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FULL-LENGTH REPORT

Negative emotions mediate the association between the topology of the complex brain network and smartphone use disorder: A resting-state EEG study

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ABSTRACT

Background: Increasing research has examined the factors related to smartphone use disorder. However, limited research has explored its neural basis. *Aims:* We aimed to examine the relationship between the topology of the resting-state electroencephalography (rs-EEG) brain network and smartphone use disorder using minimum spanning tree analysis. Furthermore, we examined how negative emotions mediate this relationship. *Methods:* This study included 113 young, healthy adults (mean age = 20.87 years, 46.9% males). *Results:* The results showed that the alpha- and delta-band kappas and delta-band leaf fraction were positively correlated with smartphone use disorder. In contrast, the alpha-band diameter was negatively correlated with smartphone use disorder. Negative emotions fully mediated the relationship between alpha-band kappa and alpha-band diameter and smartphone use disorder. Furthermore, negative emotions partially mediated the relationship between delta-band kappa and smartphone use disorder. The findings suggest that excessive scale-free alpha- and delta-band brain networks contribute to the emergence of smartphone use disorder. In addition, the findings also demonstrate that negative emotions and smartphone use disorder share the same neural basis. Negative emotions play a mediating role in the association between topological deviations and smartphone use disorder. *Discussion:* To the best of our knowledge, this is the first study to examine the neural basis of smartphone use disorder from the perspective of the topology of the rs-EEG brain network. Therefore, neuromodulation may be a potential intervention for smartphone use disorder.

KEYWORDS

smartphone use disorder, negative emotions, resting-state EEG, minimum spanning tree

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INTRODUCTION

Smartphone use disorder, characterized by a strong desire to use a smartphone and restlessness when unable to access it (Kayis, Satici, Deniz, Satici, & Griffiths, 2021; Montag, Wegmann, Sariyska, Demetrovics, & Brand, 2021), has become a common problem in today's society.

Smartphone use disorder can result in physical and adjustment problems, such as distorted vision, low self-esteem, materialism, sleep disturbances, depression, and academic failure (Kim, Kim, & Jee, 2015; Lee, Kang, & Shin, 2015; Lemola, Perkinson-Gloor, Brand, Dewald-Kaufmann, & Grob, 2015; Samaha & Hawi, 2016; Seo, Park, Kim, & Park, 2016; Wang & Lei, 2019; P. Wang, Liu et al., 2019; P. Wang, Nie et al., 2020). Therefore, exploring its causes is imperative.

Researchers have identified various personal and environmental risk factors associated with smartphone use disorder, including negative emotions, general self-efficacy, self-esteem, and student-student relationships (Bian & Leung, 2014; Gökçearslan, Mumcu, Haşlaman, & Çevik, 2016; Ouyang et al., 2020; Roberts, Pullig, & Manolis, 2015; Wang et al., 2017). Negative emotions are especially a crucial risk factor, as they often drive smartphone use disorder (Kardefelt-Winther, 2014; Matar Boumosleh & Jaalouk, 2017; Xie, Zimmerman, Rost, Yin, & Wang, 2019). However, few studies have examined the relationship between negative emotions and smartphone use disorder from a neuroscientific perspective. Hence, exploring the relationship between the neural basis, negative emotions and smartphone use disorder will enable us to prevent and intervene in smartphone use disorder. Therefore, this study aimed to establish a theoretical model to explain whether and how negative emotions mediate the association between the topology of the complex brain network and smartphone use disorder using means of resting-state electroencephalography (rs-EEG) and minimum spanning tree (MST) analysis.

Association between the topology of the rs-EEG brain network and smartphone use disorder

Rs-EEG captures the intrinsic activity of the brain to reveal how different brain areas communicate at millisecond timescales (van Diessen et al., 2015), providing a convenient and cost-effective method to study the neural basis underlying smartphone use disorder. On the one hand, we can combine rs-EEG and MST to quantify the topology of complex brain networks (Bullmore & Sporns, 2009). MST is a network analysis technique that involves creating a subnetwork to connect all nodes while minimising whole-network link weights and preventing loops (Kruskal, 1956; Prim, 1957). The resulting network is a hybrid between a path and a star-shape network (Stam et al., 2014). In a path network, nodes have lower load distribution but longer information dissemination distances, while a star network exhibits the opposite characteristics. A healthy brain possesses an optimal topology of the complex brain network to maintain a balance between a path and a star network (Stam, 2014). In contrast, behavioural abnormalities or cognitive dysfunction are usually accompanied by deviations from the optimal topology (Das & Puthankattil, 2020; Xue et al., 2020; Youssef et al., 2021). In practice, we commonly use four MST metrics to quantify topology: leaf fraction (LF), diameter (D), kappa (K), and tree hierarchy (TH) (see the Methods section for more details on these four metrics). The path network had low LF and K values and a high D value, whereas the star network exhibited the opposite. TH captured a topological configuration, characterised by a combination of short distances and the prevention of node overload.

On the other hand, the multi-frequency nature of rs-EEG can help us examine the relationship between smartphone use disorder and different functional networks. We commonly classify rs-EEG into delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), and beta (13–30 Hz) bands, each of which represents a different cognitive function (Herrmann, Struber, Helfrich, & Engel, 2016). For example, the delta band is usually associated with the inhibitory function and motivational processing (Knyazev, 2007, 2012); the theta band is usually associated with the memory function (Klimesch, 1999); the alpha band is associated with the attention and vigilance function (Hanslmayr, Gross, Klimesch, & Shapiro, 2011; Laufs et al., 2003; Sadaghiani et al., 2012); and the beta band is usually associated with the sensorimotor interaction (Kilavik, Zaepffel, Brovelli, MacKay, & Riehle, 2013). As smartphone use disorder is a type of deviant behaviour (Rozgonjuk, Montag, & Elhai, 2022), we examined its neural basis via a combination of rs-EEG at multi-bands and MST in the present study.

Existing studies have provided evidence for the above-mentioned view. A recent study found that a higher level of internet use disorder was significantly correlated with a higher kappa and lower diameter in the alpha and beta-bands, respectively (H. Wang, Sun, Lv, & Bo, 2019). This indicated that participants with internet use disorder possessed a more scale-free network topology. Scale-free networks are characterized by the presence of highly connected hub nodes (i.e., the star network) (Stam, 2014). Moreover, recent rs-EEG research that used the traditional graph theory showed that people with internet use disorder tended to have a more random state of the brain network (Sun, Wang, & Bo, 2019). Related studies that used rs-fMRI also found a similar relationship between internet use disorder and alterations in resting-state brain networks (Patil, Madathil, & Huang, 2021; Wee et al., 2014). These findings suggested that internet use disorder could be associated with abnormal brain network organisation. Smartphones are a type of internet terminal. Prior literature suggests that smartphone use disorder should be regarded as a subtype of internet use disorder (i.e., a predominantly mobile form of internet use disorder) (Montag et al., 2021). Furthermore, smartphone use disorder shares similar symptoms with internet use disorder (Lin et al., 2014). Thus, it is reasonable to assume that topological deviation of the rs-EEG brain network could be associated with increased smartphone use disorder. However, no previous studies examined this assumption. Thus, we proposed the following hypothesis:

Hypothesis 1: The scale-free levels of the rs-EEG brain network in the alpha and beta bands are correlated with smartphone use disorder.

Association between the topology of the rs-EEG brain network and negative emotions

Negative emotions refer to ‘a general dimension of subjective distress and unpleasurable engagement that subsumes a variety of aversive mood states, such as depression, anger, contempt, disgust, guilt, fear, and nervousness' (Watson, Clark, & Tellegen, 1988). Previous studies confirmed that the topological deviation of the rs-EEG brain network effectively reflected emotional status (Cao et al., 2020; Farashi & Khosrowabadi, 2020; Li et al., 2017; Zhang et al., 2018). The topology of the brain network tended to form a star shape from high to low emotional valence, which suggested that the brain network was more activated when experiencing negative emotions (Cao et al., 2020). These star-like networks have also been observed in individuals with major depressive disorders (Li et al., 2017). Additionally, one study showed that when MST was used to detect emotions, the alpha frequency band was the most informative during negative emotion processing (Farashi & Khosrowabadi, 2020). Given that the alpha frequency band is related to attention function, one possible explanation is that excessive attentional bias to negative emotional cues may be an important trigger for negative emotions. This idea is consistent with the fact that attentional control training can lead a reduction in negative attention bias, which in turn reduces negative emotions (Sanchez, Everaert, & Koster, 2016). Thus, the topological deviation of the rs-EEG brain network may also be the neural basis of negative emotions. However, no previous empirical studies examined this assumption. Thus, we proposed the following hypothesis:

Hypothesis 2: The scale-free level of the rs-EEG brain network in the alpha band is correlated with negative emotions.

Association between negative emotions and smartphone use disorder

Negative emotions can also lead to smartphone use disorder. Based on the compensatory internet use theory (Kardefelt-Winther, 2014), internet use disorder can be understood from a motivational perspective. Specifically, when people experience stressful events or dysphoric moods, they may turn to the internet to escape or alleviate these negative experiences (Kardefelt-Winther, 2014). Thus, it is logical that negative emotions positively correlate to internet use disorder. Moreover, given that smartphone use disorder is regarded as a subtype of internet use disorder (Montag et al., 2021), and given that smartphones are constantly available and accessible to people (Elhai, Levine, & Hall, 2019), it is reasonable to deduce that negative emotions can be regarded as a precursor of smartphone use disorder. Abundant research confirmed that people who experienced negative emotions were more likely to become addicted to smartphones (Gao et al., 2021; Hussain, Griffiths, & Sheffield, 2017; Li, Griffiths, Mei, & Niu, 2020; Matar Boumosleh & Jaalouk, 2017; Xie et al., 2019; Yen et al., 2009; Yue et al., 2021). Recent studies also found that individuals with depressive symptoms tended to use their smartphones excessively to eliminate psychological distress (Matar Boumosleh & Jaalouk, 2017; Xie et al., 2019; Yen et al., 2009). Therefore, negative emotions may be significantly correlated with smartphone use disorder. Thus, we proposed the following hypothesis:

Hypothesis 3: Negative emotions would be correlated with smartphone use disorder.

Mediating role of negative emotions

Since negative emotions have a strong relationship with both the topological deviation of the rs-EEG brain network and smartphone use disorder, there may be a theoretical model where negative emotions could explain the association between the topology of the rs-EEG brain network and smartphone use disorder. As the interaction of the person-affect-cognition-execution (I-PACE) model (Brand, Young, Laier, Wolfling, & Potenza, 2016) suggested, the bio-psychological constitution could affect cognitive and affective responses to perceived situations, and eventually lead to internet use disorder. This model was also consistent with the perspective of brain network science, which posited that a disruption of topology in the brain network, such as a scenario of hub overload and failure, could be a potentially common pathway for certain psychological abnormalities (Stam, 2014). Thus, topological deviations in the rs-EEG brain network could be related to an increase in negative emotions, which, in turn, could be related to an increase in smartphone use disorder. Thus, we proposed the following hypothesis:

Hypothesis 4: Negative emotions would mediate the association between the scale-free level of the rs-EEG brain network in the alpha or beta-bands and smartphone use disorder.

The present study

To examine our hypotheses, we employed well-validated instruments to assess participants' levels of negative emotions and smartphone use disorder. Furthermore, we also employed rs-EEG and MST analyses to explore whether the topology of the complex brain network was related to the level of smartphone use disorder. Additionally, we also examined whether this topological deviation affected smartphone use disorder through negative emotions. Specifically, this study aimed to examine whether (a) the scale-free level of the rs-EEG brain network was correlated with smartphone use disorder, (b) the scale-free level of the rs-EEG brain network was correlated with negative emotions, (c) negative emotions were correlated with smartphone use disorder, and (d) negative emotions mediated the association between the scale-free level of the rs-EEG brain network and smartphone use disorder.

METHODS

Participants

According to the power analysis performed with G*power, a correlation analysis required a minimum sample size of 84 participants to detect a medium-sized effect (r = 0.30, α = 0.05, 1–β = 0.80). We collected measurements and rs-EEG data from 113 healthy, young individuals (60 females, mean age = 20.87 years, SD = 2.42) from eight universities in Northern China in 2021. Each participant was right-handed and had no mental or neurological conditions. Age difference by sex was not significant (t (111) = −0.005, p = 0.996). Before the experiment, each participant provided written informed consent as per the protocols approved by the ethics committee of the first author's university. After the experiment, they received monetary compensation. Regarding confidentiality, we maintained anonymity among the participants, coded them according to their participation order, and informed them that all data collected would be used for research purposes only. We excluded four participants because they did not complete large portions of the measurements. Additionally, two others were excluded as their EEG data exceeded the artefacts, Hence, we included 107 participants in the subsequent analyses.

Measures

Negative emotions. Negative emotions were measured using the Negative Affect Scale, a subscale of the Subjective Well-Being Scale (Diener, 1984). This scale contains five items. A representative item is 'depressed or very unhappy'. Participants were asked to report their negative emotions from the past 4 weeks. They rated each item on a 7-point Likert scale ranging from 1 (*strongly disagree*) to 7 (*strongly agree*). Higher scores indicated higher levels of negative emotions. In our study, the scale showed good reliability (Cronbach's α = 0.86).

Smartphone use disorder. Smartphone use disorder was measured by the Chinese version of the Smartphone Addiction Scale (Fu et al., 2020), which was translated from the short version of the Smartphone Addiction Scale (Kwon et al., 2013). This scale contains 10 items. A representative item is 'missing planned work due to smartphone use'. Participants rated each item on a 6-point Likert scale ranging from 1 (*strongly disagree*) to 6 (*strongly agree*). Higher scores indicated higher levels of smartphone use disorder. In our study, the scale showed good reliability (Cronbach's α = 0.92).

Experiment procedure

Participants sat in a comfortable armchair in a well-shielded, soundproof room. Before beginning the experiment, the participants were informed of the requirements. They were urged to remain awake, relax, avoid large head movements, and not think of anything. We recorded rs-EEG data for each participant for six minutes. The acquisition duration is in line with previous rs-EEG studies (Babiloni et al., 2023; Lapomarda, Valer, Job, & Grecucci, 2022; Sun et al., 2019). In addition, because opening and closing the eyes reflect different resting states (Barry, Clarke, Johnstone, Magee, & Rushby, 2007), we included both opened and closed eyes to detect an entire resting state. Participants opened their eyes for one minute, closed them for two, opened them again for two, and closed them again for one. Through this ABBA way, we tried to balance errors caused by the order of eyes opened and closed. The ABBA order was also counterbalanced across participants. We continuously monitored all participants' EEG records to ensure that they followed the instructions and did not exhibit any fatigue symptoms. Following the EEG recording, the participants completed questionnaires.

EEG recording and pre-processing

Electroencephalogram (EEG) data were collected from the scalp using 64 non-polarisable Ag/AgCl sintered electrodes and a Neuroscan system with a 500 Hz sampling rate. The electrode sites adhered to the extended 10–20 convention. All electrode impedances were kept below 5 kΩ. We used four external electrodes to record the vertical electrooculogram (EOG) between the supraorbital and suborbital regions of the left eye and the horizontal EOG at the outer canthi of both eyes. When the signals were recorded online and offline, they were referenced to the left mastoid electrode and average electrode, respectively.

EEG pre-processing was performed using the EEGLAB toolbox (Delorme & Makeig, 2004) and custom MATLAB scripts (MathWorks). Continuous EEG data were digitally filtered using a high-pass filter of 0.5 Hz and low-pass (30 Hz) filters. Faulty electrodes (no more than six) were detected using the kurtosis approach and were interpolated using data from the surrounding electrodes. Six minutes of continuous EEG data were segmented into 180 epochs of 2000 ms duration. Contaminated epochs were visually evaluated and manually deleted. To eliminate eye movement artefacts, the ICA algorithm implemented in the EEGLAB toolbox (Delorme & Makeig, 2004) was applied to all EEG epochs. Furthermore, the to-be-corrected components were determined visually based on the component topography and waveforms. Epochs of EEG data were subjected to an artefact rejection procedure in which amplitudes greater than ±70 μV were removed. Subsequently, we conducted a complex brain network analysis using the pre-processing data, as shown in the flowchart in Fig. 1.

Power spectral analysis and functional connectivity analysis

The fieldtrip toolbox (Oostenveld, Fries, Maris, & Schoffelen, 2011) was used to analyse the spectral power and functional connectivity for pre-processed data in the delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), and beta (13–30 Hz) bands. To extract the frequency representations, a multitaper method, the fast Fourier transform (MTMFFT), was used. Specifically, we calculated the power spectrum from 0.5 to 30 Hz using discrete prolate spheroidal sequences (DPSS) tapers with 2 Hz smoothing. Subsequently, we calculated the complex Fourier spectrum for each frequency band of interest for the subsequent functional connectivity analysis.

The Phase Lag Index (PLI) measured the asymmetry of the distribution of the phase angle differences between two signals towards the positive or negative side of the imaginary axis. It was less sensitive to volume conduction, common sources, and montages (Stam, Nolte, & Daffertshofer, 2007). The PLI was less sensitive to outliers;

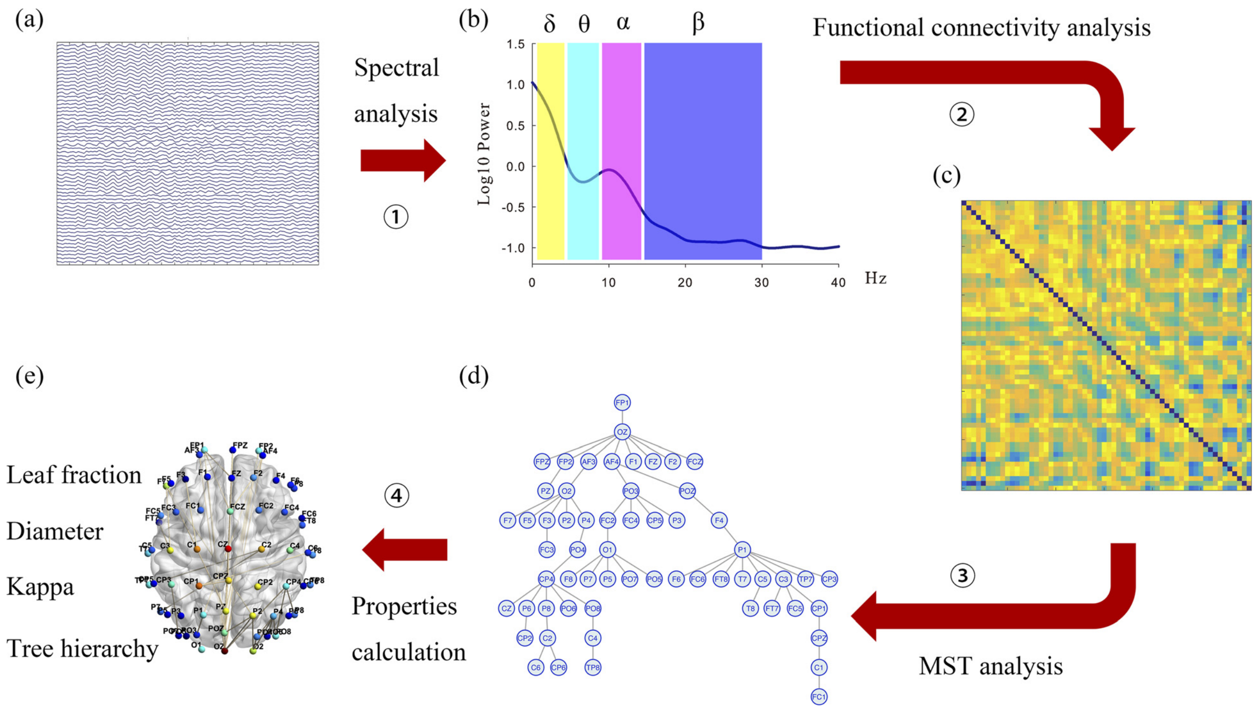

Fig. 1. **Schematic representation of the EEG complex brain network analysis**. (a) Pre-processed EEG data; (b) Power spectra. Coloured boxes indicate the delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), and beta (13–30 Hz) bands; (c) Functional connectivity matric; (d) Minimal span tree; and (e) Topology of the MST brain network

however, this characteristic also made it difficult to reflect the amount of clustering in the distribution. Thus, we employed the weighted phase lag index (WPLI), which extended the PLI by weighted angle differences according to distance from the real axis (Vinck, Oostenveld, van Wingerden, Battaglia, & Pennartz, 2011).

$$WPLI_{xy} = \frac{n^{-1}\sum_{t=1}^{n}\left|imag\left(S_{xyt}\right)\right|sgn\left(imag\left(S_{xyt}\right)\right)}{n^{-1}\sum_{t=1}^{n}\left|imag\left(S_{xyt}\right)\right|}$$

In the above equation, imag(S) represents the imaginary part of the cross-spectral density at time point (or trial) t; the value of function sgn() is -1 for negative values, $+1$ for positive values, and 0 for zero values. The WPLI varies from -1 to 1. When the WPLI was greater than zero, the phase angle difference distribution was oriented towards the positive side of the imaginary axis. In contrast, when the WPLI was lower than zero, the phase angle difference was distributed towards the negative side of the imaginary axis. |WPLI| value 1 indicated perfect phase locking at all phase differences other than 0 (mod π). Thus, a larger |WPLI| corresponded to stronger phase locking, that is, stronger functional connectivity. In this study, the WPLI analysis generated 60×60 weight adjacency matrices in each frequency band, which were converted to absolute values and used in the MST analysis.

MST analysis

MST forbids recurrent connections and builds networks with the weight adjacency matrices obtained from the WPLI analysis using Kruskal's algorithm (Kruskal, 1956). First, the weights of all possible connections, which were calculated as 1-|WPLI|, were arranged in ascending order. Subsequently, the lowest weight connections were sequentially added to the network until all 60 nodes were connected in a loopless subgraph. Finally, to evaluate the topology in the rs-EEG brain network, we calculated the four MST metrics: leaf fraction (LF), diameter (D), kappa (K), and tree hierarchy (TH) (Stam, 2014; Stam et al., 2014).

Nodes in a tree with a single link (i.e. degree 1 nodes) were referred to as 'leaves' or 'leaf nodes'. LF quantified the fraction of leaf nodes relative to the total number of nodes. D measured the shortest path along the minimum spanning tree, that is, the path that involved the fewest number of connections between any two nodes. K measured the scale-free degree distribution (Stam, 2014; Stam & van Straaten, 2012). A high level of the scale-free property meant that the network possessed high-degree hubs. Detailed algorithms for these topological metrics are shown in Table 1.

Statistical analysis

Topological metrics were log-transformed to meet the statistical assumption of a normal distribution. According to a previous study (H. Wang, Sun et al., 2019), higher severity of internet use disorder was correlated with higher K and lower D in the alpha and beta-bands, respectively. Therefore, we performed correlation analyses to confirm the association between the four topological metrics and smartphone use disorder. Additionally, we further

Table 1. Algorithms of the MST metrics used in the present study

Symbol	Concept	Explanation	Formula
L	Leaves	The number of nodes with a single link	
N	Nodes	The number of nodes	
dg	Degree	The number of links for a given node	
m	Links	The number of links	N – 1
LF	Leaf fraction	Fraction of leaf nodes (L) in the MST	LF = L/N
D	Diameter	The longest link between two nodes of an MST	$D = d_{logest}/m$
K	Kappa	Measure of the broadness of the degree distribution	K = <dg.^2>/<dg>
TH	Tree hierarchy	Quantifies the trade-off between large scale integration in the MST and the overload of central nodes	$TH = L/(2\ mBC_{max})$

Note: D is normalized by the number of links. BC_{max} is the highest betweenness centrality of any node in the tree. Betweenness centrality is the fraction of all paths on the tree that include (but do not end at) that node.

conducted an exploratory analysis to examine the relationship between the remaining topological metrics and smartphone use disorder. Permutation tests were performed on the correlations using the PERMUTOOLS toolbox in MATLAB (https://github.com/mickcrosse/PERMUTOOLS) to control the family-wise error rate by shuffling the data via 5000 Monte Carlo randomisations.

In the subsequent mediation analysis, we selected the topological metrics that showed a significant correlation with smartphone use disorder. As the mediation analysis relies on specific topological metrics, there is a potential for double-dipping errors. To resolve this problem, we further examine the robustness of the relationship between the brain and smartphone use disorder with a machine learning approach via fourfold balanced cross-validation using linear regression (Ball, Squeglia, Tapert, & Paulus, 2020). This approach is commonly used in similar research (Kong, Zhao, You, & Xiang, 2020; S. Wang, Zhao et al., 2018). In the regression model, the independent and dependent variables were the topological metrics and smartphone use disorder, respectively. First, we divided the data into four folds to ensure that there were no significant differences between the distributions. Subsequently, we used three folds to train the model and the remaining data to assess the model. After this procedure was repeated four times, we computed $r_{(predicted,\ observed)}$ based on the average association between the observed and predicted data. To obtain stable results, we repeated the entire procedure of the four-fold balanced cross-validation 100 times. Finally, non-parametric testing methods were used to examine the significance of the model by generating 1,000 surrogate datasets. The statistical significance (p-value) for the model was obtained by dividing the number of $r_{(predicted,\ observed)}$ of the surrogate datasets greater than $r_{(predicted,\ observed)}$ of the actual data by the number of datasets (1,000).

The mediation analysis was performed in two steps using SPSS version 26. First, the data were analysed using descriptive statistics and zero-order correlation analysis. Second, the PROCESS MACRO for SPSS (Model 4) was used to examine the mediating effect of negative emotions (Hayes, 2013). Model 4's analysis provided bootstrap 95% confidence intervals (Cis) for mediating effects. If the 95%CI did not include zero, the effect was considered significant ($p < 0.05$). Before the mediating effects were detected, all variables involved were standardised to reduce problems linked to multicollinearity between the interaction items and main effects. Furthermore, we also used negative emotions as the dependent variable and smartphone use disorder as the mediating variable to explore the possibility of an alternative model.

Ethics

The study procedures were carried out in accordance with the Declaration of Helsinki. The Institutional Review Board of the School of Psychology, Northwest Normal University approved the study. All subjects were informed about the study and all provided informed consent.

RESULTS

Descriptive statistics

Table 2 shows the descriptive statistics for all the research variables. Data of all the measures complied with the normal distribution based on the criteria that skewness and kurtosis were less than 2 and 5, respectively (Ghiselli, Campbell, & Zedeck, 1981). The mean smartphone use disorder score was 3.58 ($SD = 1.06$), which indicated that the sample had an average level of smartphone use disorder.

Table 2. Descriptive statistics of all the variables ($N = 107$)

Variables	Mean	*SD*	Min	Max	Skewness	Kurtosis
Age	20.98	2.58	17.00	29.00	1.30	1.36
Negative emotion	3.26	1.31	1.00	6.20	0.35	−0.63
Smartphone use disorder	3.58	1.06	1.20	6.00	−0.20	−0.31

Topology of the rs-EEG brain network related to smartphone use disorder

First, we performed correlation analyses to confirm the association between the alpha-bands K and D, beta-bands K and D, and smartphone use disorder. Consistent with a previous study (H. Wang, Sun et al., 2019), smartphone use disorder was positively associated with alpha band K and negatively associated with alpha band D (see Table 3). However, we did not find a significant correlation between beta-bands K and D and smartphone use disorder. Additionally, we also conducted a correlation analysis for the remaining topological metrics and found that smartphone use disorder was positively associated with the delta-bands K and LF (see Table 3).

To examine whether the associations between topological metrics and smartphone use disorder were robust and stable, we performed a confirmatory cross-validation analysis. The results revealed that the alpha-bands K ($r_{(predicted,\ observed)} = 0.22$, $p = 0.024$) and D ($r_{(predicted,\ observed)} = 0.21$, $p = 0.029$), as well as delta-bands K ($r_{(predicted,\ observed)} = 0.33$, $p < 0.001$) and LF ($r_{(predicted,\ observed)} = 0.25$, $p = 0.010$), reliably correlated with smartphone use disorder.

Bivariate correlations analysis

Based on the topology results of the rs-EEG brain network, the alpha-bands K and D and delta-bands K and LF were chosen in the following analysis. The bivariate correlations for all the study variables are shown in Table 4. The results demonstrated that people with high alpha or delta band K were likely to experience high levels of negative emotions. Furthermore, those with short alpha band D were also likely to experience high levels of negative emotions. However, delta band LF was not correlated with negative emotions, which was not consistent with the mediating effect hypothesis. Therefore, LF was not subjected to subsequent

Table 3. Correlations between the network topological metrics and smartphone use disorder

	M	*SD*	Stats			
			r	*p* (*p*-permutation test)	95% CI	
Delta band						
LF	**0.67**	**0.08**	**0.26**	**0.007 (0.063)**	**0.08**	**0.43**
D	0.20	0.06	−0.21	0.031 (0.308)	−0.38	−0.01
K	**4.95**	**1.96**	**0.34**	**<0.001 (0.007)**	**0.14**	**0.48**
TH	0.47	0.07	0.05	0.634 (0.9882)	−0.14	0.23
Theta band						
LF	0.68	0.08	0.05	0.647 (0.9882)	−0.15	0.23
D	0.19	0.05	−0.03	0.753 (0.999)	−0.22	0.16
K	5.40	2.60	0.18	0.072 (0.488)	−0.01	0.35
TH	0.48	0.06	−0.11	0.250 (0.943)	−0.29	0.08
Alpha band						
LF	0.68	0.08	0.19	0.054 (0.414)	−0.01	0.36
D	**0.21**	**0.06**	**−0.22**	**0.022 (0.087)**	**−0.39**	**−0.03**
K	**5.35**	**2.06**	**0.23**	**0.020 (0.065)**	**0.04**	**0.40**
TH	0.48	0.06	0.04	0.679 (0.988)	−0.15	0.22
Beta band						
LF	0.69	0.07	0.18	0.070 (0.484)	−0.01	0.35
D	0.20	0.05	−0.11	0.251 (0.619)	−0.29	0.08
K	5.16	1.72	0.12	0.219 (0.538)	−0.07	0.30
TH	0.48	0.06	0.09	0.357 (0.979)	−0.11	0.27

Note: *p*-permutation test is first conducted for alpha-bands D and K and beta-bands D and K, and then for the remaining topological metrics; the 95% CI of *r* is derived from the permutation test. The bold font indicates $p < 0.05$.

Table 4. Bivariate correlations ($N = 107$)

Variables	1	2	3	4	5	6	7	8
1. Age	1							
2. Sex	0.06	1						
3. Alpha K	−0.10	−0.05	1					
4. Alpha D	0.07	0.04	-0.68^{***}	1				
5. Delta K	0.06	0.05	0.37^{***}	-0.34^{***}	1			
6. Delta LF	<0.01	0.05	0.32^{**}	-0.23^{*}	0.84^{***}	1		
7. Negative emotion	−0.14	$0.19^{\dagger}$	0.28^{**}	-0.24^{*}	0.24^{*}	0.14	1	
8. Smartphone use disorder	-0.21^{*}	−0.03	0.23^{*}	-0.22^{*}	0.34^{***}	0.26^{**}	0.52^{***}	1

Note: $\dagger p < 0.10$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p \leq 0.001$.

mediation analysis. Additionally, negative emotions were positively correlated with smartphone use disorder. Our results showed that the alpha-bands K and D and delta-band K were closely interrelated with negative emotions and smartphone use disorder.

Complex brain network linking negative emotion to smartphone use disorder

To explore whether negative emotions accounted for the association between the topology of the rs-EEG brain network and smartphone use disorder, we performed three mediation analyses. Considering that age and sex were significantly correlated with smartphone use disorder and negative emotions, respectively, we performed a mediation analysis with both as control variables.

First, the results indicated that alpha band K was positively associated with negative emotions ($b = 0.27$, $p = 0.004$), which, in turn, was related to smartphone use disorder ($b = 0.50$, $p < 0.001$). Meanwhile, the residual direct effect was not significant ($b = 0.07$, $p = 0.430$), which indicated that negative emotions fully mediated the relationship between alpha band K and smartphone use disorder (indirect effect = 0.14, 95% CI = [0.04, 0.26]) (see Fig. 2). The mediation effect accounted for 67% of the total effect. The effect size upsilon is 1.86%, 95% CL = [0.21, 6.95]. The effect size upsilon is interpreted as the variance in the dependent variable accounted for jointly by the mediator variable and the independent variable (Lachowicz, Preacher, & Kelley, 2018).

Second, alpha band D was negatively associated with negative emotions ($b = -0.24$, $p = 0.012$), which, in turn, was related to smartphone use disorder ($b = 0.50$, $p < 0.001$). Meanwhile, the residual direct effect was not significant ($b = 0.09$, $p = 0.305$), which indicated that negative emotions fully mediated the relationship between alpha band D and smartphone use disorder (indirect effect = −0.12, 95% CI = [−0.22, −0.03]) (see Fig. 3). The mediation effect accounted for 57% of the total effect. The effect size upsilon is 1.40%, 95% CL = [0.13, 4.69].

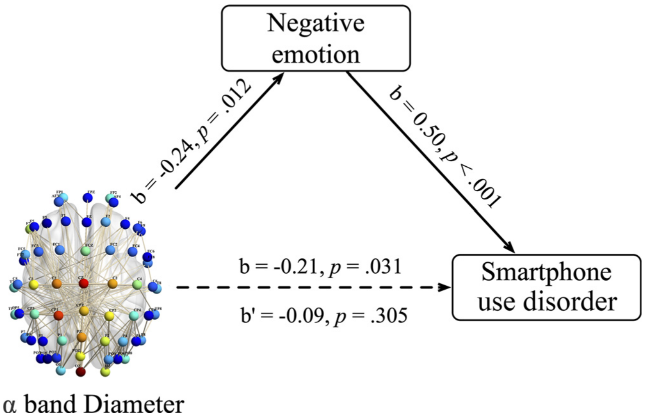

Fig. 3. **The mediation model**. The association between alpha-band D and smartphone use disorder is fully mediated by negative emotions. All path coefficients are standard regression coefficients

Third, delta band K was positively associated with negative emotions ($b = 0.24$, $p = 0.010$), which, in turn, was related to smartphone use disorder ($b = 0.46$, $p < 0.001$). Meanwhile, the residual direct effect was also significant ($b = 0.24$, $p = 0.005$), which indicated that negative emotions partially mediated the relationship between delta band K and smartphone use disorder (indirect effect = 0.11, 95% CI = [0.02, 0.21]) (see Fig. 4). The mediation effect accounted for 32% of the total effect. The effect size upsilon is 1.27%, 95% CL = [0.05, 5.16].

Furthermore, we find that the mediating effect is equally significant in the alternative model. However, the mediating effect of negative emotions is larger in the alpha band K (alternative model, indirect effect = 0.10, 95% CI = [0.02, 0.19]) and in alpha band D (alternative model, indirect effect = 0.10, 95% CI = [−0.20, −0.01]), while the mediating effect of problematic mobile phone use is larger in the delta band K (alternative model, indirect effect = 0.17, 95% CI = [0.08, 0.26]).

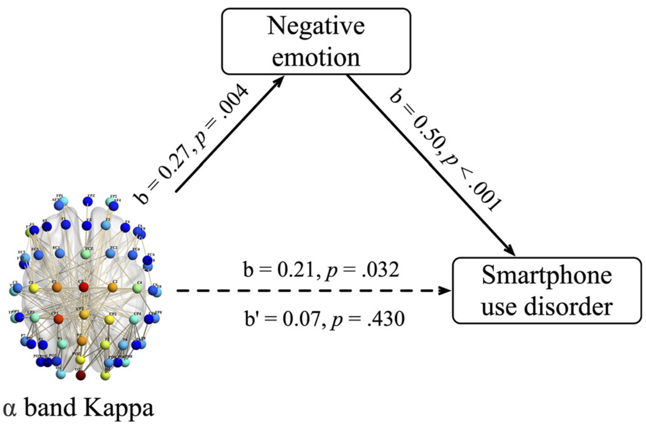

Fig. 2. **The mediation model**. The association between alpha-band K and smartphone use disorder is fully mediated by negative emotions. All path coefficients are standard regression coefficients

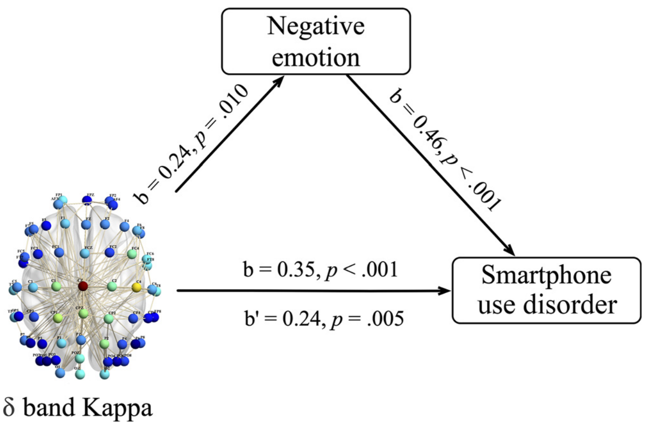

Fig. 4. **The mediation model**. The association between delta-band K and smartphone use disorder is partially mediated by negative emotions. All path coefficients are standard regression coefficients

DISCUSSION

In this study, we explored the neural basis of the association between negative emotions and smartphone use disorder from the perspective of a complex brain network using rs-EEG. Behavioural analysis confirmed that negative emotions were positively correlated with smartphone use disorder. Furthermore, alpha-bands K and D and delta-bands K and LF significantly are related to individual differences in smartphone use disorder. Importantly, alpha-bands K and D and delta-band K were significantly associated with negative emotions. Additionally, the relationships between these three topological metrics and smartphone use disorder were mediated by negative emotions. Hence, our results provided initial evidence that negative emotions were linked to smartphone use disorder based on a common neural basis.

Smartphone use disorder-related topology of the rs-EEG brain network

Our study found that smartphone use disorder was positively correlated with alpha-band K and delta-bands K and LF and negatively correlated with alpha-band D. These findings indicated that the complex brain network associated with smartphone use disorder tended to be excessively scale-free in the alpha and delta bands. Normal brain networks prioritise local information flow processing and, when necessary, execute global processing, resulting in an efficient and balanced optimal processing architecture (Stam, 2014). However, an excessively scale-free trend related to smartphone use disorder has broken this optimal architecture into a star-like topology. Here, many links were concentrated within a few hubs, whereas most nodes had only one link (Stam et al., 2014). Consequently, network hierarchies and information transmission distances between the nodes were reduced. This caused local processing to spread uncontrollably to the entire brain, thereby interfering with the overall processing. Furthermore, this change increased the traffic loads at the hubs and the risk of hub overload, which, in turn, compromised the global network (Stam, 2014). Previous research reported that internet use disorder and problematic social networking site use also showed a star-like topology of the rs-EEG brain network in the alpha band, like our results (H. Wang, Sun et al., 2019; Yin et al., 2023). Thus, for the first time, our findings reveal a close relationship between topological deviations of rs-EEG brain networks and smartphone use disorder.

The importance of our findings lies in the frequency-band information, which will help us understand the variations in cognitive functions associated with smartphone use disorder from a neuroscience perspective. According to previous research (Sadaghiani & Kleinschmidt, 2016), alpha oscillation was an indicator of top-down control network activities, such as selective attention (Laufs et al., 2003; Sadaghiani et al., 2010) and alertness (Sadaghiani et al., 2010). In contrast, delta oscillation contributed significantly to motivational processing (Knyazev, 2007, 2012). Delta activity increased when a person's desires were not met, that is, in a craving state, whereas it decreased after an actual reward was received. Furthermore, alpha- or delta-band activity was closely related to the degree of internet use disorder in both functional and resting states (Balconi, Campanella, & Finocchiaro, 2017; Burleigh, Griffiths, Sumich, Wang, & Kuss, 2020; Wang & Griskova-Bulanova, 2018; H. Wang, Sun et al., 2020). Several fMRI studies also found that smartphone use disorder was associated with functional abnormalities in attention- or reward-related brain areas (Han & Kim, 2022; Henemann et al., 2022; Pyeon et al., 2021). Thus, it is reasonable to speculate that topological deviations in top-down control and reward-motivated networks were associated with smartphone use disorder.

Based on the above-mentioned points, we believe that the plausible explanation for our findings is that a scale-free control network and reward-motivated network, which manifest as topological deviations of rs-EEG brain networks in the alpha and delta bands, will lead to excessive attention and uncontrolled desire for smartphones, resulting in smartphone use disorder.

Notably, dissimilar to a previous study, this study did not identify a significant relationship between topological deviations in the beta band and smartphone use disorder (H. Wang, Sun et al., 2019), which found a correlation between these topological deviations and internet use disorder. Despite ideas proposing that smartphone use disorder represents a mobile version of internet use disorder, it possesses unique features that further distinguish it.

Negative-emotions-related topology of the rs-EEG brain network

Consistent with Hypothesis 2, we found that the scale-free level of the rs-EEG brain network at the alpha and delta bands were significantly correlated with negative emotions. In line with previous studies (Farashi & Khosrowabadi, 2020), our results indicated that the more the alpha-band network tended to form a star-like network, the higher the degree of negative emotions. Meanwhile, we found a similar scale-free effect at the delta band. Although few studies reported the association between topological deviations in the delta band and emotions, delta frequency has been shown to play an important role in emotion regulation (Jiang et al., 2022; Lapomarda et al., 2022). Additionally, similar emotional profiles were associated with similar delta-band activities over the prefrontal and temporoparietal regions (Hu, Wang, & Zhang, 2022). These results suggested that both the alpha- and delta-band EEG activities were important biomarkers of negative emotions.

The scale-free rs-EEG brain network at the alpha and delta band may be generated by an informationally activated or overloaded brain. A similar view has been demonstrated in studies related to people with depression (Cao et al., 2020; Leuchter, Cook, Hunter, Cai, & Horvath, 2012; Li, Cao, Wei, Tang, & Wang, 2015; Rotenberg, 2004; Zhang et al., 2011). Depressive brains usually present increased overall coherence between electrodes (Leuchter et al., 2012; Li et al., 2015), lower D and higher global efficiency in brain function networks (Cao et al., 2020; Li et al., 2015; Zhang et al., 2011). Thus, by combining the cognitive functions of delta and alpha bands, we speculated that the high correlation between scale-free rs-EEG brain networks and negative emotions comes from the following possibilities. When in a negative emotional state, the attention-related network represented by the alpha band is likely to be overloaded by the negative information. Simultaneously, the inhibition-related network represented by the delta band is likely in an over-activated state when the individual tries to counteract the adverse effects of negative emotions.

Negative emotions related to smartphone use disorder

As held by Hypothesis 3, our results showed that negative emotions were associated with increased smartphone use disorder. This indicated that negative emotions were a significant trigger for smartphone use disorder. This finding was consistent with recent research that explored the relationship between negative emotions and smartphone use disorder (Gao et al., 2021; Yue et al., 2021). We provide empirical evidence for the compensatory internet use theory (Kardefelt-Winther, 2014), which posits that individuals with negative emotions are prone to use smartphones to avoid these feelings.

The mediating role of negative emotions

As held by Hypothesis 4, the mediation analysis revealed that negative emotions mediated the association between topological deviations in rs-EEG brain networks and smartphone use disorder. Specifically, the scale-free level of the rs-EEG brain network in the alpha and delta bands were related to an increase in negative emotions, which, in turn, was related to an increase in smartphone use disorder. We previously mentioned that the topological deviations found in the alpha and delta bands reflected a scale-free attentional control network and a reward-motivated network. According to the I-PACE model, these biopsychological changes influenced affective and cognitive responses to smartphone-related stimuli and eventually resulted in smartphone use disorder (Brand et al., 2016). When individuals with these biopsychological changes could not access their smartphones, they experienced negative emotions owing to withdrawal, paid more attention to smartphone-related stimuli, and compensated for such negative emotions by future excessive use. Hence, these results support the idea that topological deviations found in the alpha and delta bands are the neural basis for linking negative emotions to smartphones.

We need to note that the supplementary analyses also showed a significant mediation model when smartphone use disorder is the mediating variable, suggesting the possibility of alternative models. By comparing the effect sizes of the indirect effects, we found greater indirect effects on the alpha band when negative emotions were used as the mediating variable, but greater indirect effects on the delta band when smartphone use disorder was used as the mediating variable. Therefore, we thought that the relationship might be more consistent with the alternative model in the delta band. This implies a possible alternative explanation: individuals with more scale-free topology at the delta band tend to over-activate the reward-motivated network, which enables them to exhibit behaviours of smartphone use disorder more easily. Smartphone use disorder, as a form of negative coping, is unable to truly meet individual needs, which exacerbates negative emotions (P. Wang, Wang et al., 2018). However, as this study is cross-sectional, the hypothesis that the different functional networks (represented by different frequency bands, negative emotions and smartphone use disorder) constitute different causal models should be tested in future longitudinal studies.

Furthermore, Lachowicz et al. (2018) proposed that Cohen's benchmarks for small (2%), medium (15%), and large (25%) proportions of explained variance apply to effect size upsilon. Thus, the effect sizes upsilon in our study indicates small magnitudes for the mediation effect. When interpreting the small magnitudes of effects in the present study considering its context, we speculated on two possible causes. First, in addition to the topology of rs-EEG found here, other neurobiological indicators may exist to explain the relationship between the brain and smartphone use disorder. Second, in addition to negative emotions, other mediating variables may exist to explain the relationship between rs-EEG topology and smartphone use disorder. In addition, although the effect sizes upsilon in this study were small, the mediator accounted for a high proportion of the total effect. The indirect effect found in our study was also comparable to similar studies (Kong et al., 2020; S. Wang, Zhao et al., 2018). The combined evidence points to the validity of our findings. Finally, it is noteworthy that even small indirect effects found in the current study should not be overlooked because they provide a new perspective to capture the mechanism of smartphone use disorder.

Limitations and future directions

This study highlighted the role of complex brain networks in smartphone use disorder through negative emotions. However, this study has several limitations. First, the sample size was small, consisting of young, healthy university students from China. Future studies should include larger samples and examine whether our results can be generalised to other populations. Second, the study's cross-sectional design precludes causal inferences. Future research should adopt interventional or longitudinal designs to clarify the relationship between complex brain networks, negative emotions, and smartphone use disorder. Third, our study measured the topology of complex brain networks only from the perspective of high temporal resolution. Hence, it is necessary to continue exploring the above-mentioned relationship from the perspective of high spatial resolution using fMRI. Finally, prior research (Montag et al., 2021) indicates that individuals can become addicted to specific applications rather than the smartphone itself. Therefore, future studies should examine the specific applications people are addicted to for a more insightful understanding.

CONCLUSION

This study used rs-EEG and MST to investigate the connection between negative emotions and smartphone use disorder. Excessive brain networks in the alpha and delta bands were linked to smartphone use disorder. This indicates a complex brain network characteristic of the disorder. The study also found that negative emotions play a role in mediating the association between deviations in brain networks and smartphone use disorder. The results suggest that cognitive behavioural therapy can help with this disorder by dissolving negative emotions. Other potential treatments include transcranial magnetic stimulation or transcranial direct current brain stimulation. Future research in this field could provide further insights to alleviate smartphone use disorder.

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Conflict of interest: The authors declare no conflict of interest.

SUPPLEMENTARY DATA

Supplementary data to this article can be found online at https://doi.org/10.1556/2006.2023.00077.

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