Research Square

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Enhanced inter-network morphological coordination in high-order association networks: MIND derived cortical morphological similarity signatures for successful cognitive aging

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Research Article

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Abstract

Background

Cognitive aging exhibits substantial individual heterogeneity, and successful cognitive aging (SCA) describes older adults retaining relatively intact cognitive function. Conventional regional morphometric analyses cannot fully capture brain interactions across regions that underpin cognitive preservation. The Morphometric Inverse Divergence (MIND) supports construction of multivariate morphometric similarity networks at the vertex level to probe brain structural organization at the system level.

Methods

The present study included 63 participants, comprising 24 SCA individuals and 39 normal aging (NA) individuals. MIND networks were constructed from five morphological features at the vertex level using the Schaefer 400-region atlas. Nodal metrics for graph theory were calculated, and values for the area under the curve (AUC) were adopted for statistical tests. Partial correlation analyses examined associations between imaging indices and episodic memory performance, with FDR correction applied for multiple comparisons.

Results

Compared with the NA group, SCA participants exhibited higher inter-network cortical morphological similarity, which was concentrated in high-order association networks (DMN, CON, DAN, VAN). Participants with SCA also showed elevated Module_Z (AUC) in the left VAN.PFC1.1. Inter-network morphological similarity and nodal modularity of VAN.PFC1.1 were positively correlated with episodic memory scores.

Conclusions

Enhanced multidimensional morphological coordination across high-order association networks and specialization of key prefrontal nodes characterize SCA. These structural connectome signatures may act as neural markers of cognitive resilience and yield potential targets for neuroprotective interventions related to aging.

1 Introduction

Advances in healthcare and technology have extended human life expectancy, driving a sustained expansion of the global aging population[1]. By the end of 2024, individuals aged 65 years and older accounted for 10.2% of the world population[2], a proportion projected to rise to 16.4% by 2050[3]. This demographic transition is fundamentally reshaping social security systems, healthcare delivery, and

labor market structures[4], while concurrently intensifying the burden on medical systems and elevating the risk of disability[5] and cognitive decline among older adults[6]. Notably, more than half of adults over 65 years report concerns regarding their memory function[7]. However, substantial heterogeneity exists in cognitive trajectories during aging, a subset of older individuals maintains well-preserved cognitive performance despite advanced age, a phenomenon termed successful cognitive aging (SCA) [8]. Elucidating the neural mechanisms and protective factors underlying SCA, and developing targeted interventions to delay age related cognitive deterioration, represent critical and urgent scientific priorities in geriatric medicine.

To date, the neuroanatomical signatures of SCA remain incompletely characterized. Neuroimaging techniques without invasion, particularly structural magnetic resonance imaging (sMRI), have provided essential tools for investigating the neural substrates of cognitive preservation in aging. Regarding regional gray matter volume, Dekhtyar and colleagues demonstrated that individuals with SCA exhibited larger baseline hippocampal volumes that were preserved over a follow-up period of three years[9]. Harrison et al. further established a positive association between hippocampal volume retention and episodic memory performance[10]. With respect to cortical thickness, prior investigations have revealed that SCA individuals display thicker cortices at key nodes of the default mode network and salience network compared to typical older adults[11]. Gefen et al. noted that cortical thinning in the posterior cingulate cortex represents a hallmark of cognitive decline in normal aging, whereas SCA individuals maintain structural integrity in this region[12]. Nevertheless, these anatomical advantages have not been universally replicated. For instance, one study reported no statistically significant difference in right posterior cingulate cortical thickness between SCA and typical aging groups[13]. Such inconsistencies may partly arise from the conventional approach of treating brain regions as independent anatomical units. However, brain regions do not operate or develop in isolation; rather, they constitute an integrated, anatomically interconnected network[14]. Consequently, relying solely on localized morphometric measures may prove insufficient to capture systematic interactions across brain regions that characterize successful cognitive aging.

More recently, the construction of structural similarity networks has emerged as a promising avenue for integrating multidimensional structural features and generating biologically meaningful, individual connect[14]. Conventional morphometric similarity networks mostly rely on regional summary statistics. Such data-compression procedure inevitably leads to the loss of vertex-level spatial details. Moreover, their construction often depends on strong statistical assumptions such as Z-score standardization, which may distort true biological variation. In response to these challenges, Sebenius et al. introduced the Morphometric Inverse Divergence (MIND) approach. Diverging from region mean based methods, the MIND algorithm directly leverages vertex-level multidimensional structural features (including cortical thickness, surface area, volume, mean curvature, and sulcal depth) to construct multivariate probability distribution models for each brain region. By computing the symmetric Kullback-Leibler (KL) divergence between regional distributions and applying nonlinear mapping, MIND quantifies complex interregional similarity relationships. Empirical evidence suggests that, compared with traditional morphometric similarity networks, MIND exhibits enhanced sensitivity in detecting subtle anatomical heterogeneity

during brain aging, demonstrating superior capability in capturing age related neuroanatomical changes[15].

The individualized similarity networks constructed by MIND provide quantitative characterizations of interregional connection strength. To further elucidate how these connections assemble into efficient information processing systems, graph theoretical analysis offers a powerful analytical framework. Graph theory abstracts complex brain networks into sets of nodes and edges, enabling the quantification of topological properties that describe the brain's dynamic balance between localized information processing and global integration[16].

