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FoMO and the brain: Loneliness and problematic social networking site use mediate the association between the topology of the resting-state EEG brain network and fear of missing out

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ABSTRACT

Fear of missing out (FoMO) is a pervasive apprehension that others might have rewarding experiences from which one is absent. Recently, FoMO has been considered a negative aspect of social media's popularity. However, the neural basis of FoMO remains unknown. Here, we examined the relationship between the topology of the resting-state electroencephalography (rs-EEG) brain network and FoMO and developed a theoretical model with loneliness and problematic social networking sites (SNS) use as mediators to explain the association between the topology and FoMO in 113 young adults. Minimum spanning tree analysis revealed that the high FoMO group's rs-EEG brain network had a higher Kappa and leaf fraction in the alpha band than the low FoMO group's network, indicating that emergence of FoMO is based on excessive scale-free brain networks. Importantly, the association between alpha-band Kappa and FoMO was partially mediated by loneliness and problematic SNS use. Multiple mediation analyses revealed sequential mediation by loneliness and problematic SNS use. To our knowledge, this is the first study to consider FoMO from the perspective of a complex brain network. Our results provide neuroscientific evidence that loneliness, namely a lack of psychological need satisfaction, influences FoMO, while SNS provide platforms for this influence to propagate.

1. Introduction

In recent years, fear of missing out (FoMO) has drawn extensive academic attention as a critical and emergent aspect of the dark side of social media. According to existing reports, FoMO affects 72% of young adults (age 18–33) in the U.S. and the U.K. (Mack & Vaughn, 2012), and 78.3% of interviewees in China (Zhen, W., 2016). FoMO is defined as a pervasive apprehension that others might have rewarding experiences from which one is absent, which is characterized by the desire to stay continually connected with what others are doing (Przybylski, Murayama, DeHaan, & Gladwell, 2013). It is a form of anxiety that one will be "left behind"; therefore, people desire to remain informed and connected with other people's experiences to avoid this feeling of being "left behind," which represents a risk to their self-concept (Salem, 2015; Zhang et al., 2020). People with a high level of FoMO usually experience a range of negative life experiences and feelings, such as sleeping problems (Tandon, Kaur, Dhir, & Mäntymäki, 2020), reduced academic performance (Al-Busaidi, Dauletova, & Al-Wahaibi, 2022), and negative effects on well-being (Roberts & David, 2019). Therefore, it is necessary to explore predictors of FoMO.

Existing research has examined the effects of emotional factors (e.g., negative emotions, such as loneliness; Beyens, Frison, & Eggermont, 2016; Oberst, Wegmann, Stodt, Brand, & Chamarro, 2017), social media use (Buglass, Binder, Betts, & Underwood, 2017; Yin et al., 2019), and demographic factors (Przybylski et al., 2013) on FoMO. However, few studies have investigated the causes of FoMO from a neuroscientific perspective. To the best of our knowledge, only one study has explored the neural mechanisms underlying FoMO (Lai, Altavilla, Ronconi, &

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Aceto, 2016). Using event-related potentials (ERP) and sLoreta analyses, this study found that FoMO was positively correlated with activation of the right middle temporal gyrus (BA21) only when watching inclusive social images, indicating that the social monitoring system plays an important role in FoMO. However, as the brain is a complex anatomical and functional network (Sporns, 2013), a particular mental function does not depend solely on local brain activity. Therefore, it is essential to examine the relationship between complex brain networks and FoMO.

1.1. The association between topology in complex brain networks and FoMO

Resting-state electroencephalography (rs-EEG; i.e., EEG recording when no cognitive task is being performed) can provide a convenient and cost-effective way to study complex brain networks (Deco, Jirsa, & McIntosh, 2011; van Diessen et al., 2015). It may be combined with minimum spanning tree (MST) analysis, which allows quantification of the topology of the brain network (Bullmore & Sporns, 2009). MST is mathematically defined as a subnetwork that connects all nodes while minimizing the link weights without forming loops (Kruskal, 1956; Prim, 1957). The topology of the MST lies somewhere between a path and a star shape (Stam et al., 2014; see Fig. 1). In a path network, nodes are less loaded, but information is disseminated over a longer distance. In a star network, the opposite is true. A healthy brain presents an optimal topology characterized by a combination of short distances and prevention of overload of any node (Stam, 2014). Many rs-EEG studies have shown that deviation from the optimal topology can cause cognitive and clinical symptoms in neuropsychiatric diseases (Stam, 2014), such as dyslexia (Xue et al., 2020), cognitive impairment (Youssef et al., 2021), stutter (Ghaderi, Andevari, & Sowman, 2018), and Alzheimer's disease (Das & Puthankattil, 2020).

Considering the above arguments, one may speculate that the emergence of FoMO may also be associated with abnormal topology of the rs-EEG brain network. However, no previous study has tested this hypothesis. To address this deficit, the current study first explored topological deviation in the brain network corresponding to FoMO using MST analysis of rs-EEG data. Thus, we proposed the following hypothesis:

Hypothesis 1. High levels of FoMO result from topological deviations in the rs-EEG brain network.

On this basis, we were interested in the mediating mechanisms underlying the relationship between the topology of the rs-EEG brain network and FoMO. Thus, we generated a theoretical model in which loneliness and problematic social networking site (SNS) use account for the association between the topology of the rs-EEG brain network and FoMO.

1.2. The mediating role of loneliness

Loneliness has been shown to play an important role in predicting FoMO. According to self-determination theory (Deci & Ryan, 1985), FoMO arises from situational or chronic deficits in psychological need satisfaction, especially deficiency in stable relatedness (Przybylski et al., 2013). Loneliness is a negative emotional response to the subjective perception of such deficient stable relatedness and is distinct from social isolation (Hawkley & Cacioppo, 2010; Russell, Cutrona, Rose, & Yurko, 1984; Smoyak, 1984). Previous studies have demonstrated that lonely individuals tend to have higher levels of FoMO (Bernard, 2020; Reer, Tang, & Quandt, 2019; Uram & Skalski, 2022; Van Huynh, Phan, Hua, Tran-Thi, & Tran-Chi, 2022). For instance, a significant positive connection has been found between loneliness and FoMO, indicating that FoMO is related to feelings of isolation (Reer et al., 2019). In addition, a recent study showed that people with low life satisfaction exhibited higher loneliness, which in turn increased FoMO (Uram & Skalski, 2022). In summary, there is both theoretical and empirical evidence that loneliness can cause FoMO.

