals belonging to different age groups

For the 19-year-old subject, the edge betweenness distribution [Figure 10] is skewed towards lower values, with a mean around 0.0004. The 29-year-old subject exhibits a similar skewed distribution, with a slightly higher mean around 0.0005. The 45-year-old subject also shows a skewed distribution, with a mean close to 0.0004. These distributions suggest that edge betweenness centrality is generally low across all subjects, with most connections having relatively low centrality values. The slight variations in mean centrality values may indicate subtle age-related changes in the network structure.

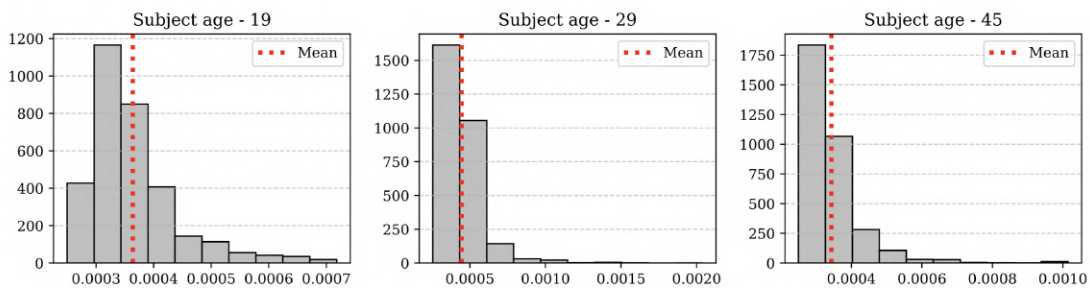


Figure 10: Distribution of Edge Betweenness Centrality of Individuals belonging to different age groups

The differences in adjacency matrices and structural connectivity graphs across ages suggest age-related changes in the brain's structural network. The 19-year-old's matrix shows sparse, localized interactions, while the 29-year-old's matrix displays more dispersed connections, and the 45-year-old's matrix reveals clusters of high connectivity. Structural connectivity graphs indicate a progression from well-connected networks with diverse edge betweenness values in the 19-year-old to more intricate and structured networks in the 29- and 45-year-olds, respectively. Centrality measures show dynamic shifts, with increasing efficiency and reliance on key pathways with age, highlighting the need for further investigation.

Analysis of Networks Across Different Age Groups

Considering the slight differences in brain network structures of individuals of different ages, we will now categorize the population into three distinct age groups: Group 1 (18-25), Group 2 (25-35), and Group 3 (35-45). For each group, we will compute the average adjacency matrices and network centrality measures. By comparing these centrality measures, we aim to determine if there are significant differences across the age groups.

The adjacency matrices [Figure 11] for three age groups (18-25, 25-35, and 35-45) demonstrate the structural connectivity patterns within each group. These matrices reveal that the majority of connections are centered around the diagonals, indicating that regions in close proximity tend to share a significant proportion of connections. For Group 1 (age 18-25), the matrix is relatively sparse with localized interactions. Group 2 (age 25-35) shows more dispersed connections, suggesting wider interactions across different brain regions. Group 3 (age 35-45) exhibits noticeable clusters of high connectivity, reflecting stronger interactions within specific regions. This progression suggests a trend towards more organized and stronger connectivity within certain brain regions as age increases, providing insight into the structural changes in brain networks across different stages of adulthood.