The present study utilizes three-dimensional T1-weighted imaging (3D-T1WI) data to construct cortical morphometric similarity networks in SCA individuals using the MIND approach. By investigating the topological characteristics of these networks and their associations with multidimensional cognitive assessments, we aim to elucidate the neural mechanisms of SCA from a systems level connectivity perspective. These findings are expected to deepen our understanding of SCA and may provide reliable structural neuroimaging biomarkers for identifying individuals with high cognitive resilience and informing precision intervention strategies in clinical practice.

2 Methods

2.1 Participants

2.1.1 Study Sample

The participants in the present study were recruited from the Community Chronic Disease Screening Program of Shanghai Fifth People's Hospital. Launched in 2024, this comprehensive health monitoring study targeted permanent community residents and collected data including demographic information, multidimensional clinical assessments, neuropsychological evaluations, and structural neuroimaging data. Permanent residents were defined as Chinese nationals who had resided at the survey site for more than six months within the 12-month period prior to the investigation. Residents living in functional-specific premises such as work sheds, military barracks, student dormitories, and nursing homes were excluded. The dataset comprised 944 participants aged 18 years and older. All participants provided written informed consent in accordance with the Declaration of Helsinki. The study protocol was approved by the Medical Ethics Committee of Shanghai Fifth People's Hospital Affiliated to Fudan University, Shanghai, China (approval number: (2023) Ethics Review No. 141).

2.1.2 Inclusion and Exclusion Criteria

Overall screening criteria for participants: Inclusion criteria: (1) Age ≥ 65 years; (2) Availability of complete 3D-T1WI neuroimaging and neuropsychological data; (3) Mini-Mental State Examination (MMSE)[17]score ≥ 27. Exclusion criteria: (1) Documented history of neurological or psychiatric disorders (e.g., epilepsy, frontotemporal dementia, Parkinson's disease, major depressive disorder, and

schizophrenia); (2) Documented history of stroke, traumatic brain injury, or intracranial space-occupying lesions. Following the above criteria, 66 participants were ultimately enrolled.

Screening criteria for individuals with SCA: Among the 66 participants described above, subjects meeting the following two dimensional criteria were defined as individuals with SCA: (1) Superior episodic memory: Auditory Verbal Learning Test–Huashan version (AVLT-H) scores were higher than the mean level of middle-aged participants aged 50–65 years within this dataset; (2) Superior executive function: Trail Making Test Part B (TMT-B)[18] performance exceeded the mean level of middle-aged participants aged 50–65 years in this dataset. Based on these criteria, 25 participants were identified as the SCA group, and the remaining 41 participants were categorized as the normal aging (NA) group.

2.2 Image Acquisition

The 3D-T1WI images used in the present study were derived from the Community Chronic Disease Screening Program of Shanghai Fifth People's Hospital, were acquired using both the 3 T Siemens Skyra scanner. Participants were instructed to lie quietly in the scanner with their eyes closed to minimize motion artifacts. The imaging parameters were as follows: voxel size = 1 × 1 × 1 mm^3, TR = 2100 ms, TE = 219 ms, slice thickness = 1 mm, flip angle = 7°.

2.3 Image preprocessing and quality control

T1WI image were preprocessed using the recon-all pipeline implemented in FreeSurfer version 8.0.0[19] to perform automated cortical reconstruction and volumetric segmentation. For group-wise vertex-wise morphological comparison, individual cortical surfaces were resampled and registered to the fs_LR 32k standard space (Conte69 atlas) via Connectome Workbench[20]. Five vertex-wise morphological features were extracted,, including cortical thickness, gray matter volume, surface area, mean curvature, and sulcal depth. Spatial smoothing was subsequently applied using a geodesic Gaussian kernel with a full width at half maximum (FWHM) of 10 mm.

For quality control, manual visual inspection was performed on raw images, brain extraction outputs, tissue segmentation, and surface reconstruction results. Participants with anatomical abnormalities, prominent artifacts, or processing failures were excluded.

Following quality-control procedures, 63 participants remained for final analysis, comprising 24 individuals with SCA and 39 individuals with NA.

2.4 MIND similarity network construction

The cerebral cortex was parcellated into 400 regions of interest (ROIs) using the Schaefer 400 atlas[21]. Vertices with biologically meaningless zero values and extreme outliers (modified Z-score > 7 based on the median absolute deviation) were removed following rigorous quality-control procedures. After Z-score normalization of all morphological features, MIND networks were constructed for each participant. Specifically, a symmetric KL divergence[22] estimation algorithm based on k-nearest neighbors was applied to quantify multidimensional morphological distribution differences between

every pair of ROIs, which were further transformed into similarity weights ranging from 0 to 1. Higher values indicated greater anatomical architectural similarity between brain regions. Finally, a 400 × 400 morphological similarity matrix was generated for each participant.

