

Original Research

Resting-State EEG Graph Analysis Reveals Enhanced Alpha-Band Integration in High-IQ Individuals: The *MENSA*-Connect Project

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Abstract

Background: To assess whether resting-state electroencephalography (EEG) connectivity differs between high-intelligence individuals (MENSA members) and controls using graph-theory metrics: clustering coefficient, characteristic path length, and small-worldness. **Methods:** Resting-state 64-channel EEG data were recorded in 29 MENSA participants and 20 controls. Functional connectivity was estimated using Lagged Linear Coherence across delta, theta, alpha, and beta bands. Graph-theory measures were computed using sLORETA and the Brain Connectivity Toolbox. Between-group comparisons were performed using the Mann–Whitney U test; *p*-values were corrected for multiple comparisons using the Benjamini–Hochberg false discovery rate (FDR) procedure, and effect sizes with 95% confidence intervals were calculated. **Results:** Compared with controls, MENSA participants showed significantly lower characteristic path length in the alpha band (Benjamini–Hochberg (BH) critical value = 0.004), indicating greater global network integration. In the beta band, they showed a higher clustering coefficient (BH critical value = 0.008), reflecting greater local specialization; together with a higher characteristic path length (BH critical value = 0.013), suggesting reduced global communication. No significant group differences were observed in small-worldness across frequency bands. **Conclusions:** High-Intelligence Quotient (IQ) individuals show a frequency-dependent resting-state cortical organization, characterized by enhanced alpha-band integration and increased beta-band local specialization. These findings support a nuanced neural-efficiency model of intelligence without changes in small-world architecture. Given the cross-sectional and observational design, these findings should be regarded as associative rather than causal and require replication in larger, independent samples. These findings indicate frequency-specific differences in functional network organization, although their cognitive implications remain to be established.

Keywords: intelligence; electroencephalography; connectome; brain mapping; cognitive reserve

1. Introduction

The brain is a complex network of interconnected regions that spontaneously organize into distinct functional systems [1,2,3]. Information integration within and between these specialized functionally linked regions occurs continuously, even at rest [4,5,6]. Growing evidence suggests that this intrinsic functional architecture correlates with cognitive abilities and may underlie individual differences in intelligence, personality, and behavior [7]. However, the precise relationship between functional network topology and cognitive abilities remains a subject of intense investigation, with studies yielding inconsistent findings regarding the correlation between graph metrics and intelligence. These discrepancies highlight the need for methodologically robust studies to clarify the neurophysiological substrates of human intellect.

Functional connectivity analysis is a powerful tool for investigating complex brain networks [8]. Graph theory (GT) effectively models these networks, representing brain regions as nodes and their functional connections as edges [9]. With its high temporal resolution, electroencephalography (EEG) is well-suited to the study of these connections, capturing the fast oscillatory activity of cortical pyramidal cell assemblies and thereby offering an advantage over techniques with lower temporal resolution, such as functional magnetic resonance imaging (fMRI) [10,11]. Applying GT to EEG-based connectivity has been proposed for neurological assessment [12,13], where nodes correspond to EEG sources (Brodmann areas) and edges reflect their synchronization, often measured via lagged linear coherence [14,15]. This approach highlights two key properties: local specialization, measured by the clustering coef-



ficient (Cw), and global integration, assessed through the average shortest path length (Lw) [8,16]. Unlike standard graphs, brain networks maintain a balance between specialization and integration, ensuring efficient information transfer even as complexity increases. This phenomenon, known as small-worldness, is characterized by high segregation (high Cw) and strong global integration (low Lw) [17].

The theoretical definition of intelligence and the explanation of its neurobiological basis are among the most intriguing, yet controversial issues in modern psychology and neuroscience [18,19,20,21]. Several studies have shown that the volume [22,23], structural wiring [24], magnitude of local coherence [25] and system efficiency [19,21,26] of the brain may explain a consistent portion of interindividual variability in intellectual performance, as well as genetic-molecular factors behind its heritability [27,28]. Lesion mapping studies further support a network-based model of intelligence, showing that damage to a distributed but circumscribed left fronto-parietal network, including the frontal pole and long-range white-matter tracts, selectively impairs general intelligence, highlighting the importance of integrative control processes across multiple cognitive domains [29]. Earlier works demonstrated that intellectual performance, expressed in terms of Intelligence Quotient (IQ), which is a weighted sum of crystallized (the experience-dependent component of intelligence-cG) and fluid intelligence (reflecting brain efficiency regardless of education and experience-fG), correlated with overall brain global efficiency, measured as the mean length of all paths [26,30,31,32,33,34]. However, recent large-scale and methodologically rigorous investigations have not replicated earlier associations between intelligence and global network efficiency, suggesting prior findings may reflect limited statistical power or publication bias [35]. Current evidence indicates that regional (e.g., fronto-parietal, sensorimotor, visual) rather than global efficiency is more consistently related to specific cognitive domains, while the link between global efficiency and IQ remains weak and inconsistent across studies [36].