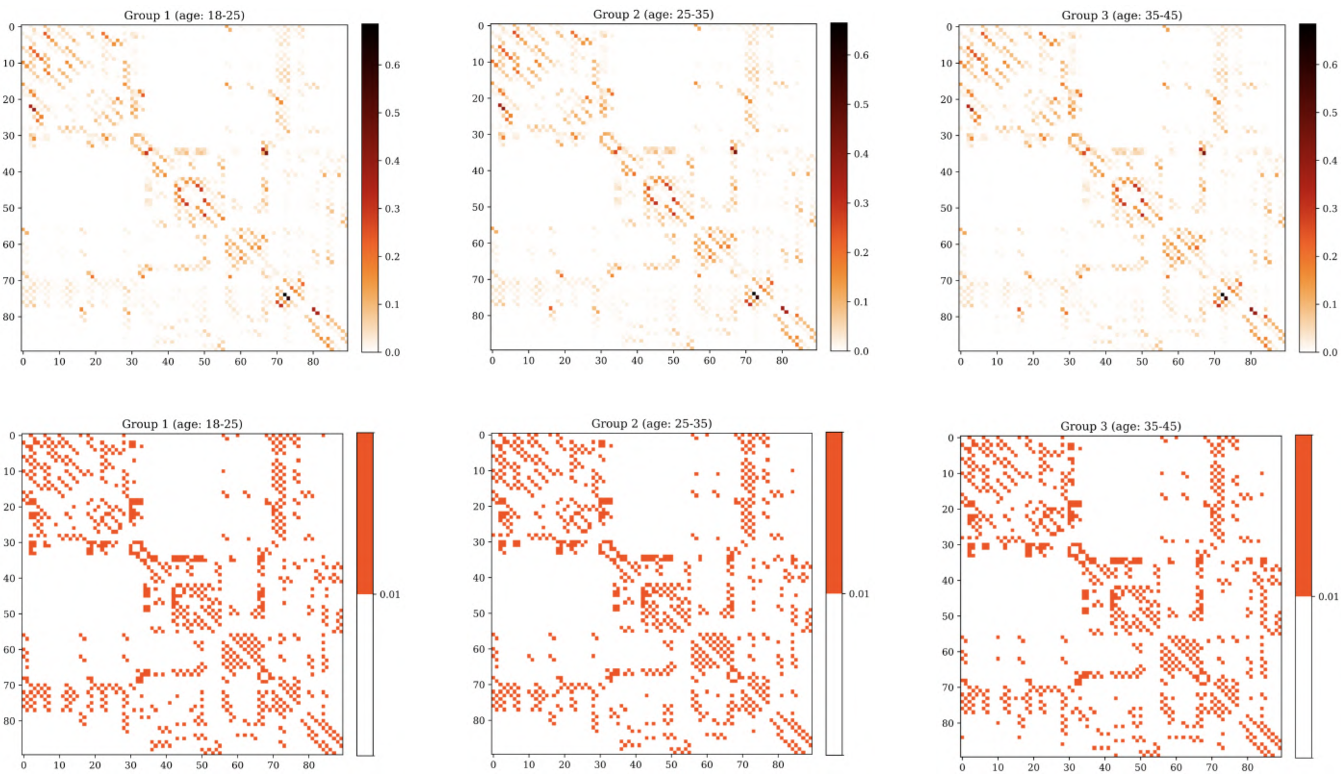


Figure 11: Adjacency matrices of individuals averaged across different age groups

The network representation of the averaged Adjacency Matrices [Figure 12] indicates that Group 1 (age 18-25) has a well-connected network with diverse edge betweenness values, indicating balanced hemispheric distribution and multiple pathways for information flow. Group 2 (age 25-35) exhibits a similarly dense network, but with more pronounced critical pathways, suggesting increased specialization and integration across hemispheres. Group 3 (age 35-45) displays a more structured network with distinct high-betweenness edges, reflecting further specialization and reliance on key pathways as the brain network ages. This progression highlights the evolving nature of brain connectivity, with increasing specialization and the prominence of critical pathways supporting brain function across different age groups.

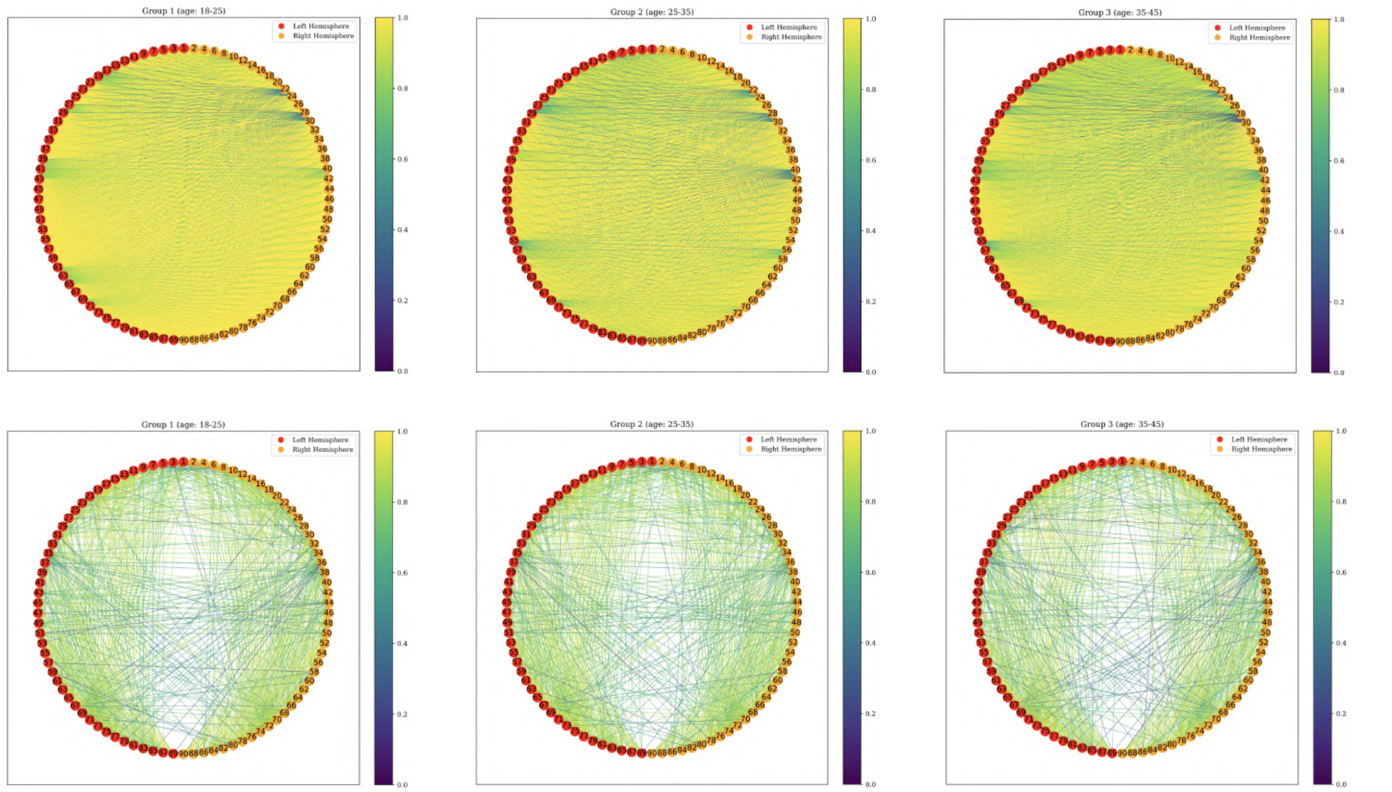


Figure 12: Structural connectivity graphs of individuals averaged across different age groups

Centrality Measures

Figure 13 displays the average shortest path length distributions. It show that most paths are relatively short in all groups, with a peak around 1.1 to 1.2. Group 2 and 3 have a slightly wider distribution, suggesting more variability in path lengths, which could be due to increased specialization and more complex network structures with age.

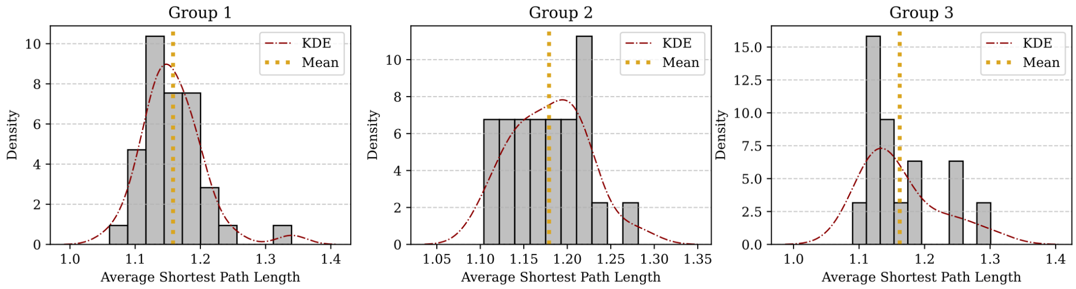


Figure 13: Average Shortes Path Lenght across different age groups

The degree centrality distributions [Figure 14] indicate that most nodes have a high degree in all groups. There is no significant difference across the groups. This implies that the core functional architecture of the brain network is preserved, even as it undergoes age-related adaptations.