2.5 Graph Theoretical Analysis

Graph theoretical topological properties of individual MIND matrices were computed using the Brain Connectivity Toolbox (BCT) within MATLAB R2023b[23]. Weighted undirected networks were constructed across a proportional threshold range of 10% to 30% (5% step size) to remove weak connections while preserving network sparsity. A set of nodal topological metrics were calculated at the node level, including node strength, local efficiency, betweenness centrality, clustering coefficient, participation coefficient, and nodal modularity Z-score. To avoid threshold dependent results, the area under the curve (AUC) was computed for all above mentioned topological metrics across the threshold range, and the resulting AUC values were adopted for subsequent statistical analyses. Beyond topological metrics, the 400 ROIs were mapped onto seven canonical functional networks according to the Yeo atlas[24]: visual network (VIS), sensorimotor network (SMN), dorsal attention network (DAN), ventral attention network (VAN), limbic network (LIM), control network (CON), and default mode network (DMN). Mean within network and between network connection weights were separately calculated for group level comparisons.

2.6 Statistical analysis

Analysis of covariance (ANCOVA) was used to compare group differences between the SCA and the NA group in macroscopic network connectivity (within network and between network) and topological metrics (area under the curve), with age, sex, and years of education strictly controlled as covariates. Furthermore, a generalized linear model (GLM) was applied for exploratory whole connectome analysis to test group differences across all 79800 independent morphological edges while adjusting for the same demographic covariates. To investigate the clinical implications of structural covariation alterations, morphological features showing significant group level differences at the nodal or network level were extracted. After regressing out the effects of age, sex, and years of education, partial correlation analyses (Pearson or Spearman correlation selected according to data normality) were performed to examine associations between neuroimaging metrics and cognitive scale scores. All statistical tests were two tailed. The Benjamini-Hochberg false-discovery rate (FDR) procedure was adopted for rigorous multiple comparison correction across topological analyses, whole connectome edge-wise analyses, and correlation analyses, with the corrected statistical significance threshold set at $p < 0.05$.

All statistical analyses were implemented in MATLAB and Python.

3 Results

3.1 Demographic and Neuropsychological Characteristics

Regarding demographic characteristics, there were no statistically significant differences in age, sex, and years of education between participants with SCA and NA ($p > 0.05$). In terms of neuropsychological performance for global cognition, no significant difference was observed in MMSE scores between the SCA group and the NA group ($p > 0.05$). For episodic memory and executive function, participants with SCA exhibited significantly better performance on the AVLT-H and TMT-B than participants with NA ($p < 0.001$).(Table 1).

Table 1
Demographic and cognitive assessments.

Age(years)	**SCA(n = 24)**	**NA(n = 39)**	**t/F/χ2 value**	**p value**
	69.46 ± 2.52	**70.44 ± 3.39**	**-1.22**	**0.227**
Gender (Female/Male)	12/12	22/17	0.06	0.814
Eduction(years)	9.85 ± 3.36	8.55 ± 2.98	1.6	0.114
MMSE	28.63 ± 0.92	28.03 ± 1.04	1.84	0.07
AVLT-H	6.38 ± 1.56	2.59 ± 1.25	10.23	<0.001***
TMT-B	120.71 ± 22.99	221.08 ± 63.36	-6.89	<0.001***

Note: For continuous variables, data are presented as the mean ± standard deviation for each group. *** indicates $p < 0.001$. Abbreviations: SCA, successful cognitive aging; NA, normal aging; AVLT-H, Auditory Verbal Learning Test Huashan version; MMSE, Mini-Mental State Examination; TMT-B, Trail Making Test B.

3.2 Differences in Cerebral Cortical Similarity Between Individuals with SCA and NA

MIND analysis identified five significantly different similarity edges between the two groups after FDR correction ($p < 0.05$), showing higher cortical morphological similarity in the SCA group relative to the NA group. Anatomical localization of these five significant edges further revealed that all edges belonged to high-order association networks, including the DMN, CON, DAN, and VAN. Three of these edges involved the DMN, and the similarity difference between the DMN and CON exhibited the largest F-statistic from ANCOVA, indicating the most prominent group difference (Fig. 1).

3.3 Graph Theory Results

Graph theory analyses revealed that after FDR correction, individuals with SCA exhibited higher Module_Z values in the VAN.PFC1.1 brain region compared with those with NA (lh.VAN.PFC1, $t = 0.379$, $p = 0.022$) (Fig. 2). No other graph theoretic metrics showed statistically significant between-group differences.

3.4 Correlation Results

3.4.1 Correlations Between Cortical Morphological Similarity and Cognitive Function

Correlation analyses revealed that after FDR correction, multiple pairs of inter-network cortical morphological similarity exhibited significant positive correlations with AVLT-H scores across participants with SCA and NA. Cortical morphological similarity features centred on the DMN were closely associated with episodic memory performance in both groups. Specifically, cortical similarity between the DMN and CON, DMN and DAN, as well as DMN and VAN was positively correlated with episodic memory (DMN & CON, $r = 0.408$, $p = 0.018$; DMN & DAN, $r = 0.404$, $p = 0.018$; DMN & VAN, $r = 0.396$, $p = 0.018$). In addition, cortical morphological similarity between the DAN and VAN showed a positive correlation with episodic memory (DAN & VAN, $r = 0.379$, $p = 0.022$) (Fig. 3).