With increasing interest in the neural foundations of intelligence, investigating the topological organization of functional brain networks represents a crucial step toward understanding the relationship between cognitive abilities and cortical connectivity.

In this study, we hypothesize that individuals with high IQ exhibit specific patterns of cortical network efficiency. Using graph theoretical metrics (Cw, Lw and Sw), we analyzed resting-state functional connectivity in MENSA members (MENSA group - MG; individuals with high IQ) and the control group (CG). MG, who score at or above the 98th percentile on standardized IQ tests, serve as a valuable model for exploring the neurobiological correlates of superior cognitive function. Admission to MENSA requires documented performance at or above the 98th percentile on a supervised standardized intelligence test. In

Italy, where the present sample was recruited, eligibility can be established either through the official MENSA test, a timed 45-item task based on figural reasoning, or through a previously administered standardized test validated by the national supervising psychologist. The specific items of the supervised MENSA test are not publicly disclosed for test-security reasons, precluding a more detailed psychometric characterization. These qualifying tests predominantly assess fluid intelligence, although their cognitive composition may vary. Admission criteria are not fully uniform across national MENSA organizations. We aimed to test whether MG, as a group with presumed high intelligence, display distinctive connectivity patterns, given the heterogeneous evidence reported in the literature.

2. Materials and Methods

2.1 Participants

Forty-nine healthy adults took part in the study: 29 individuals belonging to MG and 20 CG volunteers. The MG sample included 16 men and 13 women (mean age 33 ± 6 years); the CG sample included 11 men and 9 women (mean age 35 ± 8 years). All participants were right-handed and signed written informed consent prior to enrolment. Absence of neurological or psychiatric illness was ascertained in both groups through a self-report questionnaire. The two groups did not differ significantly in sex distribution ($p = 0.990$), age ($p = 0.526$), or years of education ($p = 0.957$), full demographic and statistical comparisons are reported in Table 1.

Table 1. Demographic characteristics of MENSA group (MG) and control group (CG).

Demographic characteristics	MG	CG	p-value
Gender (males/females) [n]	16/13	11/9	0.990
Age (years) [Mean $\pm$ SD]	33 ± 6	35 ± 8	0.526
Years of education [Mean $\pm$ SD]	18 ± 2	18 ± 2	0.957

Membership in MG was certified by the national MENSA organization based on performance at or above the 98th percentile on a standardized intelligence test. Numerical IQ scores were not available, as they were confidential. CG participants were volunteers without membership in high-IQ societies and without reported learning, cognitive, or neuropsychological disorders. For CG group, IQ assessment was obtained through the Wechsler Adult Intelligence Scale (WAIS-IV): average IQ was 105 (range 92–122). Participants reported no current use of medications acting on the central nervous system. Caffeine intake and sleep duration before the EEG recording were not systematically recorded.

2.2 EEG Data Acquisition and Preprocessing

Resting-state EEG was recorded during two 10-minute sessions: one with eyes closed and one with eyes

open. The two conditions were preprocessed and analyzed separately. All results reported in the present study were obtained from the eyes-closed recordings, which constitute the standard condition for the investigation of alpha-band connectivity and avoid the pronounced modulation of alpha activity produced by eye opening. Participants sat comfortably in a quiet, dimly illuminated, electrically shielded room. Signals were collected from 64 scalp electrodes arranged according to the international 10–20 system. Vertical and horizontal eye movements were monitored through dedicated electrooculography (EOG) channels. Electrode impedance was maintained below 5 k Ω for the entire recording.

Preprocessing was carried out in MATLAB R2011b (MathWorks, Natick, MA, USA) using custom scripts built on EEGLAB 11.0.5.4b (Swartz Center for Computational Neurosciences, La Jolla, CA, USA; <http://www.sccn.ucsd.edu/eeqlab>). Raw EEG traces were band-pass filtered between 0.2–47 Hz with a finite-impulse-response filter and digitized at 256 Hz. Data were segmented into 2-second epochs. Artifact removal followed a two-step procedure: (1) initial visual inspection, with manual exclusion of epochs containing gross artifacts; (2) Independent Component Analysis (ICA) using the Infomax ICA algorithm to identify and remove components reflecting ocular, muscular, or cardiac contamination. Components were visually evaluated, and residual artifactual epochs were discarded.

2.3 Functional Connectivity Estimation

Functional connectivity analysis was conducted using standardized low-resolution brain electromagnetic tomography (sLORETA: <http://www.uzh.ch/keyinst/NewLORETA/LORETA01.htm>) [37]. For each subject and for each canonical frequency band (Delta δ : 1–4 Hz; Theta θ : 4–8 Hz; Alpha α : 8–13 Hz; Beta β : 13–20 Hz), sLORETA computed the cross-spectral density matrices and estimated the cortical current-density distribution [38]. The solution space was constrained to cortical gray matter, and the Montreal Neurological Institute (MNI) template served as the anatomical reference model [39].

