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Research article

Neurophysiological correlates of trait and behavioral impulsivity across methamphetamine and gambling Addiction

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ABSTRACT

Investigating neurophysiological markers linked to impulsivity in individuals with gambling and methamphetamine addiction using resting-state EEG data offers valuable insights into the underlying neurophysiological mechanisms associated with impulsivity in individuals with addiction. This study aims to use resting-state EEG to explore the connection between various types of addiction and different aspects of impulsivity. Participants from the methamphetamine, gambling, and healthy control groups (abbreviation: MA, GB, HC) underwent EEG recordings and completed measures of impulsivity. Group differences in trait scores and behavioral tendencies were analyzed. Abnormal connections with node linkage and importance changes were analyzed through the resting-state EEG power spectral and network analyses. Further, relationships between impulsivity scores and connectivity differences in groups were explored through correlation analysis. Finally, these abnormal connections related to impulsivity were tested for their effect of distinguishing individuals with addiction from healthy controls through the ROC analysis. Results revealed that GB displayed the highest trait impulsivity on the overall score, while MA exhibited greater attentional impulsivity. Variations in behavioral impulsivity were reflected in response times. Resting-state EEG analysis showed higher beta power in GB. Specific channel pairs demonstrated abnormal connections and altered connectivity patterns in the beta band, with MA displaying a less efficient network compared to GB. Correlation analyses uncovered associations between impulsivity scores and connectivity, which were influenced by group differences. Furthermore, resting-state EEG connections effectively differentiated individuals with addiction from healthy controls. Overall, this study contributes valuable insights into the neural mechanisms of addiction-related impulsivity, emphasizing the potential of resting-state EEG connections as an important neurophysiological correlate.

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1. Introduction

Addiction is a complex and multifaceted disorder that has been the subject of extensive research. Understanding the underlying neural mechanisms of addiction is crucial for developing effective prevention and treatment strategies. Behavioral addiction and substance addiction are two common types of addiction that have distinct but overlapping neural pathways and mechanisms [1,2]. Behavioral addiction encompasses compulsive behaviors like gaming addiction that do not rely on substance consumption, whereas substance addiction involves the compulsive use of drugs or alcohol. The fundamental symptoms and impulsive behaviors seen in both behavioral and substance addictions are similar, such as withdrawal, tolerance, craving, and impaired behavioral regulation [3,4]. Neurologically, both behavioral addiction and substance addiction share similarities in their underlying mechanisms. Research has shown that both types of addiction involve the desensitization of reward circuits, which dampens the ability to feel pleasure and motivation for everyday activities [5]. It also involves the weakening of brain regions involved in decision-making and self-regulation, leading to repeated relapse [6]. These dysregulations lead to heightened neurological and behavioral similarities in individuals with addiction, regardless of whether it is behavioral or substance-related. However, there are essential distinctions in their possible mechanisms on the brain. The potential difference between behavioral addiction and substance addiction lies in the neurochemical systems involved [2,7]. Substance addiction often consists of the activation of the brain's reward pathway, primarily driven by the release of neurotransmitters such as dopamine [8]. Behavioral addiction, on the other hand, may also involve alterations in the reward pathway but may rely on different neurotransmitter systems or neural circuits [8,9]. Hence, the neurobiological markers and neural networks in addiction are essential for understanding the similarities and differences between behavioral addiction and substance addiction.

Impulsivity is considered a core feature of addiction and plays a significant role in the development, maintenance, and treatment response of addictive behaviors [10–13]. It refers to a tendency to act on immediate urges or desires without considering the potential long-term consequences. In the context of substance addiction, impulsivity can drive individuals to seek out drugs or alcohol as a means of instant gratification despite being aware of the potential long-term adverse consequences [12]. Similarly, in behavioral addiction, impulsivity can lead individuals to engage in excessive and compulsive behaviors, disregarding the adverse effects on their well-being and personal relationships [14]. There are two main domains in impulsivity: trait impulsivity, which refers to general measures of impulsivity, and behavioral impulsivity, which refers to specific facets of impulsivity linked to emotional states [15,16]. Trait impulsivity represents a consistent characteristic that indicates an individual's overall inclination towards impulsive behavior and thinking in different situations. It can make individuals more susceptible to initiating and continuing the use of addictive substances or engaging in addictive behaviors [11,12]. On the other hand, behavioral impulsivity is manifested in the actual engagement in impulsive acts, such as consuming a substance on a whim or indulging in a gambeling session driven by an immediate desire for excitement [17]. It demonstrates the difficulty in controlling these impulsive actions, particularly at that specific time, highlighting their temporary nature. Both types of impulsivity are relevant to the development of addiction, while behavioral impulsivity might have a more direct expression in addictive episodes [18]. This illustrates that interventions focused on altering behavioral impulsivity or addressing trait impulsivity may have different effects [16]. Therefore, it is important to explore various aspects of impulsivity in studying and comprehending its connections with addiction in order to offer improved recommendations for intervention.

Research has shown impulsivity is associated with alterations in brain regions involved in decision-making and self-control. In both substance addiction and behavioral addiction, there is evidence of hyperactivity in the orbitofrontal cortex and the striatum, which are critical areas involved in reward processing and decision-making [19–21]. This hyperactivity may contribute to the strong desire for immediate rewards and the inability to resist impulsive behavior. However, there are also some differences in the neural correlates of impulsivity between substance addiction and behavioral addiction. For example, in substance addiction, there is evidence of reduced gray matter volume in the prefrontal cortex, which is associated with impaired decision-making and self-control, and it more likely explains the trait impulsivity in substance abusers [11,22]. On the other hand, in behavioral addiction, such as gaming addiction, the prefrontal cortex seems to be more intact, suggesting that other areas of the brain, such as the insula and striatum, may play a more prominent role in behavioral impulsivity and addictive behaviors [23]. Overall, impulsivity is a complex trait encompassing various facets and is associated with alterations in brain regions. Attention to the interplay between impulsivity and addiction underscores the importance of understanding the neural mechanisms that contribute to these behaviors and seeking precise intervention.

There have been several systematic reviews of neuroimaging studies investigating impulsivity and inhibitory control in people with addictions [21,24–26]. Functional magnetic resonance imaging (fMRI) studies reveal altered brain activity in the prefrontal cortex, orbitofrontal cortex, anterior cingulate cortex, and striatum, correlating with a higher tendency towards impulsive behaviors [24,27]. Positron emission tomography (PET) studies track neurotransmitter systems and show disruptions in dopaminergic pathways may underlie impulsive decision-making and substance-seeking behaviors [27]. Electroencephalography (EEG) studies highlight atypical patterns of brainwave activity, such as reduced P300 amplitudes, indicating diminished inhibitory control mechanisms in addicted individuals [24,28]. These findings highlight the commonalities between behavioral addiction and substance addiction in terms of altered neural processes. However, few studies utilized resting-state EEG to explore the parallelisms and divergencies. Resting-state EEG is a cost-effective and non-invasive method that allows for research on individuals with addiction. This technique directly measures brain activity and can detect abnormalities in functional connectivity commonly seen in addiction. Furthermore, it is well-suited for investigating trait impulsivity due to its ability to detect rapid neural oscillations and transient connectivity patterns that are not influenced by specific tasks or stimuli [29,30]. Recently, studies found that EEG network analysis could reveal abnormal brain networks associated with impulsivity in individuals with addiction [29,31]. Irregular brain networks such as the cortico-striatal-thalamo-cortical loops disrupt the functional connectivity between areas responsible for processing rewards, controlling cognition, and biasing attention [31]. Utilizing graph theory can facilitate a thorough analysis of the neurobiological networks

in individuals with addiction [32]. This method enables the recognition of important areas involved in processing and communication within intricate networks and provides several types of analyses to compare brain networks. Resting-state EEG combined with psychological features and impulsivity network analysis methods have demonstrated effective classification of behavioral and substance addiction [33]. Therefore, the neurobiological basis of addiction can be better understood through the application of resting-state EEG and network analysis techniques.

