

Supplemental Text

Text S1. Definitions of network metrics

Network strength. For a network (graph) G with N nodes and K edges, we calculated the strength of G as:

$$S_p(G) = \frac{1}{N} \sum_{i \in G} S(i)$$

where $S(i)$ is the sum of the edge weights w_{ij} linking to node i . The strength of a network is the average of the strength across all of the nodes in the network.

Small-world properties. Small-world network parameters (clustering coefficient, C_p and shortest path length, L_p) were originally proposed by Watts and Strogatz ¹. In this study, we investigated the small-world properties of the weighted brain networks.

The clustering coefficient of a node i , $C(i)$, which was defined as the likelihood of whether the neighborhoods were connected with each other or not, was computed as follows ²:

$$C(i) = \frac{2}{k_i(k_i - 1)} \sum_{j,k} (\bar{w}_{ij} \bar{w}_{jk} \bar{w}_{ki})^{1/3}$$

where k_i is the degree of node i and \bar{w} is the weight of edge, which is scaled by the largest weight of the network. The clustering coefficient is zero if the nodes are isolated or have just one connection, i.e., $k_i = 0$ or $k_i = 1$. The clustering coefficient, C_p , of a network is the average of the clustering coefficient over all nodes and indicates the extent of the local interconnectivity or cliquishness in a network ¹.

The path length between any pair of nodes (e.g., node i and node j) is defined as the

sum of the edge lengths along this path. For weighted networks, the length of each edge was assigned by computing the reciprocal of the edge weight, $1/w_{ij}$. The shortest path length, L_{ij} , is defined as the length of the path for node i and node j with the shortest length. The shortest path length of a network was computed as follows:

$$L_p(G) = \frac{1}{N(N-1)} \sum_{i \neq j \in G} L_{ij}$$

where N is the number of nodes in the network. The L_p of a network quantifies the ability for information to propagate in parallel.

To examine the small-world properties, the clustering coefficient, C_p , and the shortest path length, L_p , of the brain networks were compared with those of random networks. In this study, we generated 100 matched random networks, which had the same number of nodes, edges, and degree distribution as the real networks³. Of note, we retained the weight of each edge during the randomization procedure such that the weight distribution of the network was preserved. Furthermore, we computed the normalized L_p , $\lambda = L_p^{real} / L_p^{rand}$, and the normalized C_p , $\gamma = C_p^{real} / C_p^{rand}$, where L_p^{rand} and C_p^{rand} are the mean L_p and the mean C_p of 100 matched random networks, respectively. Importantly, two parameters correct the differences in the edge number and degree distribution of the networks across individuals. A real network would be considered small-world if $\gamma > 1$ and $\lambda \approx 1$. Thus, a small-world network not only has a higher local interconnectivity, but it also has an approximately equivalent shortest path length compared with random networks. These two measurements can be summarized into a simple quantitative metric,

small-worldness, $\sigma = \gamma / \lambda$, which is typically greater than 1 for small-world networks ⁴.

Network efficiency. The global efficiency of G measures the global efficiency of the parallel information transfer in the network ⁵, which can be computed as:

$$E_{glob}(G) = \frac{1}{N(N-1)} \sum_{i \neq j \in G} \frac{1}{L_{ij}}$$

where L_{ij} is the shortest path length between node i and node j in G.

The local efficiency of G reveals how much the network is fault tolerant and shows how efficient the communication is among the first neighbors of the node i when it is removed. The local efficiency of a graph is defined as:

$$E_{loc}(G) = \frac{1}{N} \sum_{i \in G} E_{glob}(G_i)$$

where G_i denotes the subgraph composed of the nearest neighbors of node i.

Regional nodal characteristics. To determine the nodal (regional) characteristics of the brain networks, we computed the nodal efficiency, $E_{nodal}(i)$, which is defined as ⁶:

$$E_{nodal}(i) = \frac{1}{N-1} \sum_{i \neq j \in G} \frac{1}{L_{ij}}$$

where L_{ij} is the shortest path length between node i and node j in G. $E_{nodal}(i)$ measures the average shortest path length between a given node i and all of the other nodes in the network.

References

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4. Humphries, M.D. & Gurney, K. Network 'small-world-ness': a quantitative method for determining canonical network equivalence. *PLoS ONE* **3**, e0002051 (2008).
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Table S1. Cortical and subcortical regions of interest defined in the study

Index	Regions	Abbr.	Index	Regions	Abbr.
(1,2)	Precentral gyrus	PreCG	(47,48)	Lingual gyrus	LING
(3,4)	Superior frontal gyrus, dorsolateral	SFGdor	(49,50)	Superior occipital gyrus	SOG
(5,6)	Superior frontal gyrus, orbital part	ORBsup	(51,52)	Middle occipital gyrus	MOG
(7,8)	Middle frontal gyrus	MFG	(53,54)	Inferior occipital gyrus	IOG
(9, 10)	Middle frontal gyrus, orbital part	ORBmid	(55,56)	Fusiform gyrus	FFG
(11,12)	Inferior frontal gyrus, opercular part	IFGoperc	(57,58)	Postcentral gyrus	PoCG
(13,14)	Inferior frontal gyrus, triangular part	IFGtriang	(59,60)	Superior parietal gyrus	SPG
(15,16)	Inferior frontal gyrus, orbital part	ORBinf	(61,62)	Inferior parietal, but supramarginal and angular gyri	IPL
(17,18)	Rolandic operculum	ROL	(63,64)	Supramarginal gyrus	SMG
(19,20)	Supplementary motor area	SMA	(65,66)	Angular gyrus	ANG
(21,22)	Olfactory cortex	OLF	(67,68)	Precuneus	PCUN
(23,24)	Superior frontal gyrus, medial	SFGmed	(69,70)	Paracentral lobule	PCL
(25,26)	Superior frontal gyrus, medial orbital	ORBsupmed	(71,72)	Caudate nucleus	CAU
(27,28)	Gyrus rectus	REC	(73,74)	Lenticular nucleus, putamen	PUT
(29,30)	Insula	INS	(75,76)	Lenticular nucleus, pallidum	PAL
(31,32)	Anterior cingulate and paracingulate gyri	ACG	(77,78)	Thalamus	THA
(33,34)	Median cingulate and paracingulate gyri	DCG	(79,80)	Heschl gyrus	HES
(35,36)	Posterior cingulate gyrus	PCG	(81,82)	Superior temporal gyrus	STG
(37,38)	Hippocampus	HIP	(83,84)	Temporal pole: superior temporal gyrus	TPOsup
(39,40)	Parahippocampal gyrus	PHG	(85,86)	Middle temporal gyrus	MTG
(41,42)	Amygdala	AMYG	(87,88)	Temporal pole: middle temporal gyrus	TPOmid
(43,44)	Calcarine fissure and surrounding cortex	CAL	(89,90)	Inferior temporal gyrus	ITG
(45,46)	Cuneus	CUN			

Note: The regions are listed in terms of a prior template of an AAL-atlas (Tzourio-Mazoyer et al., 2002).