Connectivity was quantified in the source space using Lagged Linear Coherence (LLC), a measure that suppresses instantaneous (zero-phase-lag) coupling and therefore minimizes the influence of volume conduction. Using a whole-brain atlas of Brodmann areas (42 regions per hemisphere), LLC values were obtained for all possible region of interest (ROI)-to-ROI pairs [14].

LLC in a specific frequency band ω is defined by the following equation:

$$\rho_{xy}^2(\omega) = \frac{[\text{Im}(s_{xy}(\omega))]^2}{s_{xx}(\omega)s_{yy}(\omega) - [\text{Re}(s_{xy}(\omega))]^2}$$

where s_{xx} and s_{yy} are the power spectral densities of two source signals x and y respectively, s_{xy} is the cross power

spectral density of x and y , and ω is the reference frequency band [14].

For each frequency band, the resulting LLC matrices constituted the weighted adjacency matrices used in the graph-theoretical analyses [40].

2.4 Graph-Theory Metrics

Graph-theory computation was performed with the Brain Connectivity Toolbox (BCT: <https://sites.google.com/site/bctnet/>). For each weighted connectivity matrix, we quantified: (1) Mean weighted clustering coefficient (C_w)—obtained by averaging the weighted clustering coefficient across all nodes in the network; (2) Mean weighted characteristic path length (L_w)—that represents the average of the shortest weighted paths connecting each node to all other nodes.

Edge weights (LLC values, range 0–1) were converted into connection-length (distance) values using the inverse transformation $L = 1/W$, consistent with the Brain Connectivity Toolbox convention, so that stronger functional coupling corresponded to shorter connection lengths. By construction, this transformation assigns proportionally larger distances to weaker edges and an infinite distance to any exact zero-weight edge, which is therefore effectively excluded from shortest-path computation—analogue to the treatment of an absent connection in a thresholded graph, but without requiring an arbitrary threshold to be defined a priori.

C_w and L_w values were normalized within each subject by dividing each band-specific metric by the global mean across all considered bands (Delta-Beta), to mitigate inter-individual variability [41,42].

To characterize the small-world configuration of the networks, we calculated a small-world coefficient (Sw) derived from the ratio between the normalized clustering coefficient and the normalized characteristic path length relative to equivalent random networks ($C_{w_{rand}}$ and $L_{w_{rand}}$). In fact, a small-world normalization was applied, benchmarking each band's topology against a degree- and weight-matched random null network [12,43].

The Sw coefficient measures the balance between the local connectedness and the global integration of a network and it is calculated for each subject. This is a scaled measure indicating the Sw property of the network when the ratio is higher than 1. Sw is described by the following equation:

$$Sw = \frac{C_w/C_{w_{rand}}}{L_w/L_{w_{rand}}}$$

In such case, L_w is similar to that of a random equivalent graph and/or the network's C_w is larger than that of the equivalent random graph.

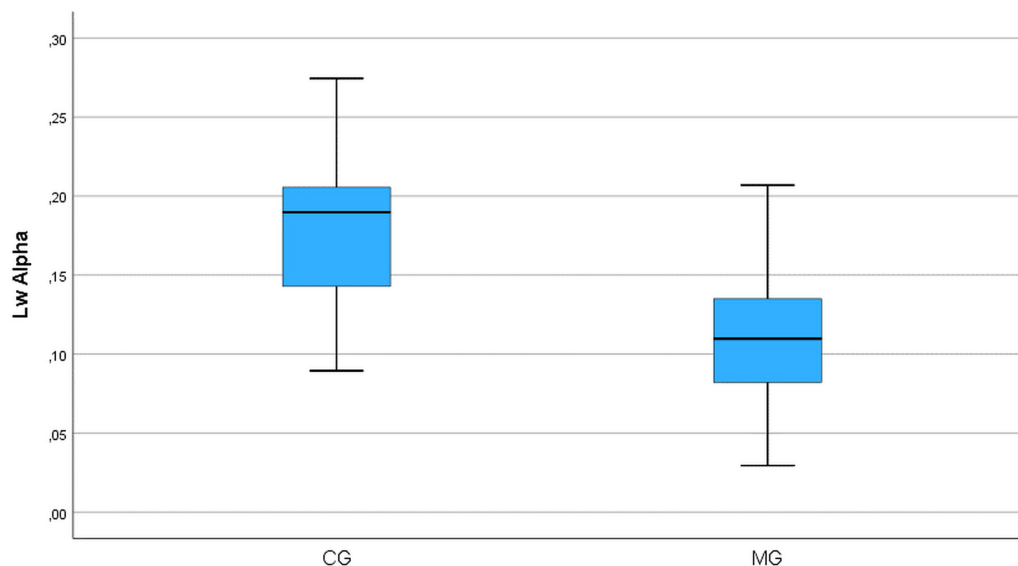


Fig. 1. Lw in the alpha band. Comparison between MG and CG (Mann–Whitney U test). Boxes represent the median and interquartile range (IQR; 25th–75th percentile); whiskers indicate values within $1.5 \times$ IQR. Lw, shortest path length; MG, MENSA group; CG, control group.