In sum, a considerable amount of research suggests that impulsivity plays a crucial role in addiction; however, there is limited evidence exploring the specific relationship between different forms of addiction and various facets of impulsivity, as well as their corresponding complex neural network. This study differentiated trait and behavioral impulsivity in individuals with behavioral and substance addictions compared to non-addicted individuals and utilizes resting-state EEG measures and network analyses to investigate brain activity patterns. To be noted, this study targeted gambling and methamphetamine addictions as they represent two significant types of addiction. Gambling addiction is a behavioral addiction marked by an uncontrollable desire to gamble, resulting in substantial personal, financial, and social repercussions. Methamphetamine addiction is explained as a persistent, recurring disorder characterized by compulsive drug seeking and usage despite harmful consequences. The goal is to uncover the parallelisms and divergencies between these addictions and the neurophysiological correlates associated with impulsivity.

2. Material and methods

2.1. Participants

Participants for the study were recruited from two specialized centers in Shanghai that cater to individuals with addiction disorders: individuals with gambling addiction were recruited from the Profit Center for Treating Gambling Addiction. Individuals diagnosed with methamphetamine addiction were recruited from a Mandatory Center for Substance Abuse and Addiction. Inclusion criteria for the participants with addiction disorders included a diagnosis of gambling or methamphetamine addiction, as per DSM-5 criteria, which was confirmed by two psychiatrists; an age range of 25–50 years; at least a fundamental level of education and the ability to write and comprehend text. Exclusion criteria for these participants included the presence of co-occurring mental health conditions such as depression or compulsive disorder. Moreover, all participants underwent a screening process to ensure they did not have any history of head injury, neurological disorders, or other medical conditions that may affect brain function. A control group with no behavioral addiction or substance use disorder history was chosen from the general population of Shanghai. Screening procedures were performed to confirm study eligibility, and participants had to be male and aged between 25 and 50 to ensure that observed differences could be attributed to addiction disorders rather than confounding variables such as age, sex, education, or other mental health conditions. The research enlisted 100 participants in total. The gambling addiction (GB) group comprised 30 individuals, the methamphetamine addiction (MA) group included 40 individuals, and the health-control (HC) group consisted of 30 individuals without addiction disorders.

2.2. Procedures

The process is illustrated in Fig. 1. Throughout the study, individuals were interviewed to gather demographic information and details on their history of addiction. Information was collected on age, education level, duration of addiction, and frequency of substance use or gambling activity. Following this, participants completed assessments for trait impulsivity before proceeding to a behavioral task designed to measure their impulsive behavior. After completing the behavioral tasks, participants underwent resting-state EEG recordings.

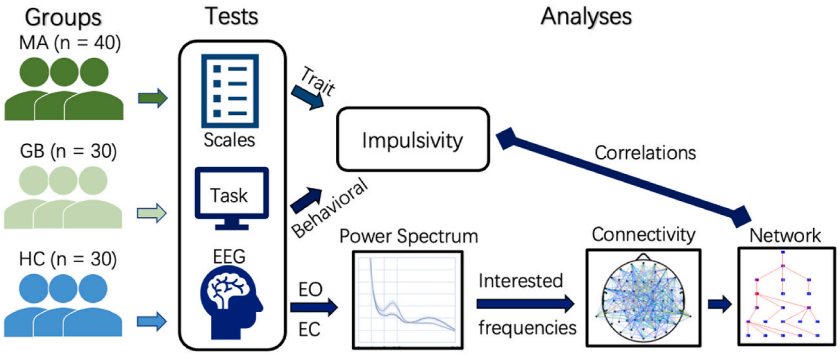

Fig. 1. Contents of the study and the analytic process.

2.3. Impulsivity measures and analysis

2.3.1. Barratt impulsiveness scale-11 (BIS-11)

The study assessed both trait and behavioral impulsivity in participants with addiction disorders and the control group. Barratt impulsiveness scale-11 (BIS-11) in Chinese was used to measure trait impulsivity, which captures individual differences in tendencies towards impulsive behavior [34,35]. This questionnaire includes subscales for attentional, motor, and nonplanning impulsivity. Attentional impulsiveness refers to difficulties in concentrating or focusing attention and making quick decisions. Motor impulsiveness focuses on acting spontaneously without considering consequences. Non-planning impulsiveness characterizes a lack of future-oriented thinking and a preference for living in the moment without planning. These measures provide an assessment of different facets of impulsivity, aiding researchers in understanding impulsive behaviors in individuals with addiction disorders compared to control groups. Participants were asked to rate statements on a 5-point Likert scale (30 items), ranging from "rarely/never" to "almost always/always", indicating how well each statement described them. Higher total scores of these subscales indicate higher levels of impulsivity. To examine differences, we utilized one-way ANOVAs to compare group differences for continuous variables. Post-hoc comparisons were analyzed with t-tests, correcting using the false discovery rate (FDR) method.

2.3.2. Balloon Analogue Risk Task

Behavioral impulsivity was measured using the Balloon Analogue Risk Task [36]. The BART involves decision-making regarding the inflation of virtual balloons to accumulate points with the inherent risk of losing potential points if the balloon bursts. Behavioral impulsivity within this task can be gauged by several outcomes. Number of burst balloons is an indicator of risk-taking behavior, as more bursts may reflect a tendency to take greater risks. Average reaction times for pumps may show how quickly participants make the decision to pump the balloon. Faster reaction times may imply less deliberation before taking action. Adjusted average pump is a more nuanced measure, adjusted for the risk of explosion, reflecting the average number of pumps participants make on balloons that did not burst. These different metrics derived from the BART allow researchers to obtain a multifaceted view of impulsivity and risk-taking behavior in participants. Group differences were analyzed similarly to the previous measures.

2.4. EEG data acquisition and analysis

2.4.1. EEG recording

During EEG recording, participants were instructed to sit quietly with their eyes closed for 5 min and their eyes opened for another 5 min. Their resting-state EEG data was recorded using a 64-channel electroencephalography system (BrainProduct, Germany). The EEG cap was positioned according to the international 10–20 system, and electrode impedance was kept below 10 kΩ. The EEG was sampled continuously at a sampling frequency of 1000 Hz.

2.4.2. EEG preprocessing

The raw EEG data was preprocessed and analyzed using MATLAB and EEGLAB toolbox. First, the raw EEG data was checked for any artifacts or noise. Any noisy channels or segments containing artifacts were identified, corrected, or removed. Next, the data was resampled to 250 Hz to ensure consistency and compatibility with further analysis. After resampling, the data underwent a band-pass filter to remove unwanted frequencies. This band-pass filter ranged from 1 Hz to 50 Hz to preserve the relevant EEG frequencies and eliminate unwanted noise. Additionally, eye movement artifacts were removed using an independent component analysis algorithm. Following the artifact removal, the EEG data was re-referenced using a reference electrode standardization technique to improve the accuracy and reliability of the data. After preprocessing, the 5-min rest EEG data was segmented into epochs of 3 s to capture relevant brain activity patterns. Finally, the epochs were visually inspected to ensure data quality and consistency before further analysis. Once the preprocessing steps were completed, the resting-state EEG data was ready for analysis. In our study, eye-close and eye-open conditions were separately analyzed to investigate the differences in brain activity during rest. We categorized the channels into six regions included: (1) frontal, (2) central, (3) parietal, (4) occipital, (5) left-temporal, and (6) right-temporal.

