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Brain network alterations in mobile phone use problem severity: A multimodal neuroimaging analysis

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ABSTRACT

Background and aims: Problematic mobile phone use can disrupt social interaction and well-being, potentially influencing cognitive processes. This study investigated whether mobile phone use problem severity is associated with alterations in the topological organization of brain networks. *Methods:* Rs-fMRI and DTI data were collected from 81 healthy participants. Graph theory analyses were applied. The Mobile Phone Problem Use Scale-10 (MPPUS-10) was used to assess mobile phone use problem severity. Correlation analyses were conducted between each graph metric and questionnaire scores. *Results:* MPPUS-10 scores correlated with global fMRI metrics: higher scores linked to longer shortest path length (reduced integration) and lower global efficiency (reduced information transfer). Conversely, higher MPPUS-10 scores were correlated with a greater clustering coefficient and higher local efficiency, which reflect increased local connectivity. Furthermore, higher MPPUS-10 scores were associated with a higher sigma value from DTI, indicating altered structural network properties. Some specific brain regions also showed significant correlations with MPPUS-10 scores. *Discussion and conclusion:* These findings indicate that higher mobile phone use problem severity is associated with decreased integration and increased segregation of functional networks, alongside enhanced small-worldness in structural networks. Reduced integration aligns with addiction theories suggesting digital overload worsens network dysfunction, disrupting brain connectivity. Additionally, higher severity was correlated with altered connectivity in multiple regions, such as the precentral gyrus, supplementary motor area, and postcentral gyrus. These regions are associated with motor control, sensorimotor processing, and memory function. Further research is needed to explore whether these findings reflect shifts in the integration and integrity of brain information-processing modules.

KEYWORDS

problematic mobile phone use (PMPU), mobile phone use problem severity, brain network topological properties, graph theory analysis, functional and structural networks, digital addiction

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INTRODUCTION

The term "problematic mobile phone use" (PMPU) was first proposed in 2012 to describe situations wherein individuals struggle to control their mobile phone use, leading to negative impacts on their daily lives (Billieux, 2012). With the rapid proliferation of smartphones, the majority of mobile phones today are smartphones; in today's society, the two are nearly synonymous (Matthes, Thomas, Stevic, & Schmuck, 2021). The psychological and behavioral dependence caused by PMPU can lead individuals to excessively use their phones, exhibiting core symptoms similar to addiction.

In related studies (Bianchi & Phillips, 2005; Foerster, Roser, Schoeni, & Röösli, 2015), scales assessing PMPU were commonly used to measure the mobile phone use problem severity. Given the significant differences in average scores across samples from different countries (Kalaitzaki et al., 2024) and considering that these scales are not diagnostic tools (Demkow-Jania et al., 2021), such variations may not only reflect limitations of the scale (e.g., lack of a standard cut-off) but also cultural or environmental differences. Nevertheless, many studies despite various recommendations on threshold cut-offs continue to focus on the impact of the severity of mobile phone use problems. For example, research on the association between different personality traits and the mobile phone use problem severity has found that individuals with high neuroticism are more likely to be associated with more severe mobile phone use issues, while those with high conscientiousness are more likely to avoid this (Marengo, Poletti, & Settanni, 2020; Marengo, Sindermann, et al., 2020). PMPU has been linked to a wide range of negative effects on mood, physical health, occupational performance, and social performance (Cheng et al., 2024; Kalaitzaki et al., 2024; Wacks & Weinstein, 2021). Notably, the root cause of mobile phone-related issues is not the device itself but the multitude of functions it offers (Jeong, Kim, Yum, & Hwang, 2016). The constant influx of information and the uninterrupted access provided by mobile phones often result in "fragmented information" and lead to a "fragmentation of daily life" (Dai, Tai, & Ni, 2021; Matthes, Karsay, Schmuck, & Stevic, 2020). The overwhelming stream of fragmented information exceeds individuals' limited cognitive resources for encoding, storing, and retrieving information (Lang, 2000). This imbalance between environmental demands and cognitive resources (Lee, Son, & Kim, 2016) can impair cognitive functions such as memory, judgment, and decision-making (Primack et al., 2017).

Daily experiences require the processing of external signals and internal information retrieved from memory. PMPU can lead to an information burden and a heavy reliance on external sources for daily decisions and behaviours (Cataldo, Billieux, Esposito, & Corazza, 2022; Fineberg et al., 2022). For example, reliance on health apps for health management may cause individuals to neglect bodily signals in favor of meeting predefined metrics, leading to anxiety and stress when targets are unmet. Research suggests that excessive dependence on external information can shift mental activity away from internal reflection toward outward exploration, potentially making cognitive and emotional processing more vulnerable (Cataldo et al., 2022; Fineberg et al., 2022). This may result in decreased integration of internal information-processing modules in the brain (Tei et al., 2020; Toker & Sommer, 2019); the decrease is caused by increased transparency or blurred distinctions between external information sources and internal processing modules (Verschooren, Schindler, De Raedt, & Pourtois, 2019; Vonitsanos, Grivokostopoulou, Moustaka, & Kanavos, 2023). Graph theory can be utilized to evaluate this hypothesis by analyzing the topological properties of functional and structural brain networks, quantifying brain network integration (how interconnected different parts of the brain are) and segregation (the extent to which different parts of the brain are independent; Mheich, Wendling, & Hassan, 2020).