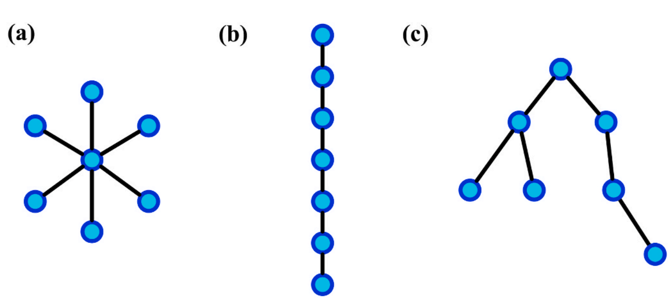

Fig. 1. An illustration of forms of MST trees. (a) Star network; **(b)** Path network; **(c)** normal shape of MST brain network.

Furthermore, resting-state functional magnetic resonance imaging (rs-fMRI) studies have shown that variations in the functional organization of brain networks can be neural substrates of loneliness (Mwilambwe-Tshilobo et al., 2019; Tian et al., 2017; Yang et al., 2019). Although no studies have directly used MST to examine loneliness to obtain similar results, previous studies have confirmed that MST can effectively reflect emotional states (Cao et al., 2020; Farashi & Khosrowabadi, 2020; Li et al., 2017; Zhang et al., 2018). For instance, the topology of the brain network tends to form a star shape from high to low emotional valence, suggesting that the brain network is more activated when faced with negative emotions (Cao et al., 2020). Such a star-like network has also been found in individuals with major depressive disorders (Li et al., 2017). In addition, one study showed that when MST was used to detect emotions, the alpha frequency band was the most informative band during negative emotion processing (Farashi & Khosrowabadi, 2020). These findings imply that people with topological deviations in the rs-EEG brain network may be more sensitive to loneliness.

A perspective from brain network science posits that disruption of topology in the brain network, such as a scenario of hub overload and failure, may be a potential common pathway underlying certain psychological abnormalities (Stam, 2014). According to this theory, loneliness and FoMO may share, to some extent, the same topological deviation in the rs-EEG brain network as their common neural bases. Moreover, according to self-determination theory, loneliness is a key variable in triggering FoMO; thus, it is logical to speculate that loneliness may serve as a mediator in the link between topological deviation in the brain network and FoMO. Taken together, topological deviations in the rs-EEG brain network could predict increased loneliness, which, in turn, could predict increased FoMO. Based on the literature reviewed above, we proposed the following hypothesis:

Hypothesis 2. Loneliness mediates the association between topological deviation of the rs-EEG brain network and FoMO.

1.3. The mediating role of problematic social networking site (SNS) use

In recent years, social media has swiftly evolved to change the fundamental form of social communication. SNS allow users to create personal files and interact with their offline or online friends by updating their status, posting comments, sending messages, and viewing the information uploaded by others (Boyd & Ellison, 2007). Despite enriching people's daily lives, excessive use of SNS can also have negative consequences for people's mental health. Recent studies have confirmed that problematic SNS use is a crucial factor in inducing FoMO (Yin et al., 2019).

Problematic SNS use refers to paying excessive attention to SNS, driven by an uncontrollable motivation to log on to or use SNS, and spending considerable time and energy on SNS, which impairs other important life areas (Andreassen & Pallesen, 2014). According to image management theory (Siibak, 2009), SNS provides a platform for individuals to reconstruct their profile images based on ideal self-identity values, resulting in people commonly uploading information that demonstrates their extravagant and interesting activities. Browsing large amounts of this information can easily result in social comparison. According to social comparison theory, people tend to evaluate and compare themselves against those who are better than themselves in some related fields in upward social comparison (Appel, Gerlach, & Crusius, 2016). Thus, the results of this comparison will lead people to believe that other people have better lives than themselves, thereby leading to feelings of being "left behind" and threatening their self-concept. Namely, people with a high level of problematic SNS use are more likely to experience FoMO. In a recent study, this proposition was supported using network analysis (Li, Niu, Mei, & Griffiths, 2022). Specifically, the study found that SNS use was positively associated with FoMO, indicating that excessive SNS use can increase FoMO (Li et al., 2022).

Interestingly, although few studies have directly tested the relationship between the topology of the rs-EEG brain network and problematic SNS use using MST, a recent study found that the topology of the rs-EEG brain network is crucial for Internet addiction (Wang, Sun, Lv, & Bo, 2019). In this study, compared with the control group, participants with Internet addiction possessed a more star-like network in the alpha and beta bands (Wang, Sun, et al., 2019). In addition, a recent rs-EEG study using conventional graph theory revealed an altered brain network organization in an Internet addiction group, shifting toward a more random state (Sun, Wang, & Bo, 2019). A body of rs-fMRI studies has also provided evidence that Internet addiction alters normal brain network organization (Patil, Madathil, & Huang, 2021; Wee et al., 2014). Given that problematic SNS use is a subtype of Internet addiction (Wang, Wang, et al., 2018), it is reasonable to assume that some type of topological deviation in the rs-EEG brain network is associated with increased problematic SNS use.

Based on the ideas presented above, problematic SNS use and FoMO may also share a neural basis, and problematic SNS use may act as another mediator to explain the relationship between topological deviations in the brain network and FoMO. Taken together, topological deviations in the rs-EEG brain network could predict increased problematic SNS use, which, in turn, could predict increased FoMO. Based on the literature reviewed above, we proposed the following hypothesis:

Hypothesis 3. Problematic SNS use mediates the association between topological deviations in the rs-EEG brain network and FoMO.

1.4. A multiple mediation model

In this study, we also examined the sequential mediating roles that loneliness and problematic SNS use play in the association between the topology of the rs-EEG brain network and FoMO. With this integrated multiple mediation model, various mechanisms can be examined simultaneously, from the antecedent to the consequent variables (Hayes, 2013), thereby providing more insight into how the topology of the rs-EEG brain network is related to FoMO.

Due to the lack of empirical evidence regarding how these two mediators interact, there may exist several possible mediation models (Liu & Ling, 2009). Parallel mediation is one possibility. That is, loneliness is one possible explanation for FoMO, followed by problematic SNS use. In parallel, loneliness and problematic SNS use mediate the relationship between the topology of the rs-EEG brain network and FoMO. Another possibility is sequential mediation. According to compensatory Internet use theory (Kardefelt-Winther, 2014), people go online to escape real-life issues or alleviate dysphoric moods; thus, it is reasonable to hypothesize that when people are trying to alleviate loneliness, they will be inclined to excessively use SNS, namely exhibiting problematic SNS use. Several studies have confirmed that loneliness is a significant predictor of problematic SNS use (Kim, LaRose, & Peng, 2009; Lee, Kim, & Kang, 2017; Shettar, Karkal, Kakunje, Mendonsa, & Chandran, 2017). A cross-lagged panel analysis revealed that loneliness at Time 1 was positively related to SNS usage at Time 2 (X. X. Zhang, Rost, et al., 2020), providing strong evidence of a causal relationship between loneliness and problematic SNS use. Thus, we proposed the following hypothesis:

Hypothesis 4. The relationship between the topology of the rs-EEG brain network and FoMO is mediated by loneliness and problematic SNS use sequentially.

We developed a multiple mediation model to examine these possibilities (Fig. 4).

1.5. The present study

To perform our investigation, we employed well-validated instruments to assess participants' levels of FoMO, loneliness, and problematic SNS use. Next, we employed rs-EEG and MST analysis to explore whether FoMO has topological deviation in the brain network, and then examined whether this topological deviation can affect FoMO through loneliness and problematic SNS use. Based on previous behavioral and neural findings regarding FoMO, loneliness, and problematic SNS use, we developed a multiple model to examine four hypotheses: (a) the emergence of FoMO is based on topological deviation in the rs-EEG brain network, (b) loneliness mediates the association between topological deviation in the rs-EEG brain network and FoMO, (c) problematic SNS use mediates the association between topological deviation in the rs-EEG brain network and FoMO, and (d) loneliness and problematic SNS use sequentially mediate the relationship between topological deviation in the rs-EEG brain network and FoMO. It is important to note that we use the term "mediate" only in the statistical sense as the cross-sectional design does not support any causal conclusions.

2. Method

2.1. Participants

In accordance with the power analysis performed using G*power, a minimum sample size of 84 participants was necessary to identify a medium-sized effect ($r = 0.3$, $\alpha = 0.05$, $1 - \beta = 0.80$) using a correlation analysis. The present study adopted a cross-sectional design and obtained rs-EEG and measures from 113 healthy young adults (60 females and 53 males: mean age = 20.87 years, $SD = 2.42$) from eight universities in northern China, using convenience sampling. In 2021, data were collected. FoMO-related effects were identified in the samples within this collection area. All participants were right-handed and free of neurological or psychiatric disorders. There was no significant age difference between females and males (t (113) = −0.381, $p = .70$). This study was approved by the ethics review board of the first author's university. All participants provided written informed consent and were compensated for their time. In terms of confidentiality, we maintained anonymity among participants, coded participants by their participating order, and informed them that all data collected would be for research purposes only. Three participants were excluded because they did not finish large parts of the measures, and two others were excluded because EEG data contained excessive artifacts, leaving 108 participants for the final analyses.

2.2. Measures

2.2.1. Loneliness

Loneliness was measured using the Chinese version of the Three-Item Loneliness Scale (Hughes, Waite, Hawkley, & Cacioppo, 2004; Wang et al., 2022). The assessment comprises three items rated on a scale ranging from 1 (almost never) to 7 (almost always). A representative item is "How often do you feel left out?" In this study, Cronbach's α for this scale was 0.90.

2.2.2. Problematic SNS use

Problematic SNS use was measured using the Chinese version of the SNS Intrusion Questionnaire (Wang, Lei, Yu, & Li, 2020; Wang, Wang, et al., 2018; Yin et al., 2019), which was modified with reference to the Facebook Intrusion Questionnaire (Elphinston & Noller, 2011). The scale consisted of eight items. A representative item is "I often use SNS for no particular reason." Each item is rated on a scale ranging from 1 (almost never) to 7 (almost always). In this study, Cronbach's α for this scale was 0.86.

2.2.3. FoMO

FoMO was measured using the Chinese version of the Fear of Missing Out scale (Wang, Wang, et al., 2019; Wang, Xie, et al., 2018), which was originally developed by Przybylski et al. (2013). The scale consists of 10 items. A representative item is, "I get worried when I find out my friends are having fun without me." Each item is rated on a scale ranging from 1 (almost never) to 7 (almost always). In this study, Cronbach's α for the scale was 0.79.

2.3. Experimental procedure

During the experiment, the participants sat in a comfortable armchair in a well-shielded, soundproofed room. Before beginning the experiment, the experimental requirements were explained to the participants. The rs-EEG data for each participant were recorded for 6 min. Participants were urged to relax, prevent large head movements, and not think about anything throughout the EEG signal-gathering procedure, but they were required to remain awake. The participants opened and closed their eyes during the recording according to the following sequence: eyes open for 1 min, eyes closed for 2 min, eyes open for 2 min, and eyes closed for 1 min. The order of eye opening and closing was counterbalanced across all participants. The EEG records of all participants were continuously monitored to ensure that they followed the instructions and exhibited no fatigue symptoms. After the EEG recording, the participants completed all three questionnaires.

2.4. EEG recording and preprocessing

An electroencephalogram (EEG) was recorded from the scalp with 64 nonpolarizable Ag/AgCl sintered electrodes using a Neuroscan system with a sampling rate of 500 Hz. The electrode sites followed the extended 10–20 convention. All electrode impedances were maintained below 5 kΩ. In addition to the scalp sites, a horizontal electrooculogram (EOG) was recorded at the outer canthi of both eyes, and a vertical EOG was recorded between the supraorbit and suborbit of the left eye. Online, the signals were referenced to the left mastoid electrode and offline and were re-referenced to the average reference.

EEG preprocessing was performed using the EEGLAB toolbox (Delorme & Makeig, 2004) and custom MATLAB scripts (MathWorks). Continuous EEG data were digitally filtered with 0.5 Hz high-pass and 30 Hz low-pass filters. Then, bad electrodes (no more than six) were identified using the kurtosis method and interpolated using data from nearby electrodes. Six-minute continuous EEG data were segmented into 180 epochs of 2000 ms duration. Polluted epochs were visually inspected and eliminated manually. To eliminate eye movement artifacts, the ICA algorithm implemented in the EEGLAB toolbox (Delorme & Makeig, 2004) was applied to all EEG epochs, and the to-be-corrected components were determined visually based on the component topography and waveforms. EEG epochs were subjected to an artifact rejection procedure in which amplitudes exceeding ±70 μV were discarded. Then, we used the preprocessing data to implement complex brain network analysis; a schematic of the analysis process is shown in Fig. 2.

2.5. Power spectral analysis and functional connectivity analysis

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

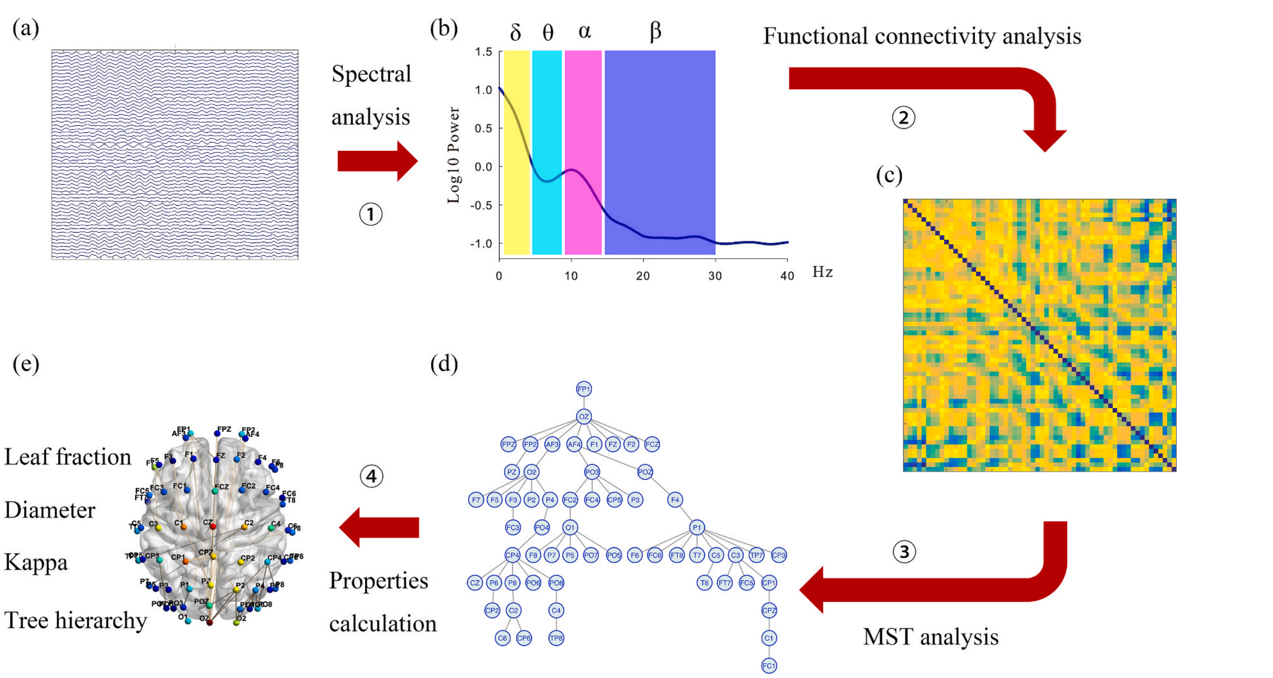

Fig. 2. Schematic representation of EEG complex brain network analysis. (a) Preprocessed EEG data; (b) Power spectra. Colored boxes indicate the delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), and beta (13–30 Hz) bands; (c) Functional connectivity matrix; (d) Minimal span tree. (e) Topology of MST brain network.

functional connectivity analysis.

The phase lag index (PLI) measures the asymmetry of the distribution of phase angle differences between two signals towards the positive or negative side of the imaginary axis. They are less susceptible to the influence of volume conduction, common sources, and montage (Stam, Nolte, & Daffertshofer, 2007). PLI is less sensitive to outliers, but it is also less sensitive to the amount of clustering in the distribution. We employed the weight phase lag index (WPLI), an extension of the PLI, whereby angle differences are weighted according to their 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) is the imaginary part of the cross-spectral density at time point (or trial) t, and sgn () is a sign function (−1 for negative values, +1 for positive values, and 0 for zero values). The WPLI ranges from −1 to 1. A positive or negative value of the WPLI indicates that the distribution of the phase angle difference is towards the positive or negative side of the imaginary axis. A |WPLI| value of 1 indicates perfect phase locking at any phase difference value other than 0 (mod π). Thus, a larger |WPLI| suggests stronger phase locking, that is, stronger functional connectivity. In this study, the WPLI analysis created 60 × 60 wt adjacency matrices, which were then converted to absolute values and later used in the MST analysis in each frequency band.

2.6. MST analysis

Based on this definition, MST does not allow recurrent connections, and constructs networks with weight adjacency matrices derived from WPLI analysis using Kruskal's algorithm (Kruskal, 1956). The weights (defined as 1-|WPLI|) of all possible connections were first sorted in ascending order. The lowest weight connections were then added to the network one-by-one until all 60 nodes were linked in a loopless subgraph. We calculated four MST metrics (leaf fraction (LF), diameter (D), kappa (K), and tree hierarchy (TH)) to evaluate the topology in the rs-EEG brain network (Stam, 2014; Stam et al., 2014).

Nodes with only one link (i.e., degree 1 nodes) in a tree are referred to as "leaves" or "leaf nodes." The number of leaf nodes in a tree is the leaf number. The LF measures the fraction of leaf nodes within the total number of nodes. D measures the shortest path along the MST. In a network, the shortest path between two nodes refers to the path involving the fewest links between them. The K metric measures the breadth of the degree distribution in a network, and is high in networks with a scale-free degree distribution and high-degree hubs (Stam, 2014; Stam & van Straaten, 2012). The high level of the scale-free property means that the network is less vulnerable to random attacks, but it has a higher vulnerability to targeted attacks and a higher overload of the most important nodes. TH captures an optimal tree configuration characterized by a combination of short distances and the prevention of overload of any node. The path network possesses low LF and K values and a high D value, whereas the star network exhibits the opposite. TH is 2/m for a path, approaches 0.5, for a star (with large N), and can take values between 2/m and 1 for trees with an intermediate topology between path and star. The Supplementary Material contains detailed explanations of the topological metrics.

2.7. Statistical analysis

To examine whether the emergence of FoMO is based on topological deviation in the rs-EEG brain network and to select topological metrics for the following mediation effect analysis, we first selected 20 individuals with the lowest FoMO scores (12 females, 8 males; mean FoMO = 2.01, SD = 0.51, ranging from 1 to 2.5) and the 20 with the highest FoMO scores (13 females, 7 males; mean FoMO = 4.84, SD = 0.38, ranging from 4.3 to 5.3) from 108 participants. FoMO levels differed significantly between the high and low FoMO groups, $t\,(38) = -19.89$, $p < .001$, 95% CI = [−3.12, −2.55], Cohen's d = 6.31. The ages of the two groups were comparable ($t\,(38) = 0.15$, $p = .883$). We then compared all four topological metrics in each frequency band between the high and low FoMO groups. To account for multiple comparisons performed in MST metrics, we used false discovery rate (FDR) correction.

Furthermore, we used data from all 108 participants to explore whether and how loneliness and problematic SNS use explained the association between topological deviation in the rs-EEG brain network and FoMO. In a mediation model, we employed the MST metrics that showed significant differences between the high and low FoMO groups to represent the topology of the rs-EEG brain network as a predictor in the following analysis. The outcome was the participants' FoMO level. To examine the robustness of the relationships between the MST metrics chosen and FoMO, we used fourfold balanced cross-validation based on machine learning algorithms paired with linear regression (Kong, Zhao, You, & Xiang, 2020; S. Wang, Zhao, et al., 2018). In the analysis, the MST metrics were treated as independent variables and FoMO was treated as a dependent variable. The data were divided into four groups under the restriction that there were no significant differences between the distributions of the data. Three folds were used as the training set, and the remaining data were used as the test set. Subsequently, $r_{(\text{predicted, observed})}$ (i.e., the correlation between the observed values and the predicted values) was computed based on the average of four repetitions of this procedure. To obtain stable results, the entire procedure of fourfold balanced cross-validation was repeated 100 times. Finally, nonparametric testing methods were used to test the significance of the model by generating 1000 surrogate data sets.

Finally, the mediation effect was analyzed in three steps using SPSS 26. First, the data were analyzed using descriptive statistics and zero-order correlation analysis. Second, the PROCESS macro for SPSS (Model 4) was used to separately test the mediation effect of loneliness and problematic SNS use (Hayes, 2013). Third, we used the PROCESS macro (Model 6) for SPSS to test the multiple mediation effects of loneliness and problematic SNS use. The analyses of Models 4 and 6 in PROCESS provided bootstrap 95% Cis for mediating effects. If the 95% CI did not include zero, the effect was considered significant ($p < .05$). Before detecting the mediating and moderating effects, all variables involved were standardized to reduce problems linked to multicollinearity between the interaction items and the main effects.

3. Results

3.1. Topological differences of the rs-EEG brain network between FoMO groups

Compared to the low FoMO group, the high FoMO group exhibited a more star-like network in the alpha band (Fig. 3). The statistical results for all MST metrics in all frequency bands are presented in Table 1.

In the alpha band, K was significantly higher in the high-FoMO group than in the low-FoMO group. LF was also significantly higher in the high FoMO group than in the low FoMO group, but the difference was not significant after FDR correction. These results suggest a tendence toward excessive scale-free brain networks in individuals with FoMO. Therefore, Hypothesis 1 was supported.

In addition, to test whether the associations of alpha-band K with FoMO were robust and stable in all 108 participants' data, we performed a confirmatory cross-validation analysis. The results revealed that alpha-band K reliably predicted FoMO ($r_{(\text{predicted, observed})} = 0.30$; $p < .001$).

3.2. Descriptive statistics and bivariate correlations

According to the results of the topology of the rs-EEG brain network,

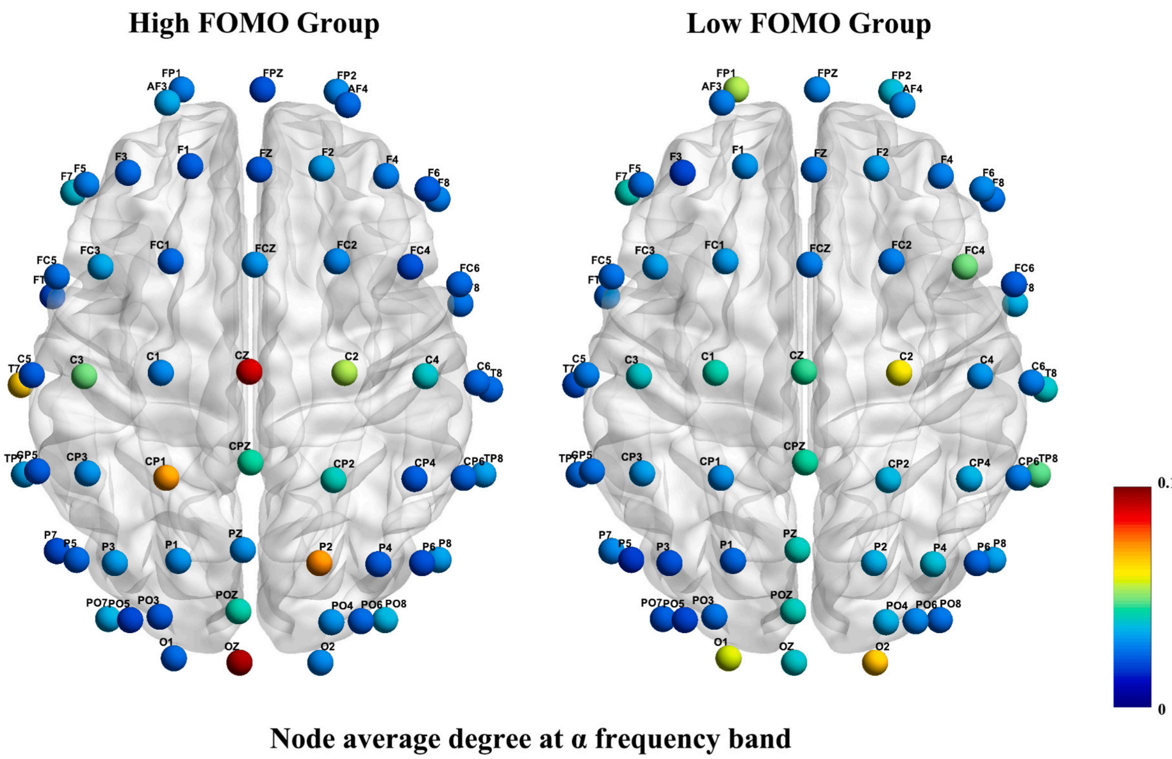

Fig. 3. Group-level node average degree for alpha bands for the high FoMO group and the low FoMO group. Each node corresponds to an EEG electrode and is colored according to the group averaged degree values. The degree values have been normalized by the number of electrodes.

Table 1
Network topology metrics in high and low FoMO groups.

	H-FoMO		L-FoMO		Stats		
	M	*SD*	*M*	*SD*	*t*	*p* (*p*-FDR)	Cohen's *d*
Delta band							
LF	0.68	0.08	0.66	0.10	−0.75	.459 (.668)	0.22
D	0.20	0.04	0.21	0.06	0.94	.356 (.570)	0.20
K	5.22	1.97	5.04	2.77	−0.24	.810 (.864)	0.07
TH	0.47	0.06	0.47	0.08	0.35	.728 (.864)	0.00
Theta band							
LF	0.69	0.08	0.68	0.09	−0.27	.788 (.864)	0.12
D	0.19	0.06	0.20	0.04	0.44	.664 (.864)	0.20
K	6.00	3.14	5.09	2.06	−1.09	.283 (.570)	0.34
TH	0.47	0.04	0.49	0.07	0.94	.352 (.570)	0.35
Alpha band							
LF	**0.72**	**0.08**	**0.66**	**0.07**	**−2.34**	**.025 (.200)**	**0.80**
D	0.19	0.07	0.22	0.07	1.04	.307 (.570)	0.43
K	**6.44**	**2.55**	**4.47**	**1.10**	**−3.16**	**.003 (.048)**	**1.00**
TH	0.48	0.06	0.48	0.04	−0.03	.976 (.976)	0.00
Beta band							
LF	0.69	0.06	0.66	0.07	−1.75	.088 (.394)	0.46
D	0.19	0.03	0.22	0.05	1.64	.110 (.394)	0.73
K	5.16	1.45	4.49	1.40	−1.48	.147 (.394)	0.47
TH	0.49	0.06	0.47	0.05	−1.48	.148 (.394)	0.36

alpha-band K was chosen to represent the topology of the rs-EEG brain network in the following mediation analysis. The data of all measures complied with the normal distribution based on the criteria that skewness was less than 2 and kurtosis was less than 5 (Ghiselli, Campbell, & Zedeck, 1981). Descriptive statistics and bivariate correlations for all study variables are presented in Table 2. The results demonstrated that people with a high alpha-band K were likely to have high levels of loneliness, problematic SNS use, and FoMO. People with high levels of problematic SNS use and FoMO were likely to experience high levels of loneliness. Problematic SNS use was positively correlated with FoMO.

3.3. Testing the mediating role of loneliness

Model 4 of the PROCESS macro (Hayes, 2013) was adopted to test Hypothesis 2, which proposed that loneliness mediates the relationship between the topology of the rs-EEG brain network and FoMO. The results indicated that the alpha-band K was positively associated with loneliness ($b = .21$, $p = .027$), which in turn was related to FoMO ($b = 0.49$, $p < .001$). The residual direct effect was also significant ($b = 0.21$, $p = .013$), indicating that loneliness partially mediated the relationship between alpha-band K and FoMO (indirect effect = 0.10, 95% CI = [0.01, 0.20]). Therefore, Hypothesis 2 was supported.

Table 2
Descriptive statistics and bivariate correlations for the full sample (N = 108).

Variables	M	SD	1	2	3	4	5	6
1. Age	20.87	2.42	1					
2. Gender	–	–	.03	1				
3. Alpha K	5.23	1.91	−.09	−.05	1			
4. Loneliness	2.94	1.40	−.09	.12	.21*	1		
5. Problematic SNS use	3.83	1.19	.02	.12	.20*	.29***	1	
6. FoMO	3.47	0.98	−.12	.01	.31***	.53***	.47***	1

Note: $^{*}p < .05$; $^{***}p \leq .001$.

3.4. Testing the mediating role of problematic SNS use

Model 4 of the PROCESS macro (Hayes, 2013) was adopted to test Hypothesis 3, which proposed that problematic SNS use mediates the relationship between the topology of the rs-EEG brain network and FoMO. The results indicated that alpha-band K was positively associated with problematic SNS use (b = .20, $p = .027$), which in turn was related to FoMO (b = 0.42, $p < .001$). The residual direct effect was also significant (b = 0.23, $p = .009$), indicating that problematic SNS use partially mediated the relationship between alpha-band K and FoMO (indirect effect = 0.08, 95% CI = [0.01, 0.17]). Therefore, Hypothesis 3 was supported.

3.5. Testing the multiple mediation effect

Hypothesis 4 predicted that loneliness and problematic SNS use would sequentially mediate the relationship between the topology of rs-EEG brain networks and FoMO. We tested this hypothesis using Model 6 of the PROCESS macro (Hayes, 2013). For alpha-band K, some pathways were significant, as presented in Table 3 and Fig. 4. First, the pathway "Alpha K → Loneliness → FoMO" was significant. Second, the pathway "Alpha K → problematic SNS use → FoMO" was not significant. Therefore, loneliness and problematic SNS use did not mediate the association between alpha-band K and FoMO in a parallel fashion. Third, the sequential pathway "Alpha K → Loneliness → problematic SNS use → FoMO" was significant. Hence, alpha-band K was serially linked to loneliness ($b = 0.21$, $p = .027$), problematic SNS use ($b = 0.25$, $p = .008$), and, eventually, FoMO ($b = 0.32$, $p < .001$). The residual direct pathway of "Alpha K → FoMO" is also significant ($b = 0.16$, $p = .040$). Therefore, loneliness and problematic SNS use partially mediated the relationship between the alpha-band K and FoMO.

Table 3
Testing the pathways of the multiple mediation model (N = 108).

Effect	b	95% CI	
		Lower	Upper
Direct effect			
Alpha K → Loneliness	.21*	.03	.43
Alpha K → problematic SNS use	.15	−.04	.34
Alpha K → FoMO	.16*	.01	.30
Loneliness → problematic SNS use	.25**	.07	.42
Loneliness → FoMO	.41***	.22	.50
problematic SNS use → FoMO	.32***	.15	.44
Indirect effect			
Alpha K → Loneliness → FoMO	.09	.01	.17
Alpha K → problematic SNS use → FoMO	.05	−.01	.12
Alpha K → Loneliness → problematic SNS use → FoMO	.02	.00	.04

Note: *$p \leq .05$; * *$p \leq .01$; ***$p \leq .001$.

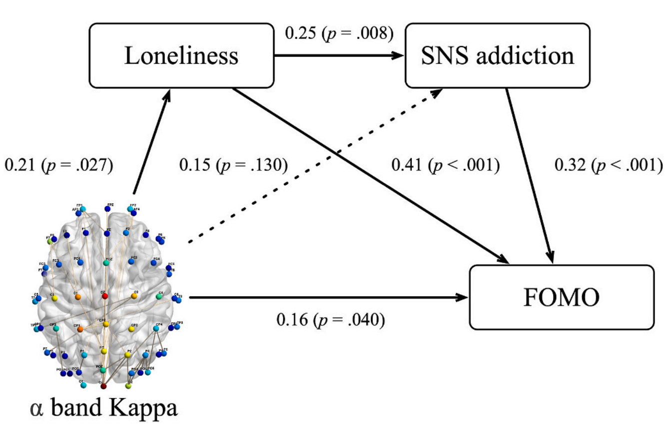

Fig. 4. The multiple mediation model. The association between alpha-band K and FoMO is mediated by loneliness and problematic SNS use. All path coefficients are standard regression coefficients.

In addition, we examined whether loneliness and problematic SNS use sequentially mediate the relationship between FoMO and the topology of the rs-EEG brain networks. The results showed that mediation effects were no longer significant after using FoMO as an independent variable and alpha-band K as a dependent variable (the pathway "FoMO → Loneliness → Alpha K," indirect effect = .03, 95% CI = [-0.08, 0.23]; the pathway "FoMO → problematic SNS use → Alpha K," indirect effect = 0.03, 95% CI = [-0.06, 0.14]; the pathway "Alpha K → Loneliness → problematic SNS use → FoMO," indirect effect <0.01, 95% CI = [-0.02, 0.02]). Taken together, these results imply that, in a multiple mediation effect, there may be a unidirectional relationship from the topology of the rs-EEG brain network to FoMO.

We also used the alpha band LF to represent the topology of the rs-EEG brain network and performed the same mediation analysis as for the alpha-band K (see the results in the supplement). This analysis revealed a similar mediation effect of loneliness and problematic SNS use between alpha band LF and FoMO.

4. Discussion

In this study, we explored the neural basis of FoMO from the perspective of complex brain networks, using rs-EEG. We also tested a theoretical model in which loneliness and problematic SNS use explained the relationship between the topology of the rs-EEG brain network and FoMO. We found that the topology of the rs-EEG brain network in the high FoMO group had higher K and LF in the alpha band, suggesting a more star-like network topology in people with high levels of FoMO. Importantly, the association between alpha-band K and FoMO was partially mediated by loneliness and problematic SNS use. The association was also sequentially mediated by loneliness and problematic SNS use. These findings substantiate that FoMO is accompanied by a change in the topology of the brain network and that loneliness and problematic SNS use may serve as an underlying mechanism that explains the effect of topological deviation in the rs-EEG brain network on FoMO.

4.1. FOMO-related topological difference of the rs-EEG brain network

Regarding Hypothesis 1, the K and LF measures were greater in the high FoMO group than in the low FoMO group in the alpha band, indicating a shift toward a star-like network in the high FoMO group. That is, in brain networks associated with a high level of FoMO, many nodes have only a single link, whereas many links are concentrated in a few hubs, resulting in an excessively scale-free network.

There are two possible implications of such changes. First, enhanced K and LF measures may be indicative of neuronal hyperexcitability in brain networks with high FoMO levels. Second, excessive link concentration on a limited number of hubs results in hub overload. Normal brain networks have an efficient hierarchical structure, in which information flow is processed locally and globally when necessary (Stam, 2014). When one node in a network cannot handle incoming information, nodes that project to this damaged node will redirect their input to other nodes higher up in the hierarchy (Stam, 2014), which will increase K and LF. In such rerouting, the hierarchical structure of the network would be shortened, allowing information from local nodes through short paths to quickly spread to the global network, thereby interfering with the overall processing of the brain network. Social anxiety and generalized anxiety disorders exhibit similar brain network properties (Schoenberg, 2020; Xing et al., 2017). For instance, people with social anxiety disorder have shorter path lengths of the brain network in the theta band than do healthy controls (Xing et al., 2017). This rerouting can also result in an increase in the traffic load of the highest node, leading to “hub overload.” When the highest node becomes damaged owing to excessive traffic load, the entire network is at risk of hub failure.

It is important to note that this reorganization of the brain network occurs in the alpha band. According to previous studies, alpha band oscillations play an important role in top-down control functions such as selective attention and sustained alertness (Sadaghiani & Kleinschmidt, 2016). Knyazev, Savostyanov, and Levin (2005) found that the number of active alpha oscillators linearly decreases in persons with low state anxiety and linearly increases in those with high state anxiety. This finding suggests that people with high levels of anxiety possess an “alpha system” that can maintain a high level of vigilance and readiness for processing stressors in the environment. This is consistent with the connection between FoMO and social monitoring systems (Lai et al., 2016). Several studies have identified a high correlation between attention problems and FoMO (Al-Furaih & Al-Awidi, 2020; Matias et al., 2021). For instance, people with high levels of FoMO are more easily captured by high social reward distractors (Matias et al., 2021).

Considering the information presented above, it is plausible to hypothesize that a high level of FoMO may be caused by excessive scale-free brain networks associated with attention and vigilance. This ensures that the individual is always prepared to receive information that can confirm that they are not “left behind.”

4.2. The mediating role of loneliness

Consistent with Hypothesis 2, the present study found that loneliness mediated the association between alpha-band K and FoMO. Consistent with previous studies (Reer et al., 2019; Uram & Skalski, 2022), our study confirmed the correlation between loneliness and FoMO. Consequently, loneliness is a significant FoMO trigger, validating self-determination theory’s explanation of FoMO (Deci & Ryan, 1985; Przybylski et al., 2013). Meanwhile, the connection between alpha-band K and loneliness is consistent with earlier rs-EEG research on negative emotions (Cao et al., 2020; Farashi & Khosrowabadi, 2020; Li et al., 2017; Zhang et al., 2018). For instance, it has been found that the brain has a star-like network when negative emotions are present, indicating that the brain is more active when facing negative emotions (Cao et al., 2020; Ma, Li, Xu, Tang, & Wang, 2012). As a negative emotional response to the experience of disparity between expected and real social relations, it is conceivable that loneliness and alpha-band K have a strong link. Given the relationship between alpha-band K and FoMO, it appears that a high alpha-band K level serves as a neural basis for both loneliness and FoMO. This is consistent with prior neuroimaging research demonstrating that loneliness is linked to aberrant attentional networks, indicating diminished capacity to filter irrelevant inputs (Tian et al., 2017). Thus, the increased alpha-band K might indicate a deficit in brain function related to attentional processing, thereby lowering the capacity to interpret social information efficiently, leading to greater loneliness, all of which further contribute to increased FoMO.

4.3. The mediating role of problematic SNS use

As predicted in Hypothesis 3, our findings revealed that problematic SNS use served as a mediator of the relationship between alpha-band K and FoMO. Consistent with earlier research (Yin et al., 2019), problematic SNS use can predict increased FoMO. This result is consistent with social comparison theory (Appel et al., 2016), which argues that upward social comparison during extensive SNS browsing could contribute to higher FoMO because it distorts one’s self-concept. Furthermore, we replicated a previous study’s finding that participants with Internet addiction had a higher level of alpha-band K than healthy controls (Wang, Sun, et al., 2019). As attentional bias is a common mechanism associated with problematic SNS use (Nikolaidou, Fraser, & Hinvest, 2019), we speculate that increased alpha-band K may be associated with attentional bias related to problematic SNS use, which would then lead to a high level of FoMO.

4.4. The sequential mediation effect of loneliness and problematic SNS use

Finally, our results indicated that the impact of alpha-band K on FoMO was sequentially mediated by loneliness and problematic SNS use, supporting our hypothesis that topological deviation in the rs-EEG brain network corresponds to a state of loneliness, which drives individuals to extensively browse social media to satisfy social relational needs. However, the browsing process generates upward comparisons, thereby increasing the risk of FoMO. Additionally, it is necessary to note the following three points. First, loneliness fully mediated the relationship between alpha-band K and problematic SNS use, which indicates that loneliness, that is, the need to fulfill social relationships, is a more significant factor than problematic SNS use in explaining the relationship between topological deviation in the rs-EEG brain networks and FoMO. Second, the model demonstrated that the paths “Alpha K → Loneliness → problematic SNS use → FoMO” and “Alpha K → Loneliness → FoMO” were both valid. This result supports the notion that problematic SNS use is not a determining factor for the emergence of FoMO. However, SNS provide a convenient platform for accessing information about others, through which individuals can easily justify whether they have been “left behind,” and this has contributed to FoMO becoming a widespread phenomenon in modern society. Third, loneliness and problematic SNS use partially mediated the relationship between the alpha-band K and FoMO. This means that additional variables may explain the association between topological deviation in rs-EEG brain networks and FoMO.

4.5. Limitations and future directions

Although this study illuminates how complex brain networks are related to FoMO via loneliness and problematic SNS use, it has several limitations. First, this study adopted a small and convenient sample consisting solely of Chinese university students to explore the above question. It is unclear whether the results can be generalized to people from other demographic backgrounds, such as those of a different age or culture. Future research should increase the sample size and use stratified sampling including participants from different backgrounds to confirm the findings of the current study. Second, as the first study to examine the neural basis of FoMO using EEG complex brain networks, we used a data-driven approach to select MST metrics related to FoMO for subsequent analysis, which leaves the possibility of double-dipping error. Although we used a fourfold cross-validation analysis to exclude the possibility of double-dipping error to a certain extent, the best approach is to repeat the results using new independent data in future studies. Third, as noted above, it is important not to draw any causal inferences regarding the findings of the present study because of the cross-sectional design. The relationships between the study variables could be bidirectional. Although the multiple mediation effect was not significant after using FoMO as an independent variable and alpha-band K as a dependent variable, there remains the theoretical possibility of a positive reinforcing loop for alterations between neural basis and behavior. That is, individuals with topological deviations in a complex brain network are prone to feelings of loneliness and are motivated to spend a lot of time browsing SNS, thereby generating high levels of FoMO. These extrinsic behaviors may exacerbate topological deviations in the complex brain network, which in turn reinforces the behavior of the individual. To gain better understanding of how to model the interaction between neural basis and behavior, longitudinal designs or experiments are required in the future. Fourth, EEG was used in this study. Although it has a high temporal resolution and can help measure the topology of complex brain networks, it cannot address the question of whether functional or anatomical changes in some brain regions play a significant role. Therefore, it is necessary to continue to explore the relationship between the emergence of FoMO and complex brain networks from the perspective of fMRI. Finally, it is likely that other individual or environmental variables may mediate or moderate the relationship between complex brain networks and FoMO; however, these variables were not included in the current study. Future research could demonstrate how these variables affect the relationship between complex brain networks and FoMO by acting as mediators or moderators. This would help us better understand this phenomenon.

5. Conclusion

In summary, this study concludes that the emergence of FoMO is based on excessive scale-free brain networks and further substantiates that loneliness and problematic SNS use serve as underlying mechanisms to explain the association of this topological deviation in complex brain networks with FoMO. Our results provide initial evidence of the neural basis of FoMO from a complex brain network perspective. From this neuroscientific perspective, these findings contribute to a better understanding of the nature of FoMO, which distinguishes the different roles of addressing the needs of social relations and using SNS appropriately in the prevention of and intervention against FoMO.

Credit author statement

Yulong Yin: Conceptualization, Data curation, Formal analysis, Funding acquisition, Writing – original draft. Xiao Cai: Data curation, Writing – original draft. Mingkun Ouyang: Data curation, Funding acquisition, Writing – original draft. Sen Li: Writing – review & editing. Xu Li: Writing – review & editing. Pengcheng Wang: Conceptualization, Supervision, Writing – review & editing.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

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