2.4.3. EEG analysis

Power spectrum analysis was conducted to examine the frequency characteristics of the resting-state EEG data. The power spectrum analysis involved calculating the EEG data's power spectral density to determine power distribution across different frequency bands. Relative power is a measure used in EEG studies to quantify the contribution of a specific frequency band to the overall electrical activity recorded. It is calculated by dividing the power spectrum density of a frequency band by the total power spectrum density across all frequency bands. This value is then typically expressed as a percentage, representing the fraction of total brain oscillations accounted for by that frequency band at a given time. For instance, a higher relative alpha power means that a greater proportion of the overall EEG activity is composed of alpha waves, which is relevant for indicating states of relaxation and alertness in individuals. By quantifying the EEG activity in this way, researchers can identify patterns that might relate to specific cognitive processes or pathological conditions. The relative power of specific frequency bands in this study included theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (30–50Hz) [37,38]. All analyses were performed using MATLAB scripts based on the FieldTrip toolbox (http://www.fieldtriptoolbox.org/). A standard "mtfft" routine with a hanning window was utilized for the analysis. Epochs for relative (%) power were calculated by applying a fast Fourier transform to each frequency band. A one-way ANOVA was conducted to examine group differences in the averaged relative power for the power spectrum. Between-condition comparisons were analyzed using cluster-based permutation tests. Monte Carlo p-values were computed based on 1000 permutations, and clusters were defined as neighboring

electrodes with $p < 0.05$, controlling for multiple spatial comparisons ($p < 0.025$, two-tailed test). The electrodes were grouped into six scalp regions referred to in the previous study for statistical comparison [39]. The representative electrodes from each region were taken for analysis, as shown in Fig. 2. A repeated measure factorial ANOVA was used for region-level analysis, with each frequency band within regions (frontal, central, parietal, temporal, occipital) as a within-subject factor. The partial eta squared (η_p^2) was reported to measure effect size in the context of ANOVA tests. It indicates the proportion of total variability in the data attributed to a specific factor or interaction after considering other factors in the model.

Connectivity analysis was performed at the sensor level across specific frequency ranges to investigate the interactions among different scalp regions. This type of analysis involves computing coherence or spectral coherence measures, which assess the level of synchronization between pairs of electrodes. These measures offer insights into the functional connectivity of the brain and can reveal communication patterns and information exchange between distinct brain areas. Unlike power measures, this analysis indicates how different neural populations operate temporally correlated or synchronized. These measures are often related to the fact that greater coherence or connectivity may exist within brain region on that frequency band of higher power. By conducting connectivity analysis, we can uncover crucial information about the functional communication and coordination between different brain regions and frequency bands, contributing to a comprehensive understanding of the differences in brain activity patterns among the groups under study [40]. In our study, we used the Weighted Phase Lag Index (WPLI) to assess connectivity at the sensor level. The WPLI is a connectivity metric measuring the phase lag consistency between electrode pairs. It considers the asymmetry of the phase differences. It provides a more accurate connectivity estimate than other measures, such as coherence or phase locking value [41]. Network-based statistics (NBS) can be employed to identify distinct patterns of brain functional connectivity among the three groups [42]. This statistical method utilizes a permutation-based approach to minimize the chance of false discoveries and effectively reduces the family-wise error rate associated with multiple tests. Additionally, permutation tests based on threshold-free cluster enhancement were used to compare functional connectivity among the three groups. This analysis allowed us to identify significant differences in functional connectivity patterns between individuals with addiction and controls.

Furthermore, network analysis could examine the organization and properties of the brain networks identified through connectivity analysis, and graph theory-based network analysis can characterize the brain networks. Graph theory-based network analysis is a powerful approach to studying the organization of brain networks. It allows us to quantify various network measures such as node degree, clustering coefficient, and path length, which provide insights into the brain network's efficiency, resilience, and integration [43]. In our study, we constructed a functional connectivity matrix based on the weighted phase lag index for the interested frequency band across the time window, which was then used to build a graph representation of the brain network with each electrode corresponding to a node and the connectivity between electrodes corresponds to edges in the network. Node-wise, edgewise, and network-wise analyses were conducted to explore the characteristics and properties of the brain networks using the Minimum spanning tree (MST), which can be obtained using Prim's algorithm or Kruskal's algorithm [44]. We sorted all the weighted links in the WPLI matrix from highest to lowest. Then, we gradually added these links, starting with the heaviest ones while ensuring no loops were formed until all nodes were incorporated. Finally, some MST network characteristics were quantified.

Node degree centrality (Deg) refers to the number of edges connected to a node. Betweenness centrality (BC) measures the node's importance as a "hub" within the network by calculating the fraction of all shortest paths that pass through that node [45]. For our analysis, we calculated Deg and BC for each node separately. Other parameters of network organizations are included. Assortativity refers to the tendency of nodes in a network to form connections with other nodes that have similar characteristics or degrees [46].

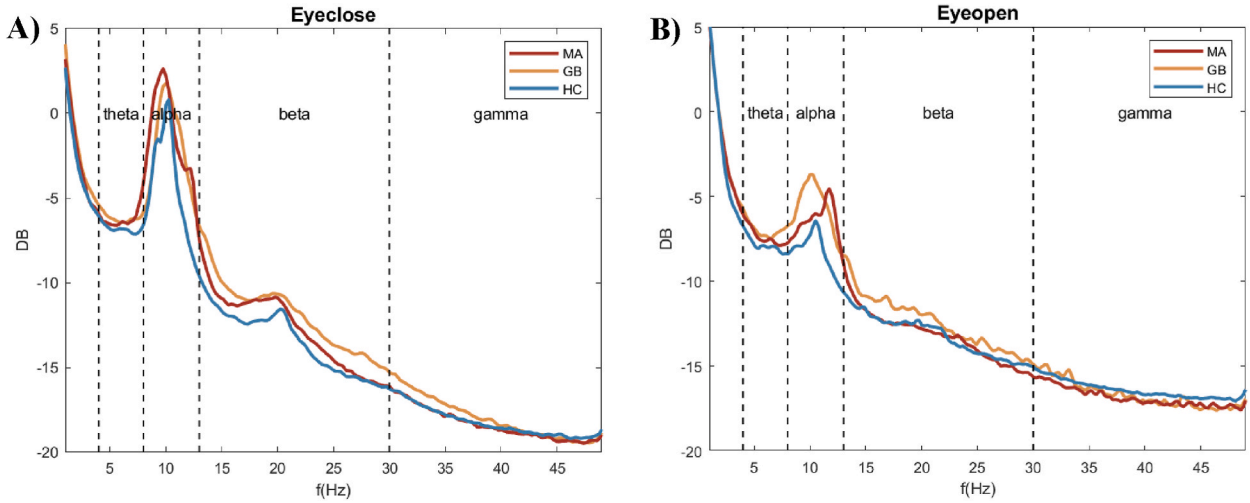

Fig. 2. EEG Spectrum Power Analysis Across Frequency Bands for each group. The power spectral density was analyzed across all brain regions during eye-closed (Panel A) and eye-open (Panel B) conditions. The relative powers for specific frequency bands such as theta (4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (30–50 Hz) were included in the plot. Comparable high-power distributions of alpha frequencies were observed across all groups in the eye-closed condition.

Modularity measures how a network is divided into communities, where nodes within a community have dense connections and sparse connections to nodes in other communities [47]. Small-world describes networks with high clustering and short average path lengths, which allows for efficient local and global communication [48]. Clustering relates to the propensity of nodes to form closely interconnected groups or clusters, quantifying the level of connectivity within a cluster compared to outside it [49,50]. This approach enables us to pinpoint the most vital connections within the brain network and assess its topological characteristics. These parameters were computed using the Brain Connectivity Toolbox (BCT, https://sites.google.com/site/bctnet/). Group comparisons of global MST measures were conducted using a one-way ANOVA. The network characteristics averaged across epochs, and participants at the interested frequency band were compared between groups using Bonferroni correction for multiple comparisons. Regions with significant differences based on Degree and Betweenness Centrality were explored. Also, hub locations were identified based on each group's highest BC and Deg values.

To investigate the connection between functional connectivity, network measures, and impulsive characteristics, we utilized Pearson's correlation coefficient to find the links between addiction- and impulsivity-related topological properties. Additionally, linear regression was employed to examine the influence of group differences on these associations. Receiver operating characteristic curves (ROCs) analysis was performed to evaluate the accuracy of network metrics in predicting specific types of addiction. This method is commonly used to illustrate the relationship between sensitivity and specificity, with the area under the curve representing diagnostic capability in prediction.