The human brain's networks may be optimised to balance minimising wiring costs (neuronal connections) and maximising adaptive value, thereby ensuring robust and efficient brain network organization (Bullmore & Sporns, 2012). Adaptive behaviours, such as information processing capacity and robustness to adverse perturbations, are likely linked to topological properties (Achard & Bullmore, 2007). The topological organization of brain networks significantly impacts their function, performance, and behaviour (Bashan, Bartsch, Kantelhardt, Havlin, & Ivanov, 2012). Concurrent high local and global efficiency is thought to enhance information processing and mental representations (Bullmore & Sporns, 2009). In graph theory, the brain is modelled as a network of nodes (brain regions) and edges (connections) (Liao, Vasilakos, He, & Reviews, 2017), with the complete set of pairwise connections defining the graph's topological organization (Sporns, 2018). Nodal metrics (e.g., degree centrality and betweenness centrality) and global metrics (e.g., small-worldness and clustering coefficient) are commonly utilized to assess these topological properties (Rubinov & Sporns, 2010; Sporns, 2018). Prior research has exhibited that the topological organization of functional networks is closely linked to cognitive performance variations (Lynall et al., 2010; Zhang et al., 2021). Structural networks, characterised by physical connections like neural fibre tracts, are crucial for understanding inter-regional connectivity and illustrate the spatial economy of the brain's layout (Chklovskii, Schikorski, & Stevens, 2002). However, the specific brain network changes that underlie PMPU remain unclear. A multimodal approach, incorporating both functional and structural network analyses, may provide a more comprehensive understanding of PMPU.

Based on the above, we hypothesised that as the mobile phone use problem severity increases, clusters of brain information-processing modules will strengthen their links with external information sources while weakening global internal connectivity among these modules. More specifically, we predicted that mobile phone use problem severity is associated with a shift in the balance between

network-integration and network-segregation among information-processing modules, shifting in the direction of more segregation. This study aimed to investigate this hypothesis by examining changes in the topological organization of brain networks resulting from mobile phone use problem severity, utilising graph theory analysis. To test this hypothesis, we obtained scores on mobile phone use problem severity and structural and functional MRI data from participants, and graph theory analysis was conducted on the brain images. We explored the issue of behavioral addiction related to PMPU by investigating how topological metrics correlate with the severity of mobile phone use problem severity; the findings provide a more nuanced understanding of its relationship with brain network organization.

METHODS

Participants

This study recruited 82 participants through advertisements and individual contact, including word-of-mouth and personal referrals from researchers' acquaintances. Participants were recruited without requiring self-reported mobile phone use problems, and no specific criteria or cutoff scores were used to determine eligibility based on problematic mobile phone use. As a result, individuals with and without such issues could be included. The participants were enrolled from July 2017 to February 2019. Data were collected at the Kyoto University Hospital in Japan. All participants were free from prior psychiatric disorders or severe medical conditions, as confirmed by two licensed psychiatrists through the Structured Clinical Interview for DSM Disorders, Non-Patient Edition.

Measures

The Mobile Phone Problem Use Scale-10 (MPPUS-10) was utilized to assess mobile phone use problem severity. This scale is a simplified version of the MPPUS-27 developed by Foerster et al. (2015). It comprises 10 items rated on a Likert scale from 1 ("not true at all") to 10 ("extremely true"). Total scores range from 10 to 100, with higher scores indicating more severe issues with mobile phone utilisation. While previous studies, such as Nahas, Hlais, Saberian, and Antoun (2018), have established a cut-off score of 59 on the Mobile Phone Problem Use Scale-10 (MPPUS-10) to define PMPU in a Lebanese sample, it is unclear whether this threshold is universally applicable across diverse cultural contexts. Therefore, in this study, we focus on the concept of 'mobile phone use problem severity' rather than adhering strictly to predefined cut-off scores for problematic use. We followed the translation process outlined by Fujiwara et al. (2018) to create a Japanese version of the questionnaire to ensure that participants fully understood each item. This process involved a qualified clinical psychiatrist and a cognitive science researcher experienced in translating psychological measures. Both were fluent in Japanese and English. Discrepancies in translation were resolved by a psychometric expert to ensure linguistic and functional equivalence. The draft was back-translated by two bilingual pairs, each comprising one native Japanese speaker and one native English speaker. A psychiatrist and cognitive science researcher then compared the original and back-translated versions to resolve any semantic discrepancies, making minor adjustments as needed. The reliability of the Japanese version of the MPPUS-10 was confirmed by calculating split-half and internal reliabilities. In this study, the Spearman-Brown coefficient for split-half reliability was 0.820, and Cronbach's α for internal consistency was 0.828.

MRI acquisition

Participants were instructed to visually focus on a fixation cross in the centre of a screen while remaining still, relaxed, awake and avoiding any specific thoughts during the scanning session. Foam rubber pads were utilized within a head coil to minimize head movement.

Structural MRI data were acquired utilizing three-dimensional magnetization-prepared rapid gradient-echo (3D-MPRAGE) sequences. Resting-state data, lasting 10 min, were collected using a single-shot gradient-echo planar imaging pulse sequence on a 3-Tesla MRI unit (Tim-Trio; Siemens, Erlangen, Germany) equipped with a 40-mT/m gradient and a 32-channel phased-array head coil.

The parameters for the 3D-MPRAGE images were as follows: echo time (TE), 3.4 ms; repetition time (TR), 2000 ms; inversion time, 990 ms; field of view (FOV), 225 × 240 mm; matrix size, 240 × 256; resolution, 0.9375 × 0.9375 × 1.0 mm; and 208 total axial sections with no intersection gaps. The resting-state parameters were: TE, 30 ms; TR, 2,500 ms; flip angle, 80°; FOV, 212 × 212 mm; matrix size, 64 × 64; in-plane spatial resolution, 3.3125 mm × 3.3125 mm; 40 total axial slices; and slice thickness, 3.2 mm with 0.8-mm gaps in ascending order. A dual-echo gradient echo dataset for B0-field mapping was acquired to correct for distortions. A high-resolution T1 image was routinely examined by an engineer to identify structural anomalies. According to visual assessments by radiologists and psychiatrists, no significant lesions were observed in either the white or grey matter of any participant's T1 images.