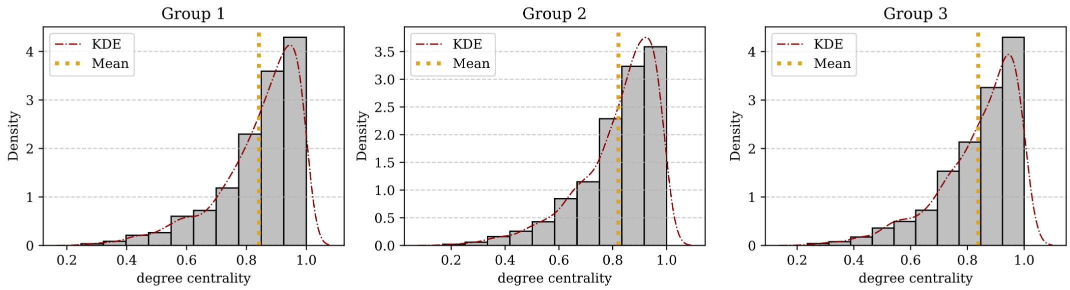


Figure 14: Degree Centrality across different age groups

The closeness centrality distributions [Figure 15] show that nodes in Group 1, 2 and 3 have similar centrality values distributions. The mean closeness centrality remains the same with age, suggesting that as the network becomes more specialized the distribution of the centrality of the nodes remains invariant.

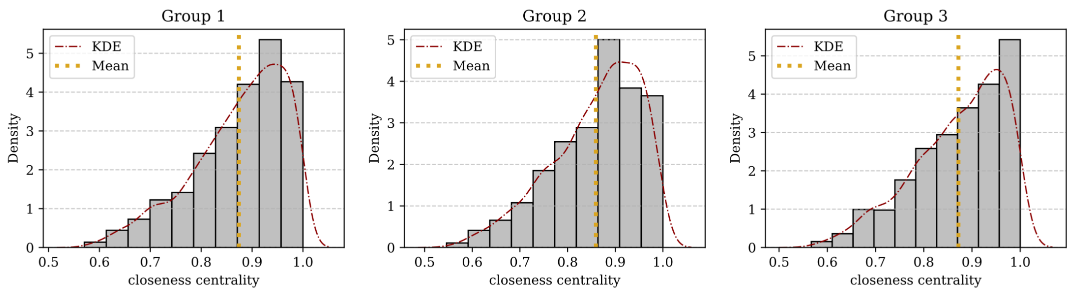


Figure 15: Closeness Centrality across different age groups

All three groups show a right-skewed distribution for betweenness centrality [Figure 16], with a majority of nodes having low values and a few nodes exhibiting high betweenness centrality. With age, the distribution of betweenness centrality becomes more concentrated around the mean, with fewer values at the extremes. A more concentrated distribution around the mean could imply that the brain's network structure becomes more stable and possibly more efficient in older age groups, with fewer extreme values. This might reflect an adaptive process where the brain optimizes its connectivity patterns to maintain functionality over time.

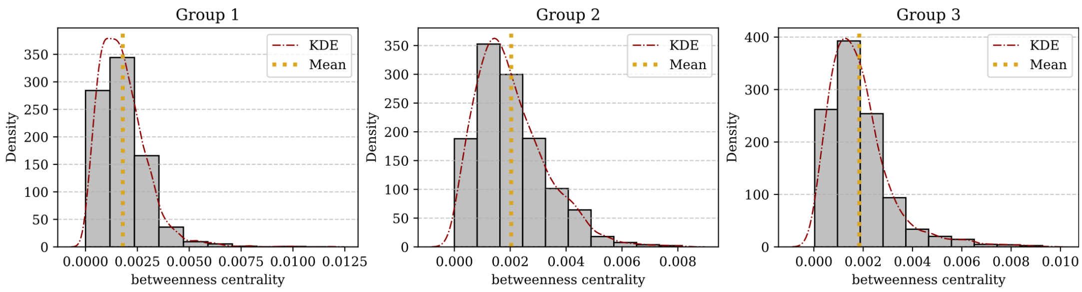


Figure 16: Betweness Centrality across different age groups

Similar to node betweenness centrality, edge betweenness centrality [Figure 17] is right-skewed, indicating that while most edges do not lie on many shortest paths, some edges are crucial for network connectivity. The mean edge betweenness centrality is relatively consistent across the groups, with a slight increase in older groups.

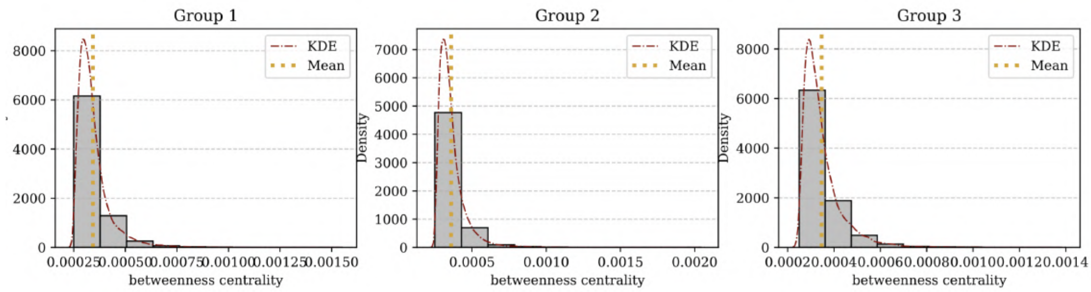


Figure 17: Edge Betweness Centrality across different age groups

Table 2 presents the mode of the top five network nodes ranked by degree centrality, closeness centrality, and betweenness centrality across three age groups: 18-25, 25-35, and 35-45. The analysis reveals that certain nodes, particularly nodes 74, and 68, consistently exhibit high centrality values across all measures and age groups, indicating their fundamental role in maintaining the brain's structural integrity and communication efficiency. The consistent prominence of these nodes across different ages points to their crucial function in the brain's network architecture.

Top 5 Nodes	Degree Centrality	Closeness Centrality	Betweenness Centrality
Group 1: 18-25	74 78 67 68 36	74 78 67 68 36	74 78 67 68 73
Group 2: 25-35	78 74 67 77 4	78 74 67 77 4	78 68 67 74 72
Group 3: 35-45	73 74 77 36 68	73 74 77 36 68	73 74 77 78 71

Table 2: Mode across age gourps of the top 5 Network nodes ranked by Degree, Closeness and Betweenness Centrality

Conclusion

The application of graph theory to neuroimaging data has significantly enhanced our understanding of the brain's structural connectivity and its evolution across the lifespan. Our study provides a comprehensive analysis of brain networks in individuals across different age groups, revealing critical insights into the topological characteristics and dynamic changes of these networks.

The structural connectivity matrices and adjacency graphs demonstrate that connections are predominantly centered around the diagonals, indicating that regions in close proximity share a large proportion of connections. This pattern is consistent across age groups but exhibits distinct variations that reflect age-related changes. For instance, the connectivity matrices of younger individuals (ages 18-25) are relatively sparse with localized interactions, while those of middle-aged individuals (ages 25-35) show more dispersed connections, and older individuals (ages 35-45) exhibit noticeable clusters of high connectivity, suggesting stronger interactions within specific regions.

Graph-theoretical measures such as degree centrality, closeness centrality, and betweenness centrality provide further insights into the network's organization. The degree and closeness centrality distributions is the same across age groups. However, betweenness centrality distributions, which highlights the presence of critical nodes that act as network connectors, varies with age. This indicates that nodes with very high betweenness are less prominent in middle-aged and older groups, suggesting that the brain relies less on specific pathways to maintain connectivity and functionality as it ages. Our analysis also identifies the top nodes by centrality measures across different age groups, reflecting the dynamic nature of brain network organization. Certain regions, such as the Putamen (region 74) and the Precuneus (region 68), consistently emerge as critical nodes, highlighting their pivotal roles in maintaining network efficiency and supporting complex cognitive functions.

In conclusion, our study reveals that, while the overall network structure shows age-related changes, key topological characteristics remain consistent. The consistent degree and closeness centrality distributions suggest stable efficiency in information flow across age groups, whereas variations in betweenness centrality highlight a shift in the network's reliance on critical nodes as it ages. The identification of top nodes (according to centrality measures), such as the Putamen and Precuneus, underscores their essential roles in maintaining network efficiency and supporting complex cognitive functions.

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