3. Results

Table 1 presents the primary characters for participants of different groups (MA, GB, HC) and provides relevant statistical measures for various variables, such as mean and standard deviation (SD). The actions of trait impulsivity among the groups were statistically significantly different in the subscales and total scores with the max p values of 0.027. The GB group had the highest BIS Total score (83.10 ± 13.01), and the HC had the lowest, while the MA group had the highest mean BIS Cognition score (29.28 ± 4.41). However, the disparities in behavioral impulsivity were only evident in the response times and not observed in BART.

3.1. Power spectral difference

One person each from the MA and GB groups and two from the HC group were excluded due to data quality issues. Additionally, one participant of the HC group was omitted as they displayed power values that strayed beyond the standard deviation for the mean across the three groups. The group-average power spectral density (PSD) plot in Fig. 2 (Group MA: N = 39; Group GB: N = 29; Group HC: N = 27). It shows the frequency components of the EEG signals recorded during eye-close and eye-open conditions across all brain regions. We observed notable distinctions between the two states, particularly in the alpha frequency. Therefore, we conducted a comparative analysis of group differences for the two conditions. The cluster-based multiple comparison correction identified significant variations among the three groups solely in the beta band on the eye-close condition (shown in S1). Therefore, an ANOVA test was conducted for the average power of 20–30 Hz across the channels and groups. There was a significant interactive effect between the brain region and groups ($F(5,94) = 2.892$, $p = 0.013$, $\eta_p^2 = 0.030$), and the most significant group-level difference existed in the parietal region. As showed in Fig. 3, the GB group showed the highest beta power and was significantly different from that of HC ($t = 2.270$, $p = 0.027$), but it was not substantially different from that of MA. The most significant group-level difference in beta power between MA and HC existed in the central region but was insignificant ($t = 1.855$, $p = 0.127$). Due to most of the observed differences in the beta band in different brain areas, subsequent network analysis will mainly focus on this frequency band.

Table 1
Basic characteristics of different groups.

Items		Group			F	P-value
		MA (n = 40)	GB (n = 30)	HC (n = 30)		
Demographics	Age	34.35 (±7.52)	32.74 (±4.52)	35.11 (±7.66)	0.523	0.595
	Education level	11.72 (±2.76)	12.18 (±4.77)	11.07 (±2.99)	0.827	0.441
Addiction History	Lasting years	7.46 (±5.84)	5.58 (±4.47)			
	Frequency (weekly)	2.25 (±1.13)	2.03 (±1.27)			
	Craving level (0–10)	2.25 (±2.64)	3.33 (±3.90)			
BIS-11 scales	Attentional impulsivity	29.28 (±4.41)	21.69 (±5.88)	23.22 (±9.71)	12.923	<0.001
	Motor impulsivity	20.64 (±3.36)	26.87 (±6.05)	25.63 (±10.55)	7.973	<0.001
	Non-planning impulsivity	26.38 (±4.91)	23.21 (±3.72)	25.81 (±5.70)	4.354	0.027
	Total score	76.31 (±7.68)	83.10 (±13.01)	74.67 (±9.00)	4.829	0.004
Task performance	Reaction time	0.40 (±0.14)	0.39 (±0.18)	0.65 (±0.39)	10.145	<0.001
	Burst number	50.95 (±11.05)	45.21 (±14.82)	49.81 (±12.30)	1.795	0.172
	Adjusted pumps	11.04 (±3.65)	10.19 (±5.47)	10.71 (±3.26)	0.336	0.716

Table Note: All variables were considered to be continuous and represented as "Mean (±SD)". The specific coding method was explained in sections 2.2. and 2.3. The abbreviations are defined as follows: MA, methamphetamine; GB, gamble disorder; HC, healthy controls; SD, standard deviation; BIS, Barrat impulsiveness scale.

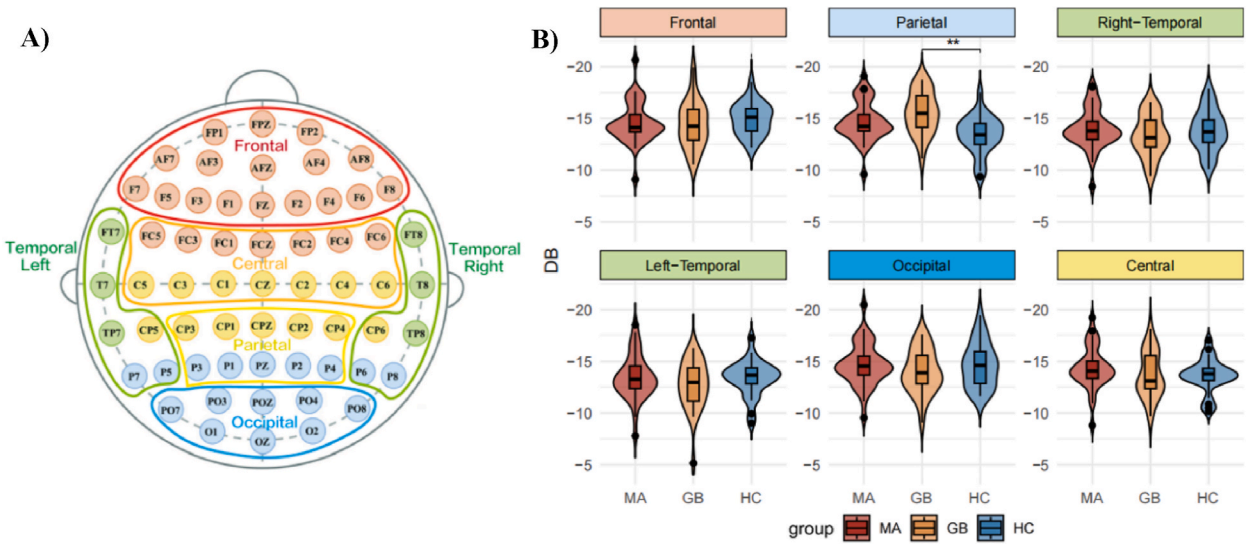

Fig. 3. Beta-band power distribution across six regions of 3 groups. These sensors were grouped into six regions, according to Kamarajan et al. The regions included frontal, central, parietal, occipital, left-temporal, and right-temporal (Panel A). Power spectral density analysis was conducted to examine the average power of the beta frequency band (20–30 Hz) across different brain regions. Violin and box plots of beta power for each group and each region were filled with different colors (Panel B). Asterisks placed above the corresponding regions indicate statistical significance ($p < 0.05$; FDR-corrected) among the three groups. EEG power was calculated by squaring the amplitude of the EEG signal in a specific frequency band and transforming it into decibels (DB).

3.2. Brain network differences

Edgewise analysis investigates the links between various brain regions and offers valuable insights into the communication and integration patterns among them. For the edgewise analysis, we employed NBS, a statistical tool that looks for a particular design or set of edges that differentiate the functional connectivity of the brain. Fig. 4 shows the group-level network with the absolute value of WPLI above 0.03, where each link denoted the synchronization and values between two corresponding channels. The significant connectivity among the three groups tested by NBS with a F-value threshold of ten was C3-P5, FC1-TP10, FC3-AF8, Oz-POz, P3-F5, and P3-TP10. The result of the post hoc comparison for WPLI with each channel pair is illustrated in Fig. 5. Except the difference in Oz-POz channel pair between GB and HC was insignificant ($t_{GB\text{-}HC} = -0.195$, $p = 0.846$), these significant differences of C3-P5, FC1-TP10, FC3-AF8, P3-F5, and P3-TP10 channel pairs showed abnormal connections in groups with addiction compared to the HC group, and the minest p value was 0.014. The connection between C3-P5 and P3-TP10 seemed to be more positively connected in the addictive group while negatively connected in HC. Inversely, FC1-TP10, FC3-AF8, and P3-F5 were more likely to be more positively connected in HC while negatively connected in the addictive group.