MRI data pre-processing and connectivity matrix

Resting-state functional magnetic resonance imaging (rs-fMRI) data were pre-processed utilizing the CONN Functional Connectivity Toolbox in MATLAB R2018b software (The MathWorks Inc.). Initially, slice-timing and head-motion corrections were applied to each participant's fMRI data. Participants with excessive head movement (≥3 mm or 3°) were excluded from further analysis. The T1-weighted image was then co-registered with the mean motion-corrected fMRI image and normalised to MNI space at $2 \times 2 \times 2\ mm^3$ resolution. Spatial smoothing was conducted utilising a 6-mm FWHM Gaussian kernel to enhance the signal-to-noise ratio. To minimise potential confounding factors, regression was employed to mitigate global mean

signals, Friston's 24-parameter motion model, and signals from the cerebrospinal fluid and white matter. Linear detrending and bandpass filtering (0.01–0.1 Hz) were also applied to reduce low-frequency drift and high-frequency noise. Functional connectivity was then assessed utilizing the GRETNA toolbox (Wang et al., 2015) by computing Pearson's correlation coefficient (r) between the mean BOLD time series from pairs of 90 brain regions (utilizing the AAL atlas). These correlation coefficients were converted to z-scores through Fisher's r-to-z transformation.

Diffusion tensor imaging (DTI) data were pre-processed utilising the PANDA toolbox (Cui, Zhong, Xu, He, & Gong, 2013). Motion and eddy current distortions were corrected, and non-brain tissues were removed from the DTI images. Fractional anisotropy (FA) maps were computed for each voxel, and FA images were co-registered with the corresponding T1-weighted anatomical images. Probabilistic tractography was then conducted utilizing ProbtrackX in FSL with the following parameters: fibres = 2, weight = 1, burning period = 1,000, and overall pathway distance (OPD) selected for probabilistic tracking type. AAL brain parcellation was nonlinearly transformed into each participant's native space through the utilisation of inverse normalisation and co-registration transformations. Each brain region, as defined by the parcellation, was treated as a node in the brain network. A 90 × 90 structural connectivity matrix was generated by quantifying the number of streamlines connecting each pair of brain parcels, providing a representation of the brain's structural connectivity patterns. In the structural connectivity matrix, each edge represents the connection strength between two nodes (i.e., brain regions). Higher correlation values suggest stronger structural connectivity between brain regions, while lower values indicate weaker connectivity. Based on the OPD matrix from the AAL90 template, a 90 × 90 undirected and weighted matrix was created for network analysis after ensuring symmetry.

Network analysis

Graph theory analysis was conducted utilizing GRETNA (Wang et al., 2015) to calculate both global network and regional node parameters for rs-fMRI and DTI data. Key topological indices were calculated across a sparsity range of 10–50% (in 1% steps) to avoid bias from the selection of a specific threshold. The area under the curve within this sparsity range was then computed for statistical analysis.

The global network parameters included global efficiency (Eg), which measures the efficiency of information transfer across the network, clustering coefficients (Cp), which quantify the local inter-connectivity, and local efficiency (Eloc), reflecting the efficiency of information transfer at the local level. The shortest path length (Lp) was utilized to assess network integration, and sigma (σ) indicated the small-worldness of the network. Regional node parameters include degree centrality (Dc), representing the number of direct connections to a node, and betweenness centrality (Bc), reflecting the influence of a node on information flow between all other nodes. Nodal efficiency (Ne), nodal local efficiency (Nle), and nodal clustering coefficient (NCp) were also calculated in line with global network metrics. The results were visualized using BrainNet Viewer (Xia, Wang, & He, 2013).

Statistical analysis

Statistical analyses were conducted utilizing SPSS (version 24.0; SPSS Inc., Chicago, IL, USA). Descriptive statistics for the MPPUS-10 scale were calculated, followed by correlational analysis. Pearson's correlation coefficient was utilized for variables with a normal distribution, while Spearman's rank-order correlation was applied to variables with a skewed distribution. Normality was assessed utilizing the Kolmogorov-Smirnov test, with statistical significance set at $p < 0.05$ (two-tailed).

To explore the correlation between changes in topological organization and mobile phone use problem severity, partial correlation analysis was performed utilizing R Software version 4.2.3 (downloaded from URL: http://www.r-project.org). The two variables include the MPPUS-10 scores as well as global and nodal parameters from the graph theory analysis, with age and sex as covariates. Bonferroni correction was applied to account for multiple comparisons.

Ethics

This study adhered to the principles of the Declaration of Helsinki and received approval from the Institutional Review Board of Kyoto University. All participants were fully informed about the study's purpose and procedures and provided written informed consent prior to participation.

RESULTS

Descriptive statistics

One participant's data was excluded due to an incomplete questionnaire, resulting in a final sample of 81 participants with a mean age of 21.77 ± 1.84 years. The MPPUS-10 scores of the participants are shown in Table 1. An independent samples *t*-test was conducted to compare the mean

Table 1. MPPUS-10 scores of the participants

MPPUS-10		Total	Sex	
			Male (n = 42)	Female (n = 39)
Mean ± SD		36.20 ± 14.03	33.88 ± 12.93	38.69 ± 14.88
Range	Min	12	12	15
	Max	72	67	72
Percentiles	25%	24.00	23.75	24.00
	50%	34.00	33.00	39.00
	75%	47.00	42.50	50.00
rho = −0.17, p = 0.13			**Correlation of Age**	
t = −1.56, p = 0.12			***T*-test of sex**	

MPPUS-10 scores between our study (M = 36.20, SD = 14.03, n = 81) and those reported by Foerster et al. (2015) (M = 28.2, SD = 15.6, n = 412). The results showed a statistically significant difference (t = 4.60, p < 0.001), indicating that the severity of the mobile phone use problem in our sample was notably higher.

Graph theory analysis

Global network metrics. Within the specified threshold range, both rs-fMRI and DTI data demonstrated typical small-worldness (normalized clustering coefficient: $\gamma > 1$, normalized path length: $\lambda = 1$, small-world characteristics: $\sigma > 1$). As exhibited in Fig. 1, MPPUS-10 scores were significantly correlated with several global network metrics. The rs-fMRI exhibited significant correlations with Lp (partial rho = 0.26, p = 0.0008), Eg (partial rho = −0.26, p = 0.0010), Cp (partial rho = 0.27 p = 0.0005), and Eloc (partial rho = 0.27 p = 0.0005). DTI exhibited significant correlations with σ (partial rho = 0.21 p = 0.0064).

Nodal network metrics. The node results (p < 0.05, Bonferroni-corrected) from rs-fMRI and DTI, correlating with MPPUS-10 scores, are presented in Table 2.

As exhibited in Fig. 2, for the rs-fMRI data, higher MPPUS-10 scores were associated with a significant decrease in Dc in the right orbital inferior frontal gyrus; decreased Ne in the right middle orbitofrontal cortex, right inferior orbitofrontal cortex, and left medial superior frontal gyrus; increased Nle in the bilateral precentral gyrus, left supplementary motor area, bilateral fusiform gyrus, and bilateral postcentral gyrus; NCp was increased in the bilateral precentral gyrus, bilateral supplementary motor area, left superior occipital gyrus, right inferior occipital gyrus, bilateral fusiform gyrus, and bilateral postcentral gyrus.

For the DTI data, as exhibited in Fig. 3, higher MPPUS-10 scores were associated with decreased Dc, Bc, and Ne in the right postcentral gyrus, increased Bc in the right anterior cingulate gyrus, and decreased NCp in the left postcentral gyrus.

DISCUSSION

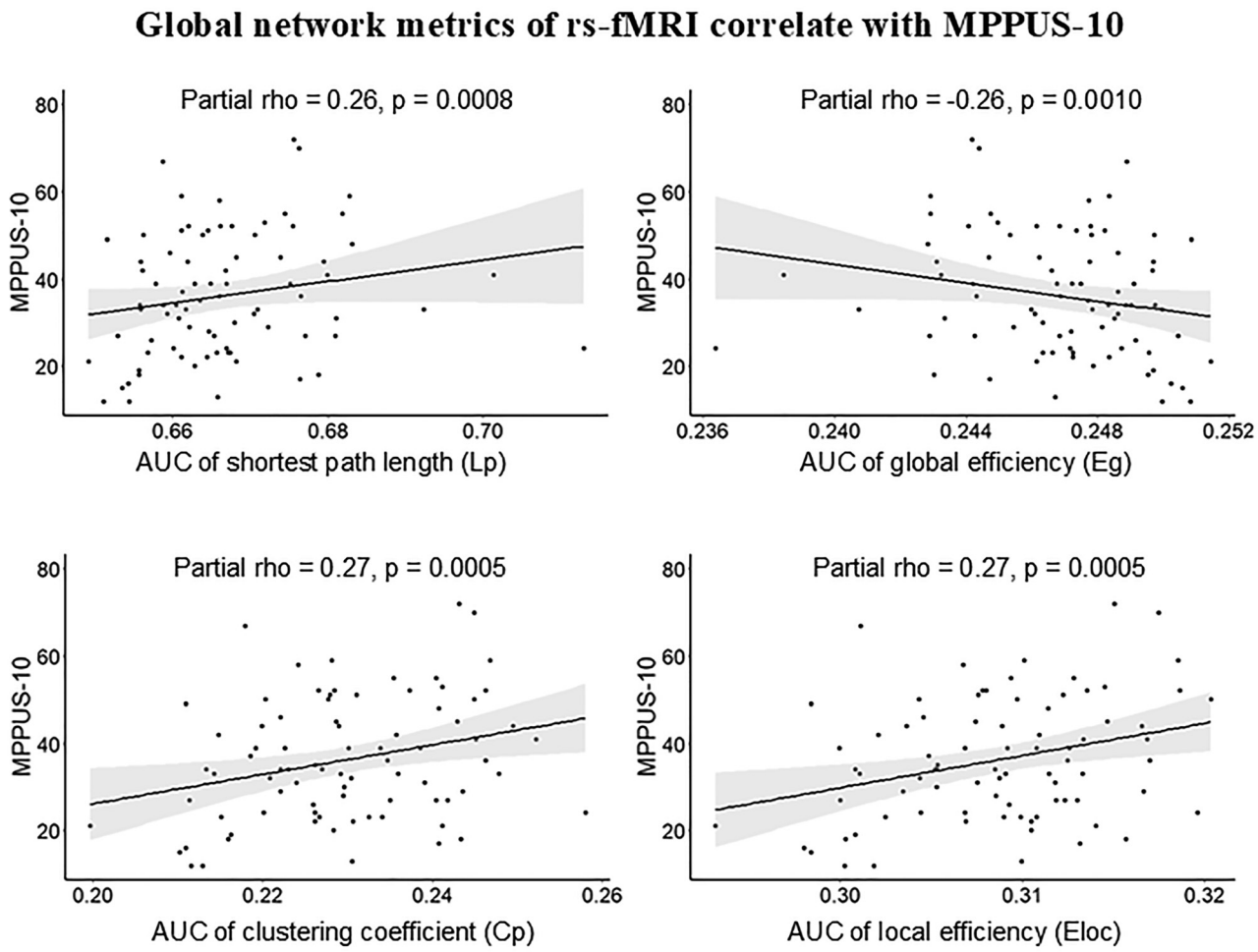
In the current study, we focused on mobile phone use problem severity and examined its impact by analyzing the correlation between MPPUS-10 scores and functional as well as structural topological organization changes in healthy Japanese participants. The study reveals novel and significant findings. First, at the global brain level, increased mobile phone use problem severity was associated with decreased integration and increased segregation of functional networks, while structural networks maintained high local clustering and efficient information transmission. Second, at the nodal level, several brain regions involved in emotional regulation and cognitive function exhibited alterations in their topological properties. Notably, the topological organization of the left postcentral gyrus was affected by mobile phone use problem severity in both functional and structural networks, though the trends differed. These findings support and expand upon previous observations of PMPU at the global brain level.

Global network metrics

Participants with higher mobile phone use problem severity exhibited increased Lp, Cp, and Eloc and decreased Eg in their functional networks. The Lp and Eg metrics reflect the ease of information integration across distributed brain regions (Xu et al., 2019), with higher Lp and lower Eg indicating weaker integration potential (Rubinov & Sporns, 2010). The Cp and Eloc metrics measure network segregation and indicate the network's ability for specialized processing, with higher values suggesting enhanced local processing within densely interconnected brain regions (Lucas et al., 2023).

Our results suggest that, as mobile phone use problem severity increases, the distance for information transmission between brain regions grows, weakening the potential for global integration of specialized information while enhancing specialized processing within densely connected brain regions. Similar patterns of reduced long-distance functional connectivity and increased local information processing have been observed in patients with Alzheimer's disease (Sanz-Arigita et al., 2010), characterised by lower global integration and higher local segregation (Kabbara et al., 2018). This implies that PMPU may lead to functional network topologies similar to those observed in Alzheimer's disease, potentially impacting cognitive functions.

In terms of structural networks, a positive correlation was found between small-worldness and mobile phone use problem severity. Small-world networks, characterized by high clustering coefficients and short path lengths, combine the advantages of both regular and random networks, facilitating both local specialization and global information processing (Liang, Wang, & He, 2010). Healthy brains typically exhibit small-world properties, indicating a balance between local and global processing (Bassett & Bullmore, 2006; Y. Li, Wang, et al., 2020). Our findings show that, with increased mobile phone use problem severity, structural networks maintain this small-world topology, suggesting a better balance compared with the lower integration and higher segregation observed in functional networks. This differing trend may reflect different regulatory mechanisms: functional network changes might indicate adaptive adjustments during PMPU, while structural network changes could signify stable connectivity patterns that support essential functional connections. This aligns with the concept of neural compensation, wherein the brain compensates for cognitive decline through increased connectivity or activity (Behfar et al., 2020). Conversely, this result suggests that changes in functional networks do not necessarily mirror changes in structural networks (Stam et al., 2009; Supekar, Menon, Rubin, Musen, & Greicius, 2008; Yang et al., 2021; Yun, Kim, & Psychiatry, 2021). The differing trends between structural and functional networks



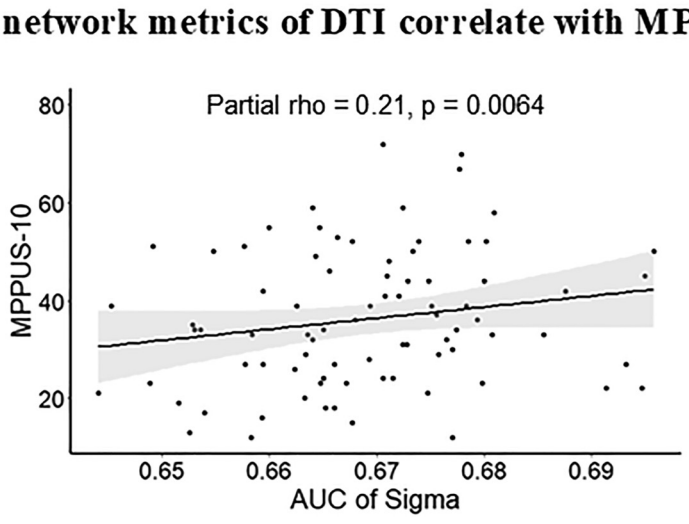


Fig. 1. Exploratory correlation analysis between global network metrics and MPPUS-10 scores. The scatter plots and the linear fitting lines with a 95% confidence interval are shown in the figure. Spearman's rank-order correlation coefficient [rho] and the significance of the correlation [p] are indicated; age and sex are treated as covariates

Table 2. Nodes with significant correlation with MPPUS-10 scores in nodal indicators ($p < 0.05$, Bonferroni corrected)

		x (mm)	y (mm)	z (mm)	rho	*p*
Degree centrality	**rs-fMRI**					
	ORBinf.R	41.01	32.34	−11.35	−0.282	0.026*
	DTI					
	PoCG.R	41.43	−25.49	52.55	−0.346	0.001***
Betweenness centrality	**DTI**					
	ACG.R	8.46	37.01	15.84	0.278	0.030 *
	PoCG.R	40.72	−25.24	52.03	−0.290	0.017*
Nodal efficiency	**rs-fMRI**					
	ORBmid.R	32.86	52.09	−10.84	−0.277	0.034*
	ORBinf.R	41.01	32.34	−11.35	−0.276	0.035*
	SFGmed.L	−6.08	49.32	31.09	−0.279	0.031*
	DTI					
	PoCG.R	40.72	−25.24	52.03	−0.343	0.001***
Nodal local efficiency	**rs-fMRI**					
	PreCG.L	−39.52	−5.69	51.17	0.300	0.010**
	PreCG.R	40.21	−8.38	52.38	0.310	0.010 **
	SMA.L	−6.12	4.60	61.02	0.322	0.003**
	FFG.L	−32.27	−39.50	−20.54	0.314	0.005**
	FFG.R	32.46	−37.90	−20.90	0.289	0.018*
	PoCG.L	−43.44	−22.26	48.75	0.270	0.048*
	PoCG.R	40.72	−25.24	52.03	0.325	0.002**
Nodal clustering coefficient	**rs-fMRI**					
	PreCG.L	−39.52	−5.69	51.17	0.322	0.003**
	PreCG.R	40.21	−8.38	52.38	0.292	0.015*
	SMA.L	−6.12	4.60	61.02	0.381	0.000***
	SMA.R	7.63	0.11	62.30	0.277	0.034*
	SOG.L	−17.66	−83.99	28.30	0.270	0.047*
	IOG.R	38.16	−81.99	−7.61	0.270	0.047*
	FFG.L	−31.16	−40.3	−20.23	0.297	0.012*
	FFG.R	33.97	−39.1	−20.18	0.288	0.019*
	PoCG.L	−42.46	−22.63	48.92	0.279	0.030*
	PoCG.R	41.43	−25.49	52.55	0.325	0.002**
	DTI					
	PoCG.L	−42.46	−22.63	48.92	−0.277	0.035*

may reflect distinct regulatory mechanisms, with functional network changes indicating adjustments during PMPU and structural network changes supporting stable functional connections.

Nodal network metrics

At the nodal level, increasing mobile phone use problem severity was associated with decreased Dc and Ne in several nodes in the functional network, while Nle and NCp increased. Dc reflects the number of connections a node has and signifies its importance within the whole-brain network (Buckner et al., 2009). As mobile phone use problem severity increases, the reduction in Dc in the right inferior orbitofrontal cortex may indicate impaired behavioral inhibition, potentially leading to impulsivity (Aron, Robbins, & Poldrack, 2014). With increased mobile phone use problem severity, the decreased nodal Ne in the orbitofrontal cortex aligns with the cortex's role in sensory integration, visceral reaction modulation, and decision-making for emotional and reward-related behaviours (Kringelbach, 2005). The orbitofrontal cortex is not only capable of integrating multimodal sensory information and guiding emotion-related decision-making by evaluating expected outcomes (Bechara, Damasio, & Damasio, 2000; Sonkusare et al., 2023), but is also considered a key component of the neural circuitry underlying the capacity to control patience (Xiao, Deng, Wei, Huang, & Wang, 2016). The decline in Ne in the orbitofrontal cortex signifies reduced communication and integration with other regions, which may impair coordination capabilities, and potentially indicates that PMPU represents a form of behavioral addiction (Billieux, 2012). Increases in Nle and NCp in regions such as the frontal lobe (PreCG, SMA), temporal lobe (FFG), and occipital lobe (SOG.L, IOG.R) suggest heightened functional segregation in these areas. These regions are involved in language processing (Silva et al., 2022), motor control (Russo et al., 2020), high-order visual information (particularly related to faces, bodies, and stimuli characterised by high spatial frequencies) (Palejwala et al., 2020), and anxiety processing (Li, Zhang, et al., 2020). This finding supports the speculation that information overload caused by PMPU is related to negative states such as depression and anxiety (Matthes et al., 2020). Combined with the local result that decreased integration

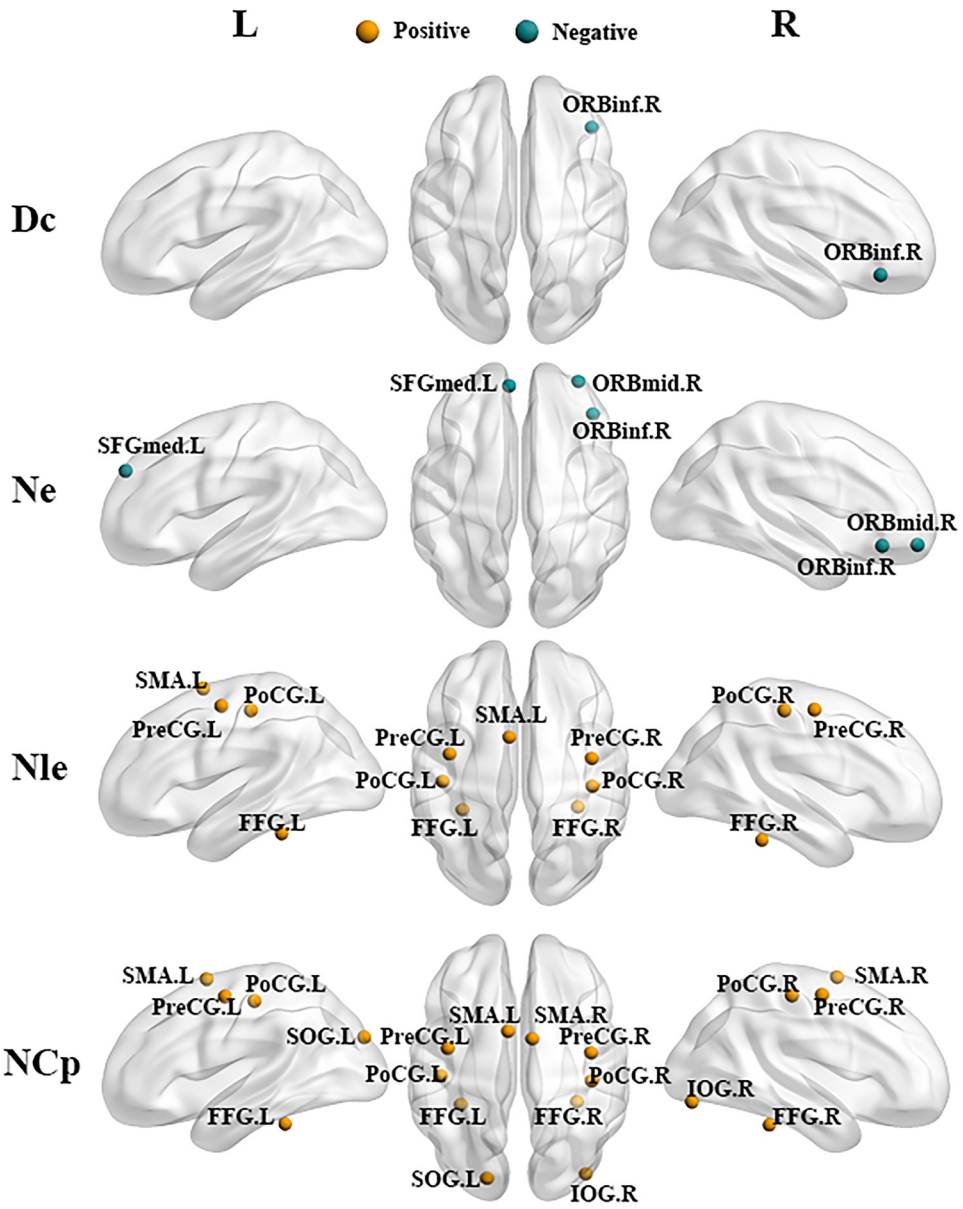


Fig. 2. The nodal findings of rs-fMRI correlated with MPPUS-10 scores. As MPPUS-10 scores increase, there is a significant decrease in degree centrality (Dc) in the right orbital inferior frontal gyrus (ORBinf.R); decrease in nodal efficiency (Ne) in the right middle orbitofrontal cortex (ORBmid.R), right inferior orbitofrontal cortex (ORBinf.R), and left medial superior frontal gyrus (SFGmed.L); an increase in nodal local efficiency (Nle) in the precentral gyrus (PreCG), left supplementary motor area (SMA.L), fusiform gyrus (FFG), and postcentral gyrus (PoCG); and increase in nodal clustering coefficient (NCp) in the PreCG, SMA, left superior occipital gyrus (SOG.L), right inferior occipital gyrus (IOG.R), FFG, and postcentral gyrus (PoCG)

within the orbitofrontal cortex not only supports the global metric findings of whole functional brain networks that PMPU leads to decreased integration and increased segregation, but also highlights specific brain regions affected by PMPU, which differ from those implicated in neuropsychiatric conditions such as autism. Although previous studies have found a significantly positive correlation between autism and PMPU (Zhou, Chen, & Liu, 2024), in autism, changes in functional connectivity are characterised by reduced local efficiency and shorter characteristic path lengths (Keown et al., 2017; Rudie et al., 2013), which differ from the trends observed in PMPU. Simultaneously, in nodal metrics, the betweenness centrality in the sensorimotor network decreases as the severity of autism increases. However, in this study, we found that the centrality of the orbitofrontal cortex decreases as the severity of mobile phone use problems increases. These findings may help identify neural biomarkers specific to PMPU.

In the structural network, significant changes were primarily observed in the right anterior cingulate gyrus (ACG.R) and postcentral gyrus (PoCG). The Bc of a brain region reflects its influence on information flow within the network (Rubinov & Sporns, 2010). As the mobile phone use problem severity increases, the Bc of ACG.R rises, which may partly

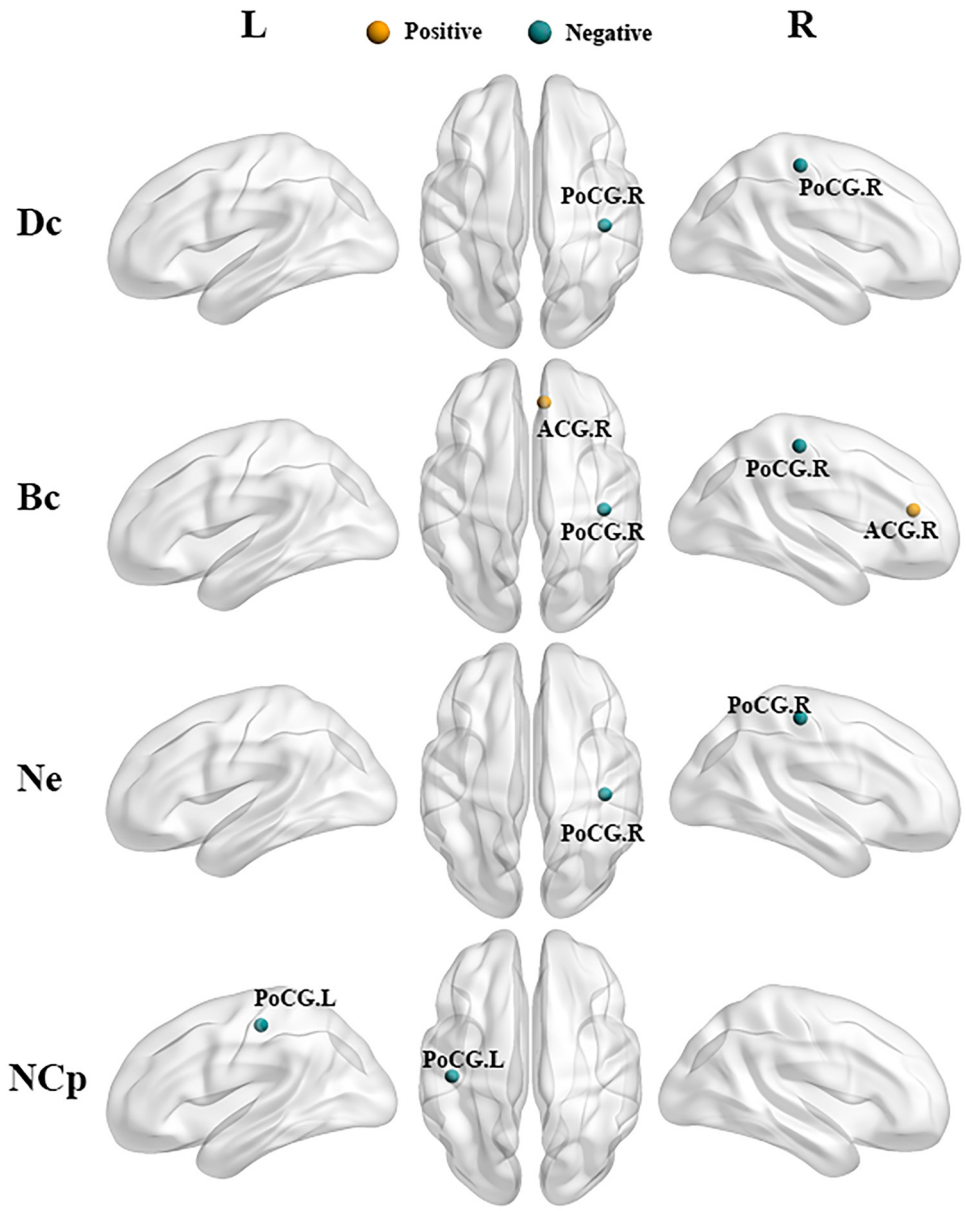


Fig. 3. The nodal results of DTI correlated with MPPUS-10 scores. As MPPUS-10 scores increase, there is a decrease in degree centrality (Dc), betweenness centrality (Bc), and nodal efficiency (Ne) in the right postcentral gyrus (PoCG.R); increase in Bc in the right anterior cingulate gyrus (ACG.R); and decrease in nodal clustering coefficient (NCp) in the left postcentral gyrus (PoCG.L)

compensate for the reduced integration in the functional network. This suggests that the structural network compensates for changes in neural activity in the context of neuroplasticity or network reorganization due to addiction and associated maladaptive experiences (Marzola, Melzer, Pavesi, Gil-Mohapel, & Brocardo, 2023). Topological changes related to mobile phone use problem severity were notably concentrated in the PoCG. This region corresponds to the primary somatosensory cortex, and its topological organization is referred to as the sensory homunculus, or the "little man" (DiGuiseppi & Tadi, 2023), which seems to play a role in the integration of somatosensory stimuli and memory formation (Chen et al., 2008). The topologically clustered nodes are all located in the left postcentral gyrus (PoCG.L) in the anatomical structure, indicating minimised wiring costs in this area (Bassett & Bullmore, 2017), aligning with the increased segregation observed in the structural network of the PoCG.L. Interestingly, Cp in the PoCG.L exhibited opposing correlations with PMPU in the functional and structural networks. A decrease in Cp in the structural network may be compensated by enhanced functional connections (Skouras et al., 2019), indicating that even with reduced structural connectivity in the PoCG, the functional network might reconfigure itself (Deco, Jirsa, & McIntosh, 2011) to maintain overall sensory processing and cognitive function.

Overload information with PMPU

According to the analysis of brain networks, more severe mobile phone use problems are associated with decreased

brain network integration and increased segregation, which negatively impacts cognitive function and emotional processing. In modern society, mobile phones have become integral to daily life, making multitasking the "new normal." This involves handling more information, solving problems, and achieving better outcomes. However, attentional resources are limited, necessitating careful allocation to critical stimuli to effectively process and integrate information (Fernandez-Duque & Johnson, 2002). Literature indicates that individuals utilise their mobile phones for at least 2.5 h per day, often immediately upon waking, during any idle time (e.g., waiting for elevators, phone calls, driving), before bed, and even at night (Deng et al., 2019).

Consequently, PMPU results in a continuous influx of fragmented information, leading to a state of constant connectivity and dependency on mobile phones (Parry, 2019). This extensive input of information and frequent task switching increases the demand on attentional resources, leading to cognitive overload (Aagaard & Sciences, 2015). PMPU contributes to information overload (Lee et al., 2016), signalling that the demands for processing environmental information exceed the available capacity. This overload generates stress, which may be linked to depressive symptoms (Reinecke et al., 2017). The information overload associated with PMPU not only demands more attentional resources but may also affect how these resources are allocated.

Studies suggest that a unified brain system manages the switch between internal processes (such as thinking, memory recall, and problem-solving) and external processes (such as responding to sensory stimuli). However, shifting between these modules incurs significant switching costs (Verschooren et al., 2019). The influx of information from mobile phone utilisation may allocate more resources to external processes, reducing the resources available for internal thought or attention to other tasks (Brinberg et al., 2023). The findings of this study regarding functional brain networks support our hypothesis of a shift in the information processing module, potentially reflecting cognitive and emotional disruptions (Das et al., 2018; Morgan, White, Bullmore, Vértes, & Neuroimaging, 2018). While the segregation approach effectively localises relevant brain functions, our integration perspective aligns with recent observations of addiction and associated maladaptive experiences (Kabbara et al., 2018; Tei, in press), viewing them as network dysfunctions characterised by disruptions in overall brain connectivity (Das et al., 2018; Tei et al., 2020). This dysfunction may worsen owing to digital information overload, which can alter the interaction between external information sources and internal processing modules (Tei, Junya, & Toshiya, 2025; Verschooren et al., 2019).

This study has some limitations. First, being cross-sectional, it is unclear whether individuals with similar topological structures are more prone to developing PMPU than not. Future research should employ longitudinal methods to clarify the direction of the relationship between PMPU and brain topological organization. Second, the study recruited 81 participants in their early twenties and focused solely on the association between brain topological organization and PMPU in young adults. Future studies should expand the age range to explore findings across different age groups. Finally, although Nahas et al. (2018) suggested a cut-off score of 59 for the MPPUS-10, it remains uncertain whether cultural differences might influence the determination of this threshold. Thus, it is unclear whether the score of 59 can be directly applied to our Japanese sample. Therefore, our study discusses PMPU in terms of the 'mobile phone use problem severity' reflected by MPPUS-10 scores. Future research could focus more on exploring whether there are differences in PMPU across diverse cultural contexts.

CONCLUSIONS

Although this study has some limitations, it holds important theoretical significance. We adopted a multimodal approach that included analyses of both functional and structural networks; the observed associations between mobile phone use problem severity and brain imaging profiles suggest that PMPU may decrease the integration between information processing modules in functional brain networks. This reduced integration could lead to neural compensation, reflected in enhanced small-worldness in structural networks to maintain more stable connectivity patterns. Functional and structural changes may be driven by PMPU, potentially leading to cognitive system overload due to excessive information input. This study enhances our understanding of the neuro-mechanisms underlying PMPU.

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Authors' contribution: L.Y., D.Q., and Z.Z. designed and conducted the study. M.A., M.S. and H.F. recruited participants and collected and compiled data. L.Y. analyzed the data, with contributions to data analysis from K.H., N.O., Y.L., and L.W. L.Y. wrote the manuscript with feedback from all co-authors. L.W., D.Q., H.Z., J.Y., S.T., T.M., Z.Z.and H.F. contributed to reviewing and editing the manuscript. L.Y., D.Q., and H.F. obtained funding support, and Z.Z., H.F., and T.M. supervised the research process. All authors have approved the final article.

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