Supplementary Material

Disrupted topology of frontostriatal circuits is linked to the severity of insomnia

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1 Supplementary Methods

Network Analysis

Small-world network parameters

The functional connectivity network can be evaluated using graph theory analysis in which a network comprised the nodes and edges. For an $N \times N$ ($N = 90$ indicates 90 nodes in the present study) binary undirected graph $G$, the topological properties were defined on the basis of the following graph construction:

$$e_{ij} = \begin{cases} 1, \text{ if } |z_{ij}| \geq T \\ 0, \text{ otherwise} \end{cases},$$

If the absolute $z_{ij}$ (the Fisher $r$-to-$z$ of the partial correlation coefficient between node $i$ and node $j$) exceeds a given threshold $T$, an undirected edge is said to exist; otherwise it does not exist.

The clustering coefficient of a node $i$ is defined as the ratio of the number of existing connections among the node’s neighbors to the number of all possible connections in the subgraph $G_i$ (Onnela et al., 2005) and is expressed as:
\[ C_i = \frac{E_i}{K_i(K_i-1)/2}, \]

in which \( E_i \) and \( K_i \) denote the number of edges and nodes respectively in the subgraph \( G_i \). Then the clustering coefficient of a functional connectivity network is the average of the clustering coefficients of all nodes:

\[ C_p = \frac{1}{N} \sum_{i \in G} C_i, \]

it measures the local interconnectivity of a network.

The mean shortest path length of a node \( i \) is defined as:

\[ L_i = \frac{1}{N-1} \sum_{i \neq j \in G} \min |L_{ij}|, \]

where \( \min |L_{ij}| \) is the absolute shortest path length (i.e. the smallest number of edges traversed between two nodes) between node \( i \) and node \( j \). The mean shortest path length of a network is then the average of the shortest path lengths between the nodes:

\[ L_p = \frac{1}{N} \sum_{i \in G} L_i, \]

The normalized clustering coefficient \( \gamma = \frac{C_p}{C_{\text{random}}} \) and normalized characteristic path length \( \lambda = \frac{L_p}{L_{\text{random}}} \) were computed, where \( C_p \) and \( L_p \) indicate the mean clustering coefficient and shortest path length of the functional connectivity network, respectively. \( C_{\text{random}} \) and \( L_{\text{random}} \) represent the mean clustering coefficient and shortest path length of 100 matched random networks that preserved the same number of nodes, edges, and degree distribution as the real network (Sporns and Zwi, 2004; Ding et al., 2011). Typically, a small-word network meet the conditions of \( \gamma > 1 \) and \( \lambda \approx 1 \), and therefore, the small-wordness scalar \( \sigma = \lambda/\gamma \) will be more than 1.

**Efficiency of small-world networks**

Network efficiency can be measured by global efficiency, \( E_{\text{glo}} \), local efficiency, \( E_{\text{loc}} \)
and nodal efficiency, $E_{nodal}$, $E_{glo}$ and $E_{loc}$ described the ability of information transmission of a network at the global and local level, respectively. The global efficiency $E_{glo}$ of a network is the inverse of the harmonic mean of the shortest path length between each pair of nodes (Latora and Marchiori, 2001; Achard and Bullmore, 2007):

$$E_{glo} = \frac{1}{N(N-1)} \sum_{i \neq j \in G} \frac{1}{\text{min}|L_{ij}|},$$

where $\text{min}|L_{ij}|$ is the absolute shortest path length between node $i$ and node $j$ in network $G$. It indicates the capability of parallel information transfer through the whole network.

The nodal efficiency $E_{nodal}$ of a node $i$ is calculated as:

$$E_{nodal}(i) = \frac{1}{N-1} \sum_{j,k \in G} \frac{1}{\text{min}|L_{jk}|},$$

The local efficiency $E_{loc}$ denoted the mean of all the local efficiencies of the nodes in subgraph $G_i$ which is defined as:

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

where $E_{nodal}(i) = E_{glo}(G_i)$. Since the node $i$ is not an element of the subgraph $G_i$, the local efficiency can also be considered as a measure of the fault tolerance of the network, suggesting how well each subgraph exchanges information when the node $i$ was eliminated (Achard and Bullmore, 2007).

The integrated area under curve (AUC) of a network metric $Y$ was computed over the sparsity threshold range from $S_1$ to $S_n$ with interval of $\Delta S$, which was expressed as:

$$Y^{AUC} = \sum_{k=1}^{n-1}[Y(S_k) + Y(S_{k+1})] \times \Delta S/2.$$
## 2 Supplementary Tables

Table S1.

Anatomical regions of interest (ROIs) and abbreviated regional labels.

| Region name                                      | Abbr.  | Region name                                      | Abbr.  |
|------------------------------------------------|--------|------------------------------------------------|--------|
| Precentral gyrus                                | PreCG  | Lingual gyrus                                   | LING   |
| Superior frontal gyrus                          | SFG    | Superior occipital gyrus                         | SOG    |
| Superior frontal gyrus, orbital                 | SFGorb | Middle occipital gyrus                           | MOG    |
| Middle frontal gyrus                            | MFG    | Inferior occipital gyrus                         | IOG    |
| Middle frontal gyrus, orbital                   | MFGorb | Fusiform gyrus                                   | FG     |
| Inferior frontal gyrus, opercular part          | IFGoper| Postcentral gyrus                                | PoCG   |
| Inferior frontal gyrus, triangular              | IFGtri | Superior parietal gyrus                          | SPG    |
| Inferior frontal gyrus, orbital                 | IFGorg | Inferior parietal gyrus                          | IPG    |
| Rolandic operculum                              | ROL    | Supramarginal gyrus                              | SMG    |
| Supplementary motor area                        | SMA    | Angular gyrus                                    | ANG    |
| Olfactory cortex                                | OLF    | Precuneus                                        | PCUN   |
| Superior frontal gyrus, medial                  | SFGmed | Paracentral lobule                               | PCL    |
| Superior frontal gyrus, medial orbital          | SFGmorb| Caudate nucleus                                  | CAU    |
| Gyrus rectus                                     | REG    | Putamen                                          | PUT    |
| Insula                                          | INS    | Pallidum                                         | PAL    |
| Anterior cingulate gyri                         | ACC    | Thalamus                                         | THA    |
| Median cingulate gyri                           | MCC    | Heschl gyrus                                     | HES    |
| Posterior cingulate gyrus                       | PCC    | Superior temporal gyrus                          | STG    |
| Hippocampus                                     | HIP    | Superior temporal gyrus: temporal pole           | STGp   |
| Parahippocampal gyrus                           | PHP    | Middle temporal gyrus                            | MTG    |
| Amygdala                                        | AMYG   | Middle temporal gyrus: temporal pole             | MTGp   |
| Calcarine fissure                               | CAL    | Inferior temporal gyrus                          | ITG    |
| Cuneus                                          | CUN    |                                                  |        |

The regions are listed according to a prior AAL atlas (Tzourio-Mazoyer et al., 2002).

Abbr., abbreviations.
Table S2.

Introduction of topological properties in the brain functional network.

| Properties      | Descriptions                                                                                                                                 |
|-----------------|----------------------------------------------------------------------------------------------------------------------------------------------|
| **Global network properties**                                                                                                                   |                                                                                             |
| $C_p$           | Clustering coefficient of a network which measures the local interconnectivity of a network. It is the average of the clustering coefficients over all nodes. |
| $L_p$           | Path length of a network which quantified the level of overall routing efficiency of a network. It is the mean minimum number of connections between any two nodes in the network. |
| $E_{glo}$       | Global efficiency of a network which indicates the capability of parallel information transfer through the whole network. It is the inverse of the harmonic mean of the minimum path length between any two nodes in the network. |
| $E_{loc}$       | Local efficiency of a network which captures the fault tolerance of a network. It is the average of the local efficiency over all nodes.         |
| **Local network properties**                                                                                                                     |                                                                                             |
| $Deg_i$         | Nodal degree which evaluates the extent to which the node is connected to the rest of other nodes in a network.                               |
| $E_{nodal}$     | Nodal local efficiency which measures the level of information propagation of a node with all other nodes in the network.                   |
| $BC_i$          | Betweenness which estimates the influence of a node over information flow with the rest of the nodes in a network.                         |
Reference

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