In a nodewise analysis, each node's degree and betweenness centrality (BC) was calculated in a graph. Both measures offer valuable insights into the structure and function of a network and aid in identifying significant nodes or subgroups within the network. Specifically, degree represents the number of edges directly linked to a node. In contrast, BC represents the significance of a node in connecting different parts of the network by identifying how often it appears on the shortest path between two nodes in the network.

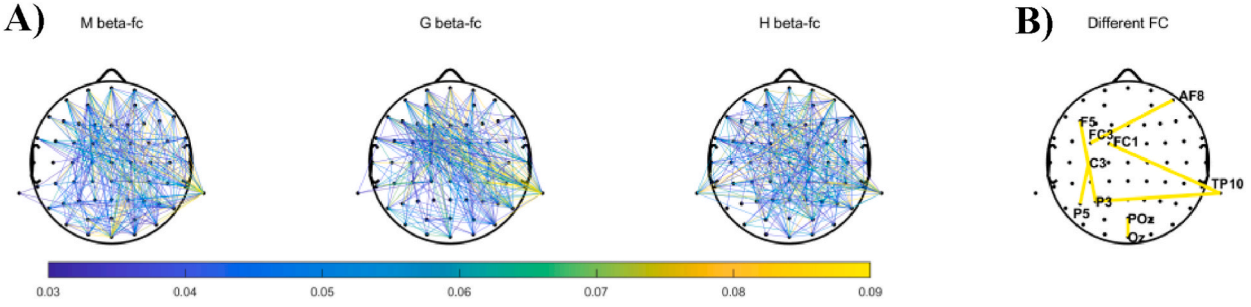

Fig. 4. The weighted network topography of three groups in the delta band (Panel A). Each link represents the channel connection indexed by the absolute value of WPLI. The color gradient on the downside of the map illustrated connection strength, progressing from blue (above 0.03) to yellow (above 0.09) to indicate a phase synchronization. Significant edges between groups were identified using network-based statistics and denoted with a yellow line (Panel B).

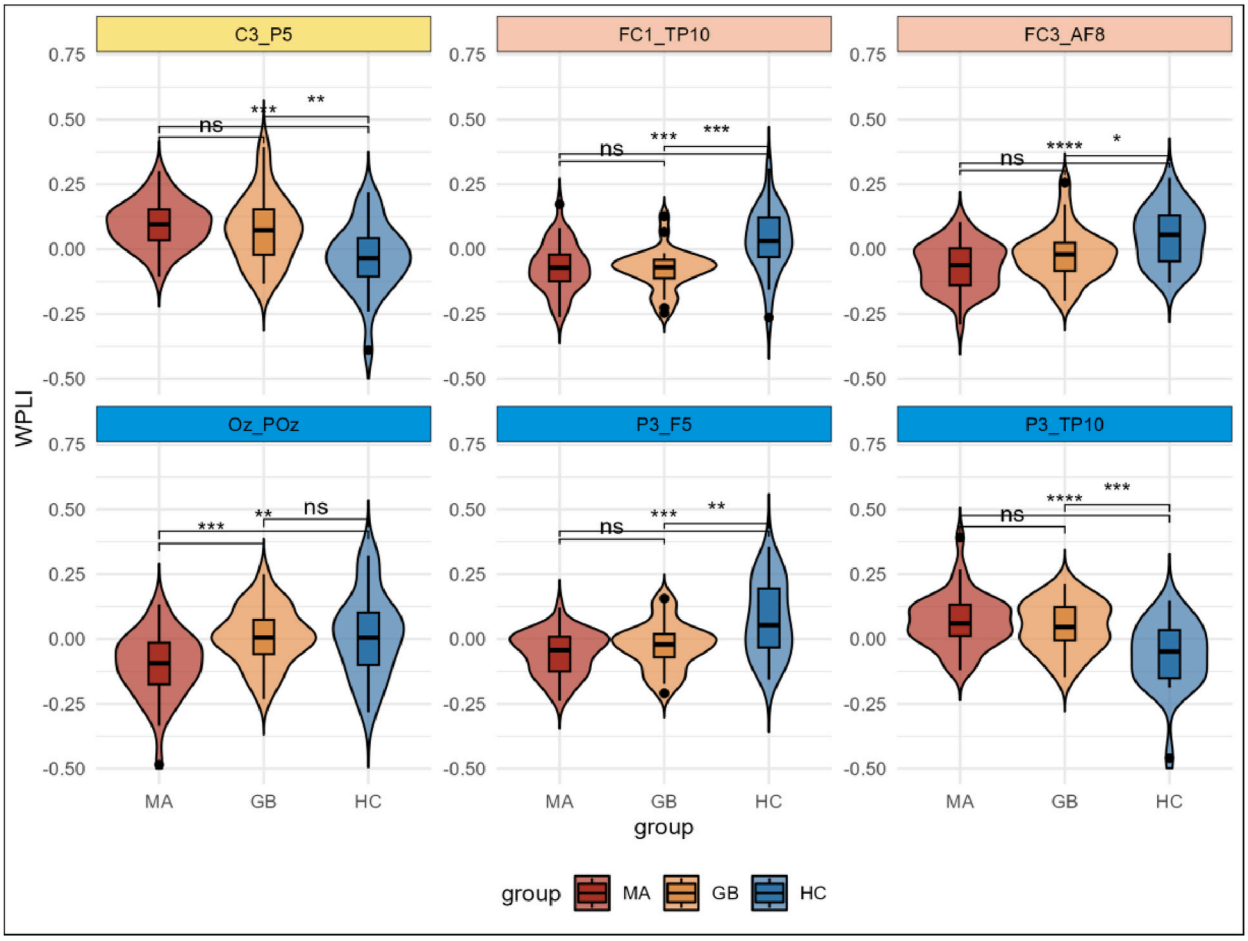

Fig. 5. Edgewise differences between the three groups. Violin and box plots of the connections for each group were filled with different colors. The strips' colors corresponded to the brain regions of channel pairs. The positive values of WPLI often indicate phase synchronization between two signals and that one signal is lagging behind the other. In contrast, a negative phase difference indicates that one signal leads the other, and zero indicates that they are in phase. Asterisks above the corresponding conditions indicate statistical significance ($p < 0.05$; FDR-corrected).

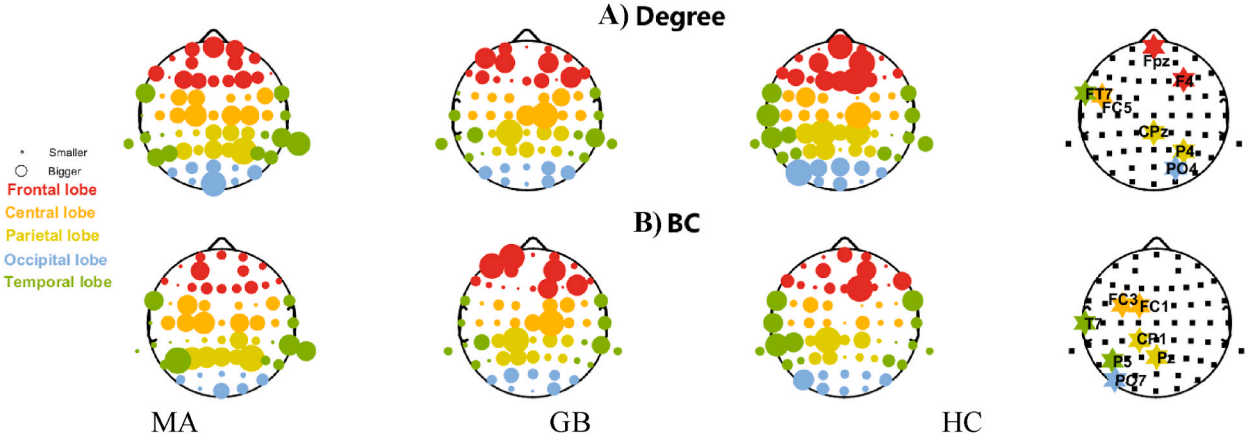

Fig. 6. Visualization of degree (Panel A) and betweenness centrality (BC; Panel B) for each group and the significantly different positions. In the illustration, circles of varying sizes and colors represent the values and brain regions corresponding to the degree and BC for each electrode site.