2.5 Statistical Analysis

Statistical analyses were performed using IBM SPSS Statistics Version 29.0 (IBM Corp., Armonk, NY, USA). Because Shapiro–Wilk tests indicated deviations from normality, group comparisons between MG and CG were conducted using the Mann–Whitney U test for each graph metric (Cw, Lw, Sw) across all frequency bands (δ , θ , α , β). To account for the increased risk of false positives arising from multiple comparisons ($4 \text{ frequency bands} \times 3 \text{ graph metrics} = 12 \text{ tests}$), Benjamini–Hochberg (BH) critical values were used for significance assessment [44] (**Supplementary Table 1**).

Outliers for each graph metric within each frequency band were identified using the standard Tukey boxplot criterion, i.e., values below $Q1 - 1.5 \times \text{interquartile range (IQR)}$ or above $Q3 + 1.5 \times \text{IQR}$ of the group-specific distribution, consistent with the convention used to display the whiskers in Figs. 1,2,3. In addition, we have also performed a sensitivity analysis, re-running the Mann–Whitney U test excluding the outliers, and we have applied FDR also without the outliers (**Supplementary Table 2**).

Statistical significance was set at $p < 0.05$. In addition to p values, effect estimates with corresponding 95% confidence intervals were calculated for each metric and frequency band (**Supplementary Table 3**).

Between-group differences in demographic variables (age, years of education) were assessed using Mann–Whitney U test, and sex distribution was compared using the Chi-square test. Results are reported in Table 1.

This study is reported in accordance with the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) guidelines for case-control studies (**Supplementary Table 4**).

Descriptive parameters (mean, standard deviation, skewness, kurtosis) were extracted for every variable. When significant differences emerged, box-plot visualizations were used to illustrate the distribution of values across groups.

3. Results

Regarding differences in topological parameters between the MG and CG, in the alpha band the Lw was significantly lower in the MG (BH critical value = 0.004, 95% CI: 0.0293; 0.1104), indicating greater global integration compared with CG (Fig. 1). No significant differences were observed in Cw or Sw in the alpha band between MG and CG.

In beta band, Cw and Lw were significantly higher in the MG (respectively, BH critical value = 0.008, 95% CI: -0.0928 ; -0.0263 and BH critical value = 0.013, 95% CI: -0.1708 ; -0.0405) suggesting increased local specialization (Fig. 2) and reduced global integration (Fig. 3). No difference was observed in Sw in the beta band between MG and CG.

No significant differences were found in the delta or theta bands for Cw, Lw, or Sw between MG and CG (all BH critical values > 0.05 ; see **Supplementary Table 1** in the **Supplementary Material** for full results).

Regarding the sensitivity analysis, reported in **Supplementary Table 2** of the **Supplementary Material**, confirms that two of the three originally significant effects remained significant (BH critical value = 0.004 and BH critical value = 0.008).

Fig. 4 and Fig. 5 show the functional connectivity networks in representative subjects of MG and CG, respectively in alpha band (Fig. 4) and beta band (Fig. 5). These

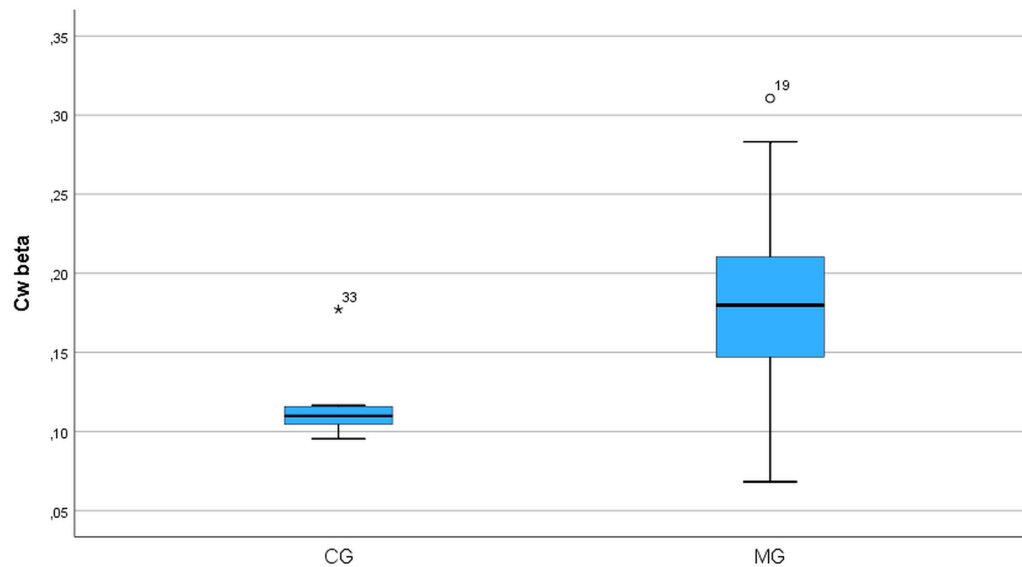


Fig. 2. Cw in the beta band. Comparison between MG and CG (Mann–Whitney U test). Boxes represent the median and interquartile range (IQR; 25th–75th percentile); whiskers indicate values within $1.5 \times \text{IQR}$. Cw, clustering coefficient.

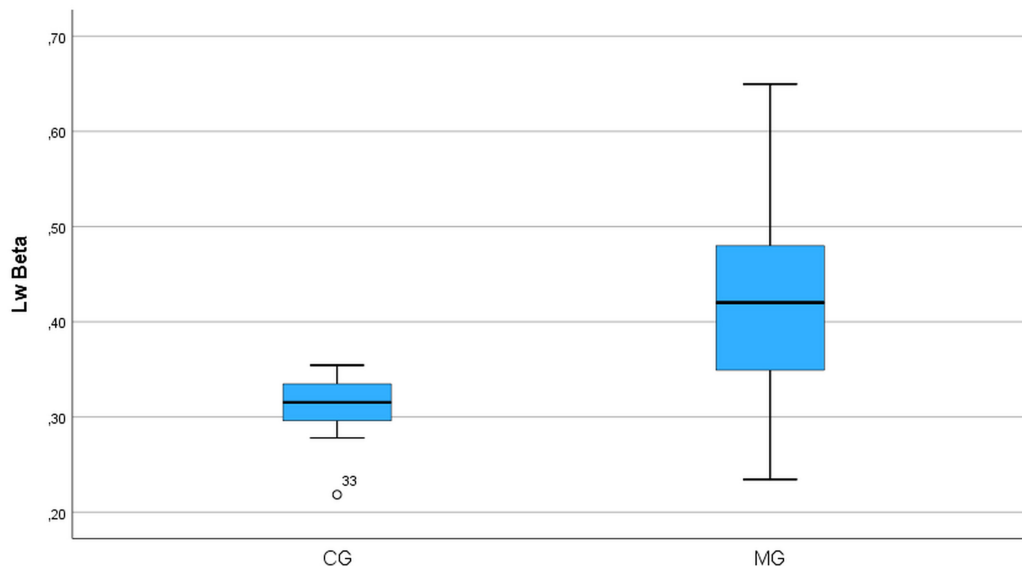


Fig. 3. Lw in the beta band. Comparison between MG and CG (Mann–Whitney U test). Boxes represent the median and interquartile range (IQR; 25th–75th percentile); whiskers indicate values within $1.5 \times \text{IQR}$.

renderings are provided for illustrative and qualitative purposes only. No regional or edge-level differences between groups should be inferred from visual inspection alone.

4. Discussion

Our findings are consistent with a frequency-dependent organization of brain networks in individuals with higher cognitive ability. They contribute to a complex and sometimes contradictory body of literature by suggesting that higher intelligence is not accompanied by a uniform increase in network efficiency, but rather by a differential balance between global integration and local specialization across spectral bands. Being cross-sectional

and observational, the present design supports statements of association only, and no causal or directional inference can be drawn from these data.

Specifically, we found that MG exhibited enhanced global integration in the alpha band, but a shift towards high local specialization and a trend toward lower global integration in the beta band. Alpha rhythms, which dominate the awake resting state, reflect thalamo-cortical and cortico-cortical interactions and are key indicators of synaptic integrity and large-scale network coordination [45]. Beta activity has been linked to top-down control, attention, and sensorimotor integration, domains often requiring precise local coordination [46,47].

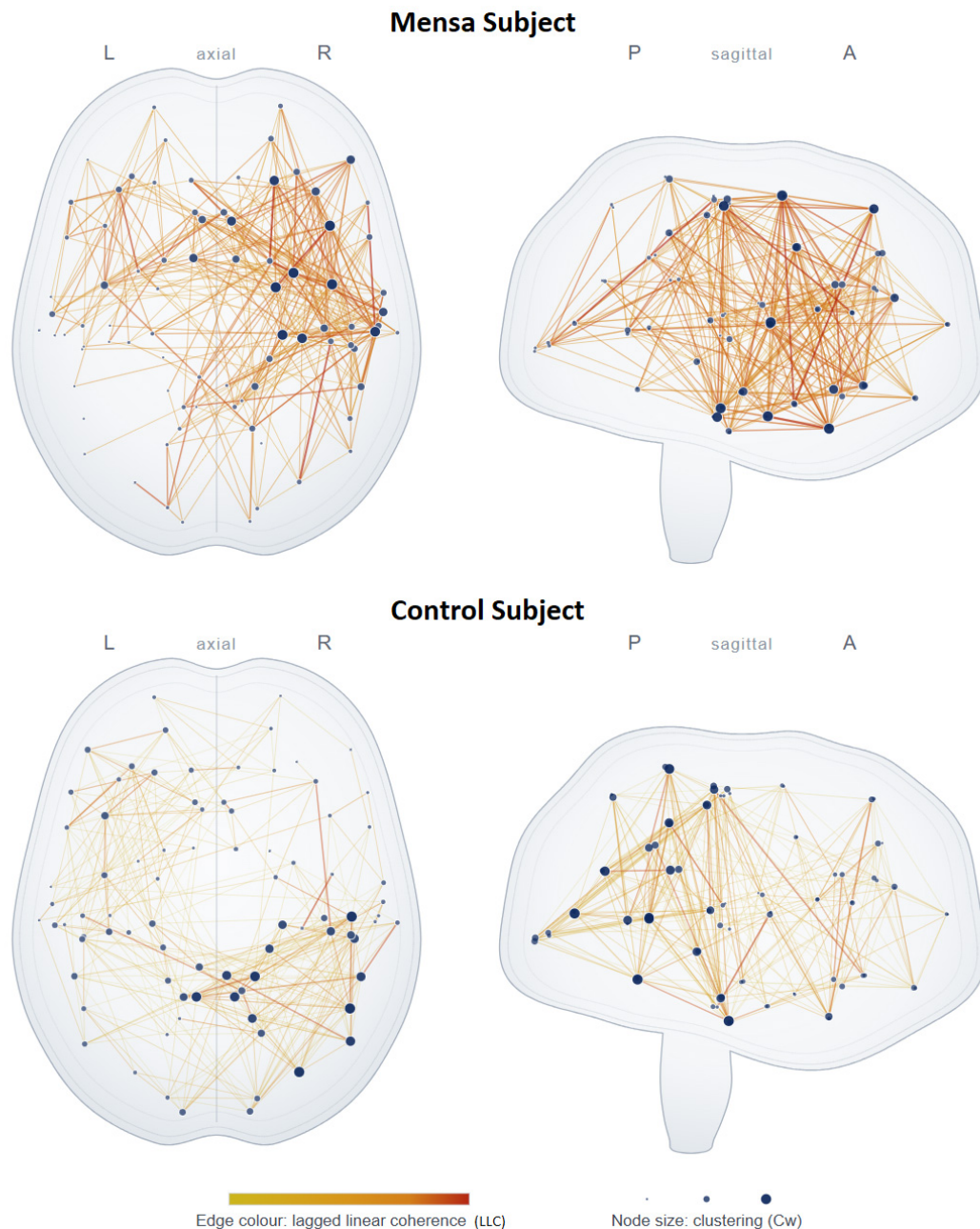


Fig. 4. Alpha-band resting-state functional connectivity networks in a representative MENSA subject (MG, top) and control subject (CG, bottom), shown in axial and sagittal views on a cortical template. Nodes represent the 84 Brodmann areas (42 per hemisphere) used as the source-space parcellation; node size encodes the weighted clustering coefficient (Cw) of each region. Edges represent lagged linear coherence (LLC) between region pairs, with colour scaling from yellow (low) to red (high).

Notably, despite these differences in Cw and Lw, we did not observe significant group differences in the Sw metric. While this contrasts with some studies that link high intelligence to a more pronounced small-world architecture [26,31], our finding is consistent with large-scale analyses that have questioned the reliability and consistency of Sw as a correlate of intelligence [35,48]. Accordingly, in a study by Santarnecchi et al. (2014) [32], interindividual variance in IQ was primarily explained by the efficiency of distributed communication supported by moderately weak,

long-distance connections, with a comparatively smaller contribution from strong local connections. These findings, in line with our results in the alpha band, support the notion that distributed communication efficiency, rather than local clustering alone, could be a key neural correlate of intelligence, highlighting the relevance of global integration of the network in shaping the functional architecture underlying IQ variability.

To place this finding in a broader neurobiological context, it is informative to consider pathological models of

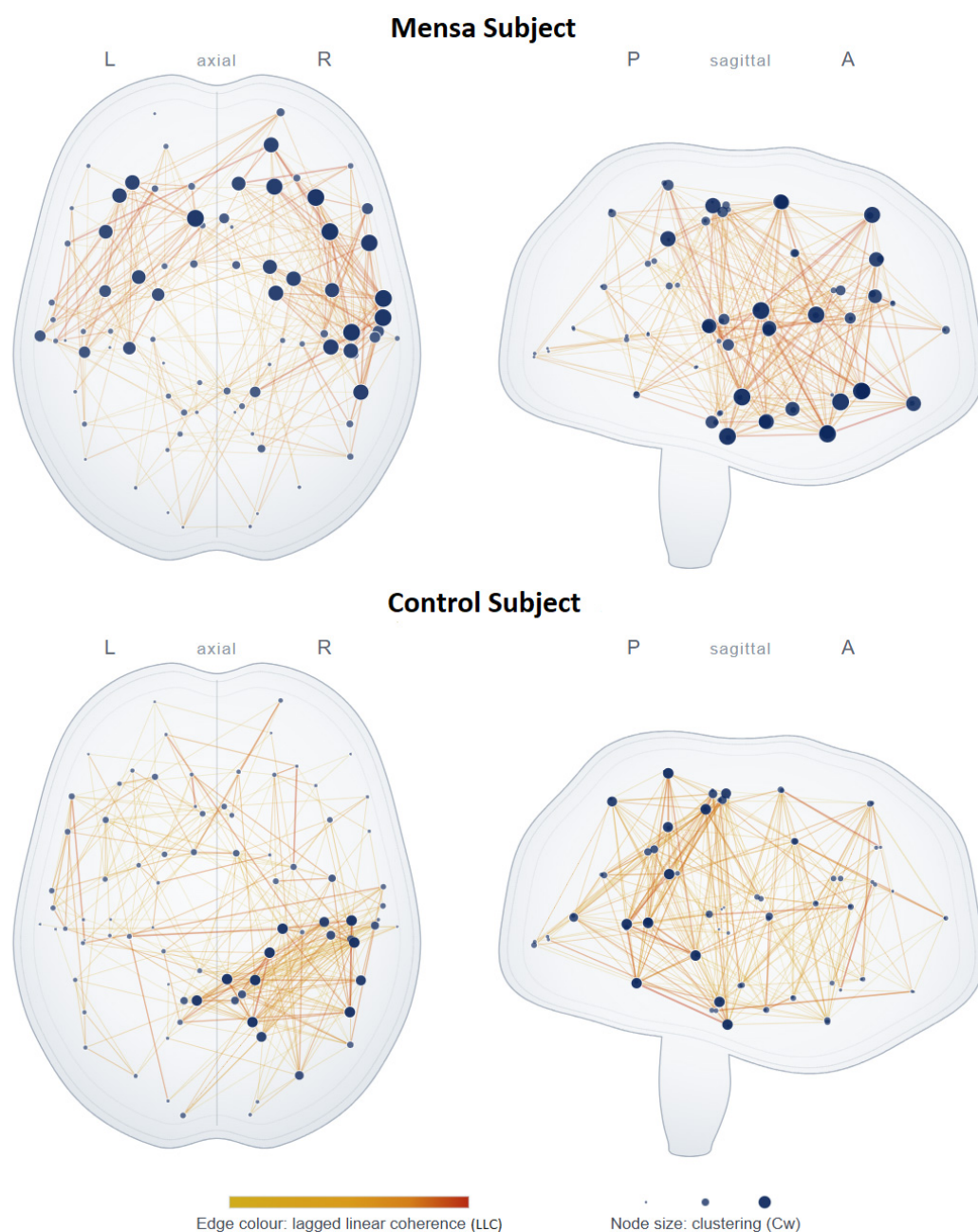


Fig. 5. Beta-band resting-state functional connectivity networks in a representative MENSA subject (MG, top) and control subject (CG, bottom), shown in axial and sagittal views on a cortical template. Nodes represent the 84 Brodmann areas (42 per hemisphere) used as the source-space parcellation; node size encodes the weighted clustering coefficient (Cw) of each region. Edges represent lagged linear coherence (LLC) between region pairs, with colour scaling from yellow (low) to red (high).

network reorganization. In our previous work on acute stroke patients, alpha2-band networks showed bilaterally reduced Lw (accompanied by increased Sw), reflecting a frequency-specific reorganization of large-scale connectivity in response to focal structural damage [12,49]. Importantly, in that pathological context, we interpreted the reduced path length and increased global integration in the alpha band as a compensatory response to damage [49]. Thus, the stroke model helps to contextualize our findings with a key distinction: in acute stroke, reduced alpha-band Lw re-

flects compensatory network reorganization in response to injury, whereas in high-IQ individuals it may reflect an intrinsically optimized alpha-band architecture within an intact brain network. The alpha-band topology observed in MG could therefore represent an organizational feature potentially related to network resilience and cognitive reserve in high-IQ individuals [26,50].

However, whether the topology observed here is specifically related to network resilience or cognitive reserve cannot be determined from the present cross-sectional

resting-state data and should therefore remain a hypothesis for future longitudinal and task-based studies.

In the beta band, MG showed a higher clustering coefficient, suggesting greater local connectivity. We also observed an increase in beta-band Lw (suggesting reduced global integration); however, this finding did not survive the sensitivity analysis after outlier exclusion (**Supplementary Table 2**) and should therefore be regarded as a less robust finding compared with the beta-band Cw effect, which remained significant. The role of the beta band in top-down visual-attentional processing is widely documented [51,52,53]; in addition, beta waves are linked to intense brain activity, stress, active thinking, and focus, among other circumstances [54,55]. Although the role of beta oscillations in the cognitive process has been explored less than alpha, some evidence suggests that they are related to the state of attention [56]. Previous studies reported increased clustering in working memory networks during retention after training, together with enhanced frontoparietal beta-band synchronization [57]. As detailed in the methods, in this study, EEG was recorded in the resting state. Therefore, our findings that the beta band exhibits a higher clustering coefficient in MG during resting-state conditions may reflect an enhanced tendency toward network clustering within the beta frequency range in individuals with higher IQ scores, even in the absence of task demands. This suggests a greater intrinsic beta-band clustering activity in high-IQ subjects.

The absence of statistically significant differences in clustering coefficient, path length and small-worldness within the delta and theta bands between MG and CG may reflect the conserved role of low-frequency oscillations in supporting large-scale homeostatic regulation and thalamo-cortical entrainment during resting state (processes that show limited modulation by individual differences in intelligence) rather than the frequency-specific cortico-cortical network reconfiguration observed here in alpha (lower Lw in MG, BH critical value = 0.004) and beta (higher Cw in MG, BH critical value = 0.008 and higher Lw BH critical value = 0.013 in MG) bands, a pattern that would be compatible with neural efficiency models linking higher cognitive ability to integration and local specialization in faster rhythms [58,59,60], although the present design does not allow this interpretation to be tested directly.

Limitations

Some limitations should be acknowledged. First, all results were derived from resting-state recordings rather than cognitive task performance. Second, the sample size was modest and restricted to a relatively young age range (~30 years), limiting the generalizability of findings. Third, several factors known to modulate resting-state EEG were not controlled: caffeine intake, sleep duration on the preceding night and time of day of the recording were not systematically recorded, so that residual confounding by

vigilance-related factors cannot be excluded. Further studies are warranted to explore how these resting-state patterns manifest during cognitively demanding tasks.

5. Conclusions

In conclusion, our data are compatible with a frequency-dependent organization of cortical networks in individuals with high IQ, characterized by greater alpha-band integration and greater beta-band local specialization, in the absence of differences in small-world architecture. Given the cross-sectional design and the size of the sample, these findings should be regarded as associative and require replication in larger and independent samples before conclusions can be drawn about the network mechanisms underlying interindividual differences in intelligence.

Abbreviations

GT, Graph theory; Cw, clustering coefficient; Lw, shortest path length; IQ, Intelligence Quotient; MG, MENSA group; CG, control group; ICA, Independent Component Analysis; LLC, Lagged Linear Coherence.

Availability of Data and Materials

All data reported in this paper will be shared by the corresponding author upon request.

Author Contributions

MM: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Visualization, Writing – original draft, Writing – review and editing. AZ: Investigation, Data curation, Writing – review and editing. CI: Investigation, Data curation, Writing – review and editing. GR: Methodology, Formal analysis, Validation, Writing – review and editing. MG: Supervision, Validation, Writing – review and editing. ELC: Data Curation and Validation, Supervision, Writing – review and editing. MSDG: Data Curation and Validation, Supervision, Project administration, Writing – review and editing. AT: Data Curation and Validation, Supervision, Writing – review and editing. SR: Methodology, Formal analysis, Validation, Writing – review and editing. PC: Conceptualization, Supervision, Project administration, Validation, Writing – review and editing. All authors have read and agreed to the published version of the manuscript. All authors have participated sufficiently in the work and agreed to be accountable for all aspects of the work.

Ethics Approval and Consent to Participate

The study protocol was approved by the Institutional Review Board of Fondazione Policlinico Universitario A. Gemelli IRCCS (protocol number 0045291/21) and was conducted in accordance with the Declaration of Helsinki. All participants provided written informed consent prior to enrolment.

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Conflicts of Interest

The authors declare no conflicts of interest. Given his role as an Editorial Board member, Pietro Caliendo had no involvement in the peer review of this article and has no access to information regarding its peer review. Full responsibility for the editorial process for this article was delegated to Bettina Platt.

Declaration of AI and AI-Assisted Technologies in the Writing Process

During the preparation of this work, the authors used Claude (Sonnet 5) solely to assist with compliance with the journal's editorial guidelines and formatting requirements. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Supplementary Material

Supplementary material associated with this article can be found, in the online version, at <https://doi.org/10.31083/JIN56100>.

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