No statistically significant correlations were observed between cortical similarity features and MMSE or TMT-B scores among individuals with SCA ($p > 0.05$).

3.4.2 Correlations Between Graph-Theoretic Metrics and Cognitive Function

Correlation analyses demonstrated that after FDR correction, the Module_Z (AUC) values in the VAN.PFC1.1 brain region showed a significant positive correlation with AVLT-H scores in participants with SCA and NA (lh.VAN.PFC1, $r = 0.467$, $p = 0.003$) (Fig. 4).

No statistically significant correlations were found between the remaining graph theoretic metrics and cognitive measures (MMSE, AVLT-H, TMT-B) among individuals with SCA ($p > 0.05$).

4 Discussion

In the present study, MIND analysis was applied to systematically investigate the characteristics of brain cortical morphological similarity and its association with cognitive function in individuals with SCA. The key findings are summarized as follows. Individuals with SCA exhibited higher inter-network global cortical morphological similarity compared to participants with NA. Group differences in cortical morphological similarity were predominantly localized to high-order association networks, and the similarity was positively correlated with episodic memory. In addition, the Module_Z (AUC) value in the VAN.PFC1.1 region was higher in participants with SCA than in those with NA, and this metric showed a positive correlation with episodic memory.

The human cerebral cortex is not a homogeneous structure and exhibits marked regional heterogeneity in cytoarchitecture and neuronal types. Based on neuronal density, laminar differentiation and cell types, classic neuroanatomy divides the neocortex into three fundamental classes: granular, agranular, and dysgranular cortex [25]. Specifically, primary sensory cortices possess a well developed internal granular layer[26], whereas the primary motor cortex is classified as agranular cortex[27]. Although high-order

association cortices retain the granular layer, their laminar organization and cellular density distribution differ fundamentally from those of primary sensory cortices. Such regional heterogeneity in cytoarchitecture constitutes the microstructural substrate for functional network segregation. Accordingly, the present study observed that group differences in cortical morphological similarity between individuals with SCA and those with NA were predominantly located within high-order association networks including the DMN, CON, DAN and VAN, rather than primary sensorimotor networks. This spatial pattern is highly consistent with the regional gradient of cortical laminar differentiation and hierarchical functional organization. In addition, von Economo neurons (VENs) are a population of large spindle shaped projection neurons predominantly enriched in high-order association regions. They are characterized by large caliber axons and simplified dendrites, enabling rapid long range neural communication[28, 29]. Previous post-mortem studies have indicated higher VEN density in individuals with SCA relative to patients with mild cognitive impairment, implying that neurons in SCA may confer greater resilience against cytopathological degeneration[12]. The finding that morphological similarity differences in our study are confined to VEN-rich high-order association networks aligns with these aforementioned microstructural observations. Notably, the MIND framework has been validated to conform to fundamental principles of cortical organization: brain regions with similar cytoarchitecture are more likely to be interconnected by white matter tracts and belong to the same cytoarchitectural class[14]. This methodological validation underpins the biological plausibility of our findings, suggesting that the detected inter-network differences in morphological similarity may reflect genuine patterns of cortical microstructural covariation.

Brain structure remains relatively stable in middle aged populations. To achieve preserved cognitive function across age, SCA individuals may not rely merely on structural preservation within isolated brain regions; instead, adaptive modulation of multidimensional morphological features including cortical thickness, volume and curvature is required. The present study identified elevated cortical morphological similarity in participants with SCA. Such high similarity may underpin the reserve mechanism for SCA: driven by brain reserve and cognitive reserve accumulated earlier in life, individuals with SCA can maintain multidimensional structural coordination across brain networks in old age, thereby sustaining cognitive function comparable to that of middle aged adults[30]. These enhanced similarity differences were predominantly localized to high-order association networks, including the DMN, CON, and attention networks (DAN/VAN). As a core hub for internally oriented cognition[31], the DMN exerts critical dynamic interactions with the CON and attention networks (DAN, VAN) for adaptive cognitive control. Within the spectrum of NA and Alzheimer's disease (AD), functional antagonism and structural covariation between the DMN and CON/attention networks are frequently impaired. Our finding that individuals with SCA exhibited significantly greater morphological similarity in DMN-CON, DMN-DAN and DMN-VAN than participants with NA suggests that SCA may facilitate inter-network communication efficiency by preserving or strengthening structural covariation between the DMN and other high-order association networks, and consequently support episodic memory encoding and retrieval. Correlation analyses further corroborated this mechanism: greater multidimensional structural coordination among high-order association brain networks corresponded to superior episodic memory performance. This finding

validates that resource stock and utilization efficiency within the reserve mechanism contribute to cognitive resilience.

Module-Z quantifies the nodal centrality within modular architecture, a high Module-Z value indicates strong local connectivity aggregation of a node within its own module, enabling it to act as a hub facilitating information exchange among intramodule nodes[32]. Graph theoretical analyses in the present study revealed that individuals with SCA showed significantly higher Module-Z values in the left VAN.PFC1.1 region relative to participants with NA. The core function of the VAN is to mediate bottom-up attentional reorientation, redirecting attention away from ongoing tasks toward unexpected or behaviourally relevant stimuli. Elevated modularity of VAN.PFC1.1 may reflect optimized efficiency of attentional reorientation in individuals with SCA. High modularity of this node suggests its potent capacity for intra-VAN information integration; meanwhile, it may serve as a hub for intermodule connections to promote information exchange between the VAN and other networks such as the DMN and CON. Meunier et al. demonstrated that brain functional networks undergo substantial modular reorganization during aging, characterised by reduced intermodule connectivity within prefrontal modules and increased connector nodes in posterior and central modules[33]. The relative preservation or enhancement of modularity at VAN.PFC1.1 among SCA participants in our study may represent optimized efficiency of this node in intra and inter-network information integration, consistent with the neural compensation hypothesis[1]. This hypothesis posits that prefrontal regions may compensate for functional decline in posterior brain regions by enhancing network organisational efficiency in the course of aging. The significant positive correlation between VAN.PFC1.1 modularity and episodic memory further implies that successful memory performance may rely on effective attentional capture and allocation. During episodic memory encoding and retrieval, individuals are required to flexibly shift attentional resources from internally generated mental processes (dominated by the DMN)[34] toward external task relevant information (bottom-up attentional capture mediated by the VAN)[35], while sustaining goal directed processing via the control network (CON)[36]. As a prefrontal node within this attentional reorientation circuit, optimised topological properties of VAN.PFC1.1 may facilitate dynamic coordination of attention-memory interactions.

The present study has several limitations. First, the relatively limited sample size may reduce statistical power to detect group differences with small effect sizes and limit the generalizability of the results. Future validation in larger cohorts is therefore needed. Second, given the cross sectional design, causal relationships between morphological similarity features and cognitive function cannot be established, which requires longitudinal follow-up data in further studies. Finally, the MIND algorithm currently concentrates mainly on the cerebral cortex. It is necessary to incorporate morphological features of subcortical nuclei to build a more comprehensive whole brain structural network model in future work.

5 Conclusion

Using the MIND approach, the present study identified distinct cortical morphological similarity signatures in SCA individuals. Our findings demonstrate that individuals with SCA exhibit effective brain

reserve capacity through enhanced multidimensional morphological coordination across high-order association networks and elevated modularity of the VAN.PFC1.1 node. These results advance our understanding of the neural mechanisms underlying SCA, and suggest that cross network integration of the structural connectome and specialisation of key nodal points may serve as core neural markers for SCA. This work also provides novel perspectives and potential targets for developing neuroprotective intervention strategies against aging.

Abbreviations

AD
Alzheimer's disease
ANCOVA
analysis of covariance
AUC
area under the curve
AVLT-H
Auditory Verbal Learning Test–Huashan version
BCT
Brain Connectivity Toolbox
CON
control network
DAN
dorsal attention network
DMN
default mode network
FDR
false discovery rate
FWHM
full width at half maximum
GLM
generalized linear model
KL
Kullback–Leibler
LIM
limbic network
MIND
Morphometric Inverse Divergence
MMSE
Mini-Mental State Examination
NA

normal aging
PFC
prefrontal cortex
PFC1
ventral prefrontal cortex region
ROI
region of interest
SCA
successful cognitive aging
SMN
sensorimotor network
T1WI
T1-weighted imaging
TE
echo time
TR
repetition time
TMT-B
Trail Making Test Part B
VAN
ventral attention network
VENs
von Economo neurons
VIS
visual network.

Declarations

Ethics approval and consent to participate

The study was conducted in accordance with the Declaration of Helsinki. The protocol was approved by the Medical Ethics Committee of Shanghai Fifth People's Hospital Affiliated to Fudan University, Shanghai, China (approval number: (2023) Ethics Review No. 141). Written informed consent was obtained from all participants.

Consent for publication

Not applicable. The manuscript does not contain identifiable individual data, images, or videos.

Competing Interests

The authors declare that they have no competing interests.

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Author Contribution

Tianyuyi Feng：Data collection；Image processing；Drafting of the manuscript；Preparation of figures and tablesJie Wang：Data collection；Image processing；Drafting of the manuscript；Preparation of figures and tablesXiaohu Zhao：Study design；Revision of the manuscript；Study supervision

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Not applicable.

Data Availability

The participant-level MRI and neuropsychological data analysed in this study are not publicly available because of participant privacy and confidentiality concerns. De-identified data supporting the findings are available from the corresponding author upon reasonable request.

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Figures

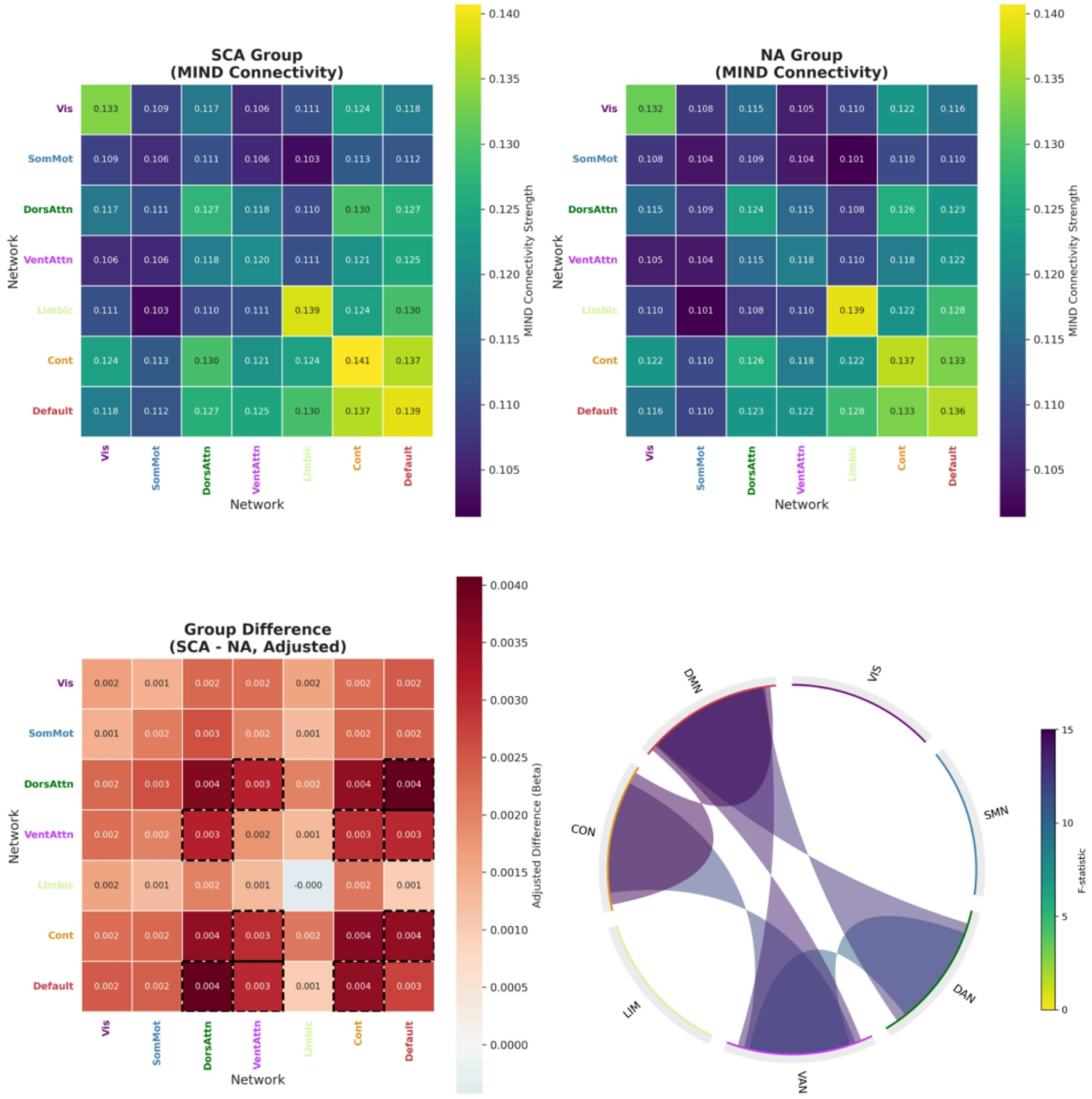


Figure 1

Differences in cortical morphological similarity between the SCA and NA groups. Upper panel: Heatmaps of MIND derived cortical morphological similarity connection strength matrices for the SCA and NA groups. Values within the matrices represent connection strength; the color bar on the right indicates the range of connection strength, with colors ranging from deep purple to bright yellow corresponding to low to high connection strength. Bottom left panel: Heatmap illustrating group differences in cortical morphological similarity; redder colors denote more pronounced differences. Brain networks marked by dashed boxes represent statistically significant between group results after FDR correction. Bottom right

panel: Chord diagram showing network distribution of significant between group differences in cortical morphological similarity. These differences are distributed across four brain networks. Line colors correspond to F-statistics derived from ANCOVA, with more purple colors indicating more significant differences. Abbreviations: SCA, successful cognitive aging; NA, aging; MIND, Morphometric Inverse Divergence; VIS, visual network; SMN, sensorimotor network; DAN, dorsal attention network; VAN, ventral attention network; LIM, limbic network; CON, control network; DMN, default mode network.

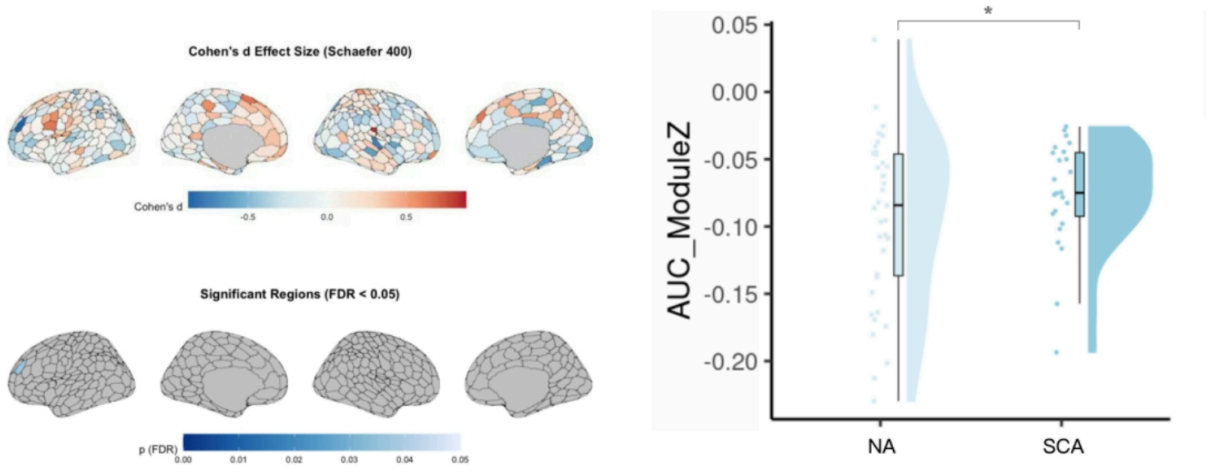


Figure 2

Differences in Module_Z values (AUC) between the SCA and NA groups. Upper left panel: Distribution of Cohen's d effect sizes for Module_Z values across 400 whole-brain ROIs in the SCA and NA groups. The color bar denotes effect size magnitude; warm colours indicate lower Module_Z values in the SCA group relative to the NA group ($d < 0$), whereas cool colours indicate higher Module_Z values in the SCA group ($d > 0$). Bottom left panel: Brain region showing statistically significant between-group differences in Module_Z values after FDR correction ($p < 0.05$). The colour bar represents corrected p values, with deeper blue denoting smaller p values and more pronounced group differences. Right panel: Rain cloud plot illustrating higher Module_Z values in the VAN.PFC1.1 region for individuals with SCA compared with those with NA. Abbreviations: SCA, successful cognitive aging; NA, normal aging.

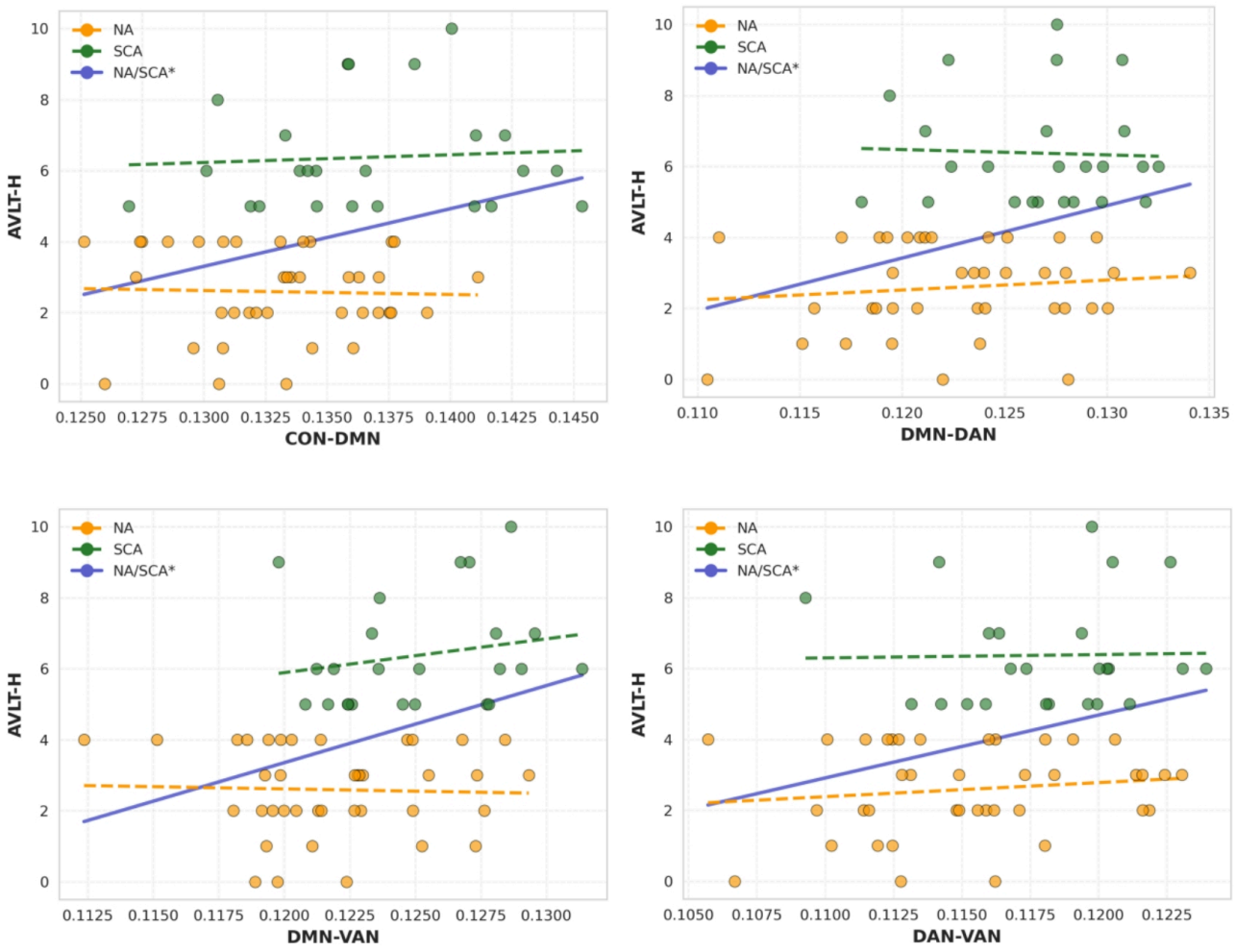


Figure 3

Correlations between cortical morphological similarity features and episodic memory. Across individuals with SCA and NA, inter-network cortical morphological similarity of DMN-CON, DMN-DAN, DMN-VAN, and DAN-VAN were positively correlated with AVLT-H scores. * indicates $p < 0.05$. Abbreviations: SCA, successful cognitive aging; NA, normal aging; AVLT-H, Auditory Verbal Learning Test Huashan version; DMN, default mode network; CON, control network; DAN, dorsal attention network; VAN, ventral attention network.

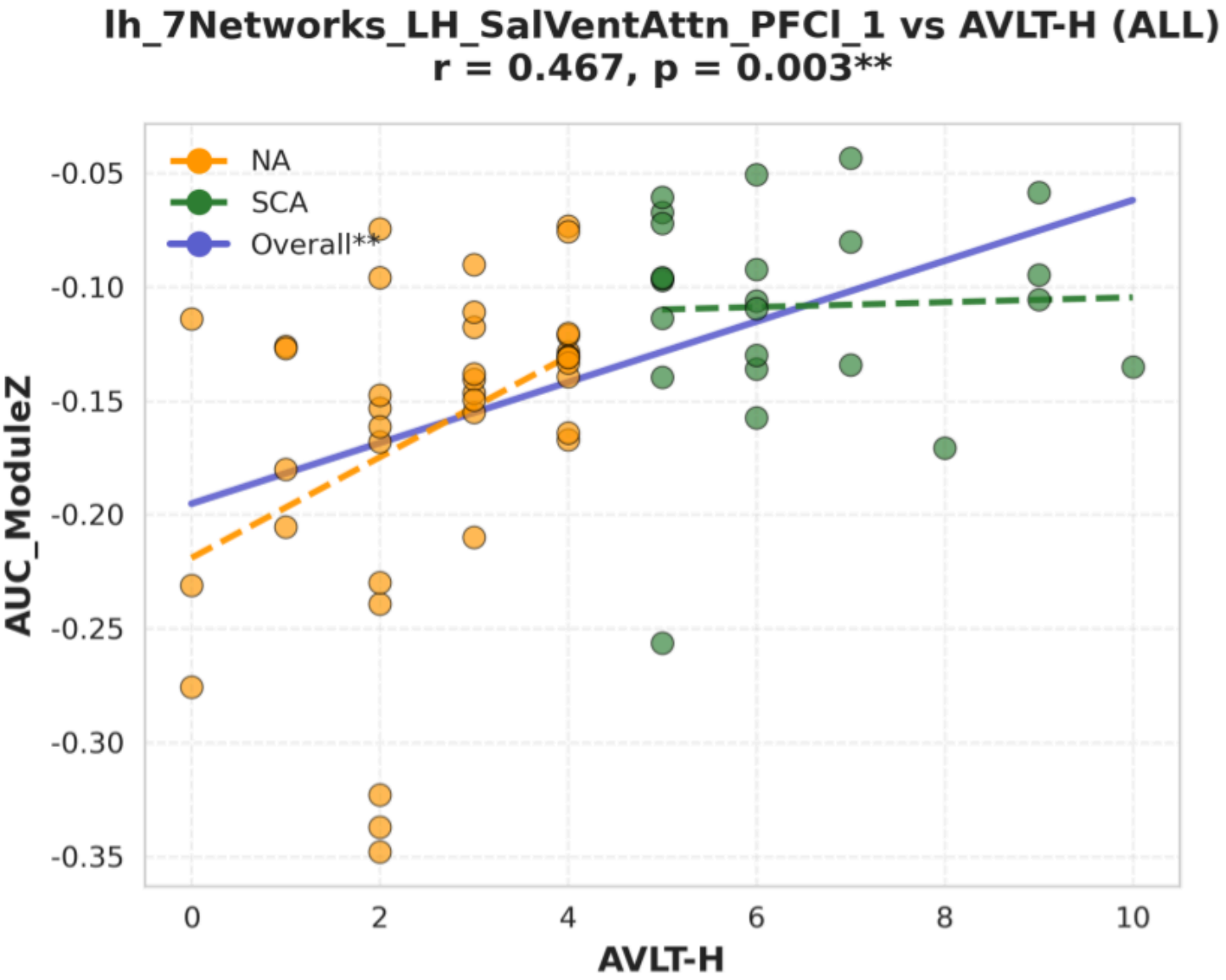


Figure 4

Correlation between graph-theoretic metric and episodic memory. Module_Z (AUC) values in the VAN.PFC1.1 brain region were positively correlated with episodic-memory (AVLT-H) scores across participants with successful cognitive aging and normal cognitive aging. **indicates $p < 0.01$. Abbreviations: SCA, successful cognitive aging; NA, normal aging; AVLT-H, Auditory Verbal Learning Test Huashan version; VAN, ventral attention network; PFC1, ventral prefrontal cortex; AUC, area under the curve.