The degree and BC values for each electrode site are displayed in Fig. 6 using circles with different sizes and colors indicating the corresponding values and positions. The results from degree and BC analyses reveal a similar trend that the MA group and GB group demonstrated subtle changes compared to the HC group, including a substantial decrease in node linkage at the frontal lobe around Fpz and F4 and a decrease in node importance at central and left parietal lobe. Based on the statistical analysis, the nodes demonstrated significant differences among the three groups, as marked in the right panel of Fig. 6.

Network-wise analysis was conducted to obtain a holistic understanding of the structure and operation of the brain network. As depicted in Fig. 7, only parameters such as global efficiency (MA vs. GB: $t = -2.635$, $p = 0.011$), betweenness centrality (MaxBC, MA vs GB: $t = -2.004$, $p = 0.049$), and functional connectivity of left hemisphere (FC_l, MA vs HC: $t = -2.069$, $p = 0.043$) were significantly different among three groups. However, statistical analysis revealed no significant differences in other metrics of network organizations. The global efficiency is the average of the inverse shortest path length and is inversely related to the characteristic path length. The MA group exhibited a less efficient network than the GB group. MaxBC of MA existed at the left temporal and parietal lobe, while that of the GB group existed at the left frontal lobe. Considering the highest value of MaxBC is deemed critical to maintaining efficient communication between the different parts of the network, these indexes' values were lower in the MA group, suggesting some brain regions have an inefficient structure. Although the deals of FC_g, a measure of the overall strength of connectivity in the left brain network, were found to be quite similar across all conditions, the left-hemisphere FC of MA was sightly significantly higher than HC; these could emphasize the existence of abnormal connection in MA group.

3.3. Relationships between addiction-related network characteristics and impulsivity

Relationships between addiction-related network characteristics and impulsivity were further examined using Pearson's correlation analysis. All the significant differences presented among the three groups were tested with impulsivity, and the detailed results were shown in S2. Herein, Fig. 8 presented the only statistically significant results. As a result, there is only a negative correlation between impulsivity scores (summed from the BIS-11 scale) and connectivity between the left central lobe (FC3) and the right frontal lobe (AF8). Specifically, higher impulsivity scores were associated with robust negative phase synchronization connectivity between the left central lobe and right frontal lobe. In particular, the relationship was moderated by the group factor. The GB group, compared to the HC group, showed a stronger negative correlation between impulsivity scores and connectivity between the left central lobe and right frontal lobe (Estimate = −63.113, SD = 26.795, $t = -2.355$, $p = 0.0211$). In contrast, the MA group was not different from the HC group. Moreover, Pearson's correlation analysis revealed a significant positive correlation between BART calculated by the behavior Pearson's and connectivity between the left central lobe (C3) and the left parietal lobe (P5). Results suggested that individuals with higher levels of impulsivity, as measured by the BART task, exhibit increased positive phase synchronization connectivity between the left central lobe and the left parietal lobe. Similarly, the group significantly moderated this relationship. The GB group displayed a higher positive correlation level than the HC group (Estimate = 84.472, SD = 21.403, $t = 3.947$, $p < 0.001$), whereas the MA group did

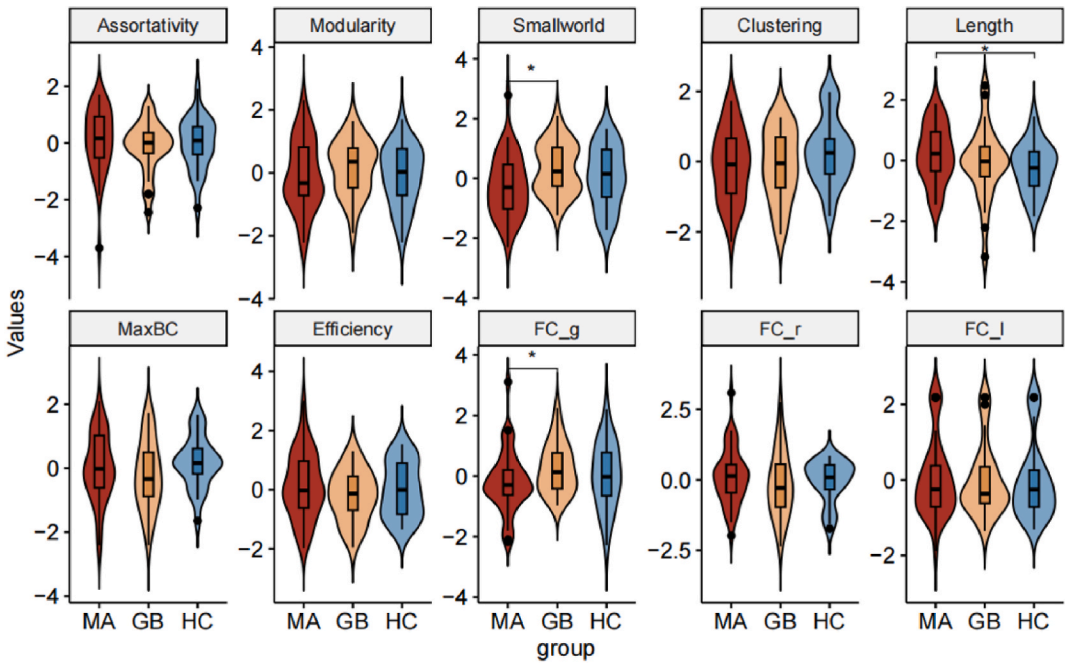

Fig. 7. The difference in network structure among the three groups. The network structure was characterized by assortativity, modularity, small-worldness, clustering, path length, maximum betweenness centrality, and global functional connectivity (FC_g) as well as the right hemisphere (FC_r) and the left hemisphere (FC_l). Significant findings are indicated with asterisks denoting statistical significance ($p < 0.05$; FDR-corrected).

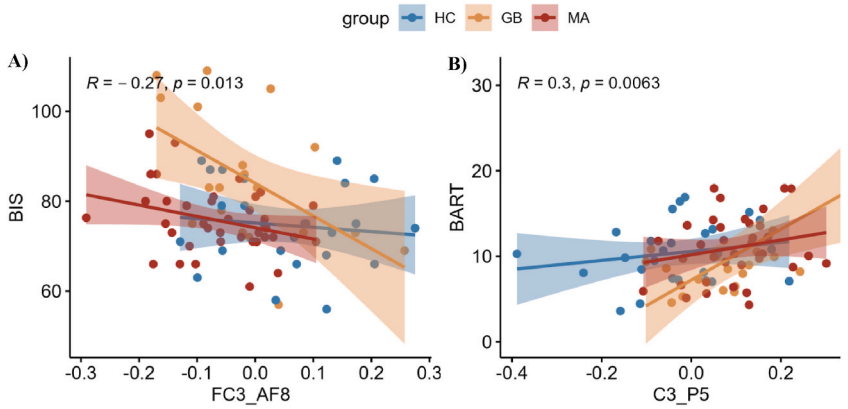

Fig. 8. The significant correlation between network characteristics and impulsivity. The plot illustrates each individual in the study, with the x-axis representing the EEG signal amplitude at FC3_AF8(Panel A) or C3_P5(Panel B) and the y-axis depicting impulsivity scores. The regression line is fitted to the data as a visual aid to emphasize the overall trend in their relationship. Shaded regions around the regression line indicate confidence intervals. Additionally, the Pearson correlation coefficient is presented on this plot to quantify the strength and direction of any linear relationship between these connected variables within this cohort.

not exhibit this pattern. Since there was no significant correlation between impulsivity and MST parameters, our results showed that individuals with higher levels of impulsivity, as measured by the BIS-11 scale and BART task, may show abnormal brain phase synchronization in network connectivity without affecting network organization. It is important to note that these findings specifically

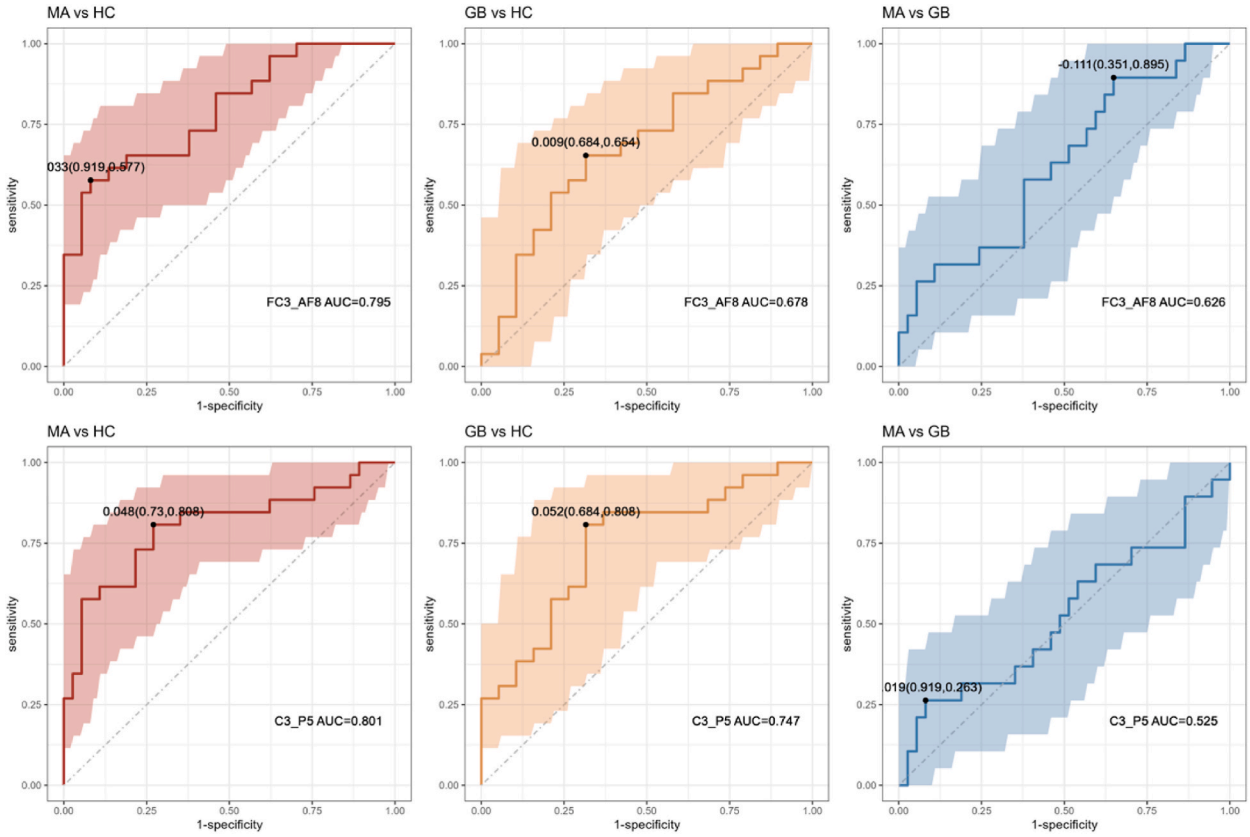

Fig. 9. ROCs of connections for the classification of individuals with specific addictions from healthy controls. In this graph, the diagonal reference line represents the performance of a random classifier, and points above this line indicate better-than-random classification. The shaded ribbon surrounding the ROC curve represents the confidence interval. A critical point, denoted by a marked point on the curve, corresponds to a specific threshold chosen based on the analysis. The legend color indicates the ROC curve for each pair, and the associated Area Under the Curve (AUC) value quantifies the classifier's overall performance.

relate to the beta frequency range.

The study used ROC analysis to investigate if the beta power network connectivity associated with impulsivity could identify and distinguish different types of addiction (shown in Fig. 9). Both the FC3_AF8 and C3_P5 connections showed an AUC above 0.699 ($p = 0.012$) for identifying individuals with addictions versus those without, but their role in discrimination was not confirmed.

4. Discussion

This study was the initial attempt to analyze the features of resting-state EEG activity in individuals with gambling disorders and methamphetamine addictions together, as opposed to a control group. The aim was to identify shared neurophysiological indicators for addiction associated with impulsivity. Consistent with the theoretical hypothesis, the GB groups displayed the most remarkable trait and behavioral impulsivity compared to the MA and HC groups. In contrast, the MA groups showed significantly higher scores in impulsivity of cognition and planning than HC but did not exhibit behavioral differences. Further, the group-level resting-state EEG activities were only significant on the eye-close beta band power condition. These results indicate abnormalities in brain activities in individuals with gambling disorders and methamphetamine addiction, specifically related to the eye close beta band. Interestingly, our results revealed some findings about the aberrant brain network of people with addiction and its relationship with impulsivity. We observed an inverse relationship between trait impulsivity scores and connectivity from the left central to right frontal lobes, with higher impulsivity linked to more robust negative phase synchronization. In addition, a clear association was found between current impulsivity scores and connectivity from the left central to the left parietal lobes, highlighting increased positive phase synchronization in individuals with higher impulsivity ratings, particularly within the GB group. In short, individuals with higher levels of impulsivity exhibit abnormal brain phase synchronization in network connectivity, specifically in the beta frequency range. These findings support previous research that implicates brain networks involved in impulsivity and addiction and highlight the potential of resting-state EEG as a neurophysiological marker for impulsivity in individuals with addiction.

4.1. Increased beta power in people with an addiction compared to the control group

The increased beta power in people with an addiction could be indicative of hyperexcitability in the brain, as seen in several other psychiatric disorders characterized by impulsivity and hyperarousal. This finding of increased beta activity aligns with previous research [51–53]. It supports the notion that individuals with addictive behaviors, such as gambling disorders and methamphetamine addiction, may exhibit hyperexcitability in the brain, potentially contributing to impulsive behavior and addiction [54,55]. The beta band is related to arousal and is thought to be involved in higher-order cognitive processes, including decision-making, attention, and response inhibition. Pathological enhancement of beta-band activity can lead to an abnormal persistence of the status quo and a deterioration of flexible behavioral and cognitive control [56]. The increase in beta power in individuals with addiction further underscores the role of the beta frequency band in the context of impulsivity [55,57]. However, the results of the relationship varied depending on the specific type of addiction. A study reviewing EEG studies on psychiatric disorders, including a part of addiction, concluded the patterns of power change within particular frequency bands and an increase in beta power for opioid and alcohol addiction, indicating higher levels of cognitive processing and alertness. In gambling disorder, the aberrant beta activity correlated to a lack of impulsive control, such as the clinical symptom severity [58]. Our findings support previous research indicating abnormal beta activity in addiction. Mainly, in our study, increased beta power in the parietal lobe of the GB group was the dominant difference. At the same time, no significant findings were observed in other frequency bands or region. It may indicated increased beta power could represent an aberrant activation pattern within these networks reflecting the impulsive decision-making and reward-seeking behaviors typically present in behavioral addictions. Although the exact relationship between beta power and addiction may vary depending on the specific type of addiction or clinical symptoms, there is consistent evidence suggesting that increased beta activity may be the critical EEG power spectrum related to addiction.

4.2. Altered topological connectivity of people with an addiction in resting-state EEG

On the condition of eye-close and resting-state EEG acquisition, our study found that individuals with addictive behaviors exhibit altered topological connectivity. Specifically, the connection between central and parietal lobes seemed to be more positively connected in the addictive group while negatively connected in HC. Inversely, the connections of the frontal lobes with other lobes were more likely to be more positively connected in HC while negatively connected in the addictive group. These suggest that individuals with addiction may have disrupted neural networks and altered communication between different brain regions, particularly in the frontal central and parietal lobes. Referred to prior results, frontal cortex dysfunction is linked to deficits in decision-making, behavioral inhibition, and attentional biases toward drug use, which can contribute to the development and persistence of addiction behavior [59]. Similarly, in pathological gambling, frontal lobe dysfunction is associated with decision-making and behavioral inhibition deficits. Parietal and central lobe dysfunction, on the other hand, has been linked to impairments in cognitive control and attentional processes. A related study that supports this idea analyzed the significant changes in the effective brain networks of heroin-abstinent individuals. The results showed that the parietal region was a dominant hub of the abnormally weaker causal pathways. Furthermore, communication between these lobes is essential as a default mode network (DMN) component. Based on previous research, MA-dependent individuals showed disruptions in DMN, anchored in the medial prefrontal cortex (mPFC) and posterior cingulate cortex (PCC) [60]. These areas are reported to be responsible for compromised cognitive function and obsessive rumination about drugs in addictive disorders. These findings from EEG and fMRI all suggest that individuals with addiction may

exhibit abnormalities in brain networks, particularly in the frontal, central, and parietal lobes, which may contribute to deficits in decision-making, behavioral inhibition, and attentional processes in individuals with addiction.

Furthermore, we conducted the nodal analysis to examine individual nodes or brain regions' overall activity and communication patterns. Nodal research investigates different brain regions' specific functions and activities based on the hypothesis that the human brain is a dynamically interconnected functional system with an optimal balance between local specialization and global integration [61]. This balance allows for efficient information processing and communication between different brain regions. By comparing the topological parameters of substance and behavioral addiction with HC during eye-close resting, our study found an inclination that the addict group demonstrated a substantial decrease in node linkage at the frontal lobe and a decrease in node importance at the central and left parietal lobes. Especially concerning the general functional connectivity of the left hemisphere, a significant distinction is observed between the MA and HC groups, which is not apparent in the GB and HC groups. In line with the functional MRI activation results in cognitive processes, the resting-state EEG findings also bolster the idea that individuals with addiction display abnormal left brain functioning, which contributes to factors associated with craving and addiction. Still, the differences between the GB and MA groups extended beyond surface-level characteristics, encompassing intrinsic attributes of networks such as efficiency and maxBC. The brain's central hub in the GB group is located in the left frontal lobe, while the temporal and parietal lobes are crucial for the MA group. These results were in line with our previous study, which found that brain network dynamics in the MA group displayed different microstate patterns compared to the HC group and observed hyperactivation of the superior temporal and parietal area in the MA group [62].

In sum, these findings indicate that behavioral and substance addiction may have different functional connectivity and abnormal nodal characteristics in distinct brain regions, especially in the frontal and parietal lobes. Notably, we found insignificance in comparing the person with an addiction and HC groups regarding global topological parameters related to the network structures. This implies that overall network organization is preserved in our cohort during eye-close resting. Nonetheless, certain discoveries from studies comparing addicted and non-addicted individuals offer variations in particular brain regions and connectivity patterns. The general structural organization of brain networks seems to resemble a more random configuration with reduced efficiency [29,63]. Therefore, more research is necessary to gain a deeper understanding of the intricate neural mechanisms associated with addiction and how they influence brain networks.

4.3. Correlation between impulsivity and atypical brain network characteristics of people with addiction

Correlation findings can serve as an explanation of the connection between impulsivity and changes in brain organization. Our results indicated a significant positive correlation between impulsivity scores and abnormal connection between left frontal, central, and parietal lobes in individuals with addiction. Subjects from GB displayed a more robust connection between impulsivity and brain networks, encompassing trait and behavioral impulsivity. Moreover, ROC analysis investigated the potential of beta power network connectivity associated with impulsivity in recognizing and differentiating different types of addiction. Findings revealed that both the FC3_AF8 and C3_P5 connections showed a greater AUC in distinguishing individuals with addictions from those without, as opposed to discriminating between addictive types. It is conceivable that the connection between FC3 and AF8 may have greater significance in MA, whereas the link between C3 and P5 could be more influential in both types of addiction, underscoring the impact of left-hemisphere connectivity between central lobes and parietal lobes. FC3_AF8 and C3_P5 connections show promise as biomarkers for addiction identification; however, these findings must be contextualized as the AUC values derived from our study are based on a specific sample and specific conditions (rest-state beta-band power). Therefore, these values might not be generalizable across different populations or under different neural recording conditions, such as during cognitive tasks or other frequency bands, which may engage different neural circuits. Overall, the correlation between impulsivity and atypical brain network characteristics in individuals with addiction suggests that impulsivity may play a role in the changes observed in brain organization and connectivity.

Referred to previous research, both forms of impulsivity are related to neural activities within the brain's reward and control systems. Trait impulsivity is viewed as an enduring aspect of one's personality that is linked to variances in brain structure and function, such as variations in the volume of gray matter in the frontal and parietal regions [64–66]. It also might include variations in connectivity within the networks responsible for self-regulation, decision-making, and behavioral control. Alternatively, behavioral impulsivity has been associated with abnormalities in their connection with the ventral striatum and anterior prefrontal cortex, two areas that are involved in mediating reward and maintaining attention to salient stimuli [67]. In summary, behavioral impulsivity is contextually driven. It can be observed as a dynamic process within specific brain regions during decision-making tasks. In contrast, trait impulsivity is a broader dispositional factor that may emerge from more widespread differences in brain function and structure.

Understanding the neural distinctions between trait and behavioral impulsivity has significant implications for understanding addiction's underlying mechanisms and tailoring effective treatments. The prefrontal cortex reductions relating more closely to trait impulsivity could underlie the long-term patterns of impulsive behavior seen in individuals with substance addictions. Hence, strategies for substance addiction treatment may include cognitive rehabilitation to improve self-control and decision-making for those with deficits in the prefrontal cortex. For behavioral addiction, behavioral impulsivity may play a more prominent role, especially GB. This indicates that their behavioral intervention should focus on modifying reward processing and decision-making patterns, as well as enduring personality traits.

Furthermore, these neural correlates may explain why certain individuals may be more prone to developing addiction. A clinical study found that dysregulated neural connectivity in EEG-based functional connectivity networks and heightened impulsivity coexisted in individuals with alcohol use disorder [68]. Furthermore, a study using resting-state fMRI data found differences in whole-brain network organization across the impulsivity spectrum, with highly impulsive individuals showing isolation of regulatory structures

from subcortical structures associated with appetitive drive [69]. These findings underscore how impulsivity, often observed among individuals grappling with addiction issues, may be tied to atypical characteristics of brain networks. Therefore, future studies should investigate the longitudinal trajectory of impulsivity and its relationship to changes in brain networks over time, as well as explore potential causal relationships between impulsivity and atypical brain network characteristics in individuals with addiction.

4.4. Limitations

Our study has several limitations. First, the sample size was relatively limited, which may restrict the applicability of our findings. Therefore, it is important to interpret the correlation and brain network results with caution due to these constraints. Furthermore, our conclusions should be viewed as preliminary. The correlations identified between impulsivity and the connections FC3_AF8 and C3_P5, along with their respective AUC values, should not be seen as definitive but rather suggestive of a pattern that warrants further investigation. Future studies should seek to incorporate larger and more diverse sample sizes in order to enhance the dependability and generalizability of these findings. Accomplishing this would not only validate the observed patterns but also advance our comprehension of the intricate connection between brain network characteristics, impulsivity, and various forms of addiction. Second, the study design was cross-sectional, which makes it difficult to establish causality and determine the direction of the observed relationships. Third, our study relied on resting-state EEG data, which provides information about brain activity but does not directly measure structural connectivity. These limitations highlight the need for future research with larger sample sizes, longitudinal designs, and a combination of different assessment measures (including neuroimaging techniques) to explore further the relationship between impulsivity and brain network characteristics in individuals with addiction.

4.5. Conclusions and practical implications

In conclusion, our study provides evidence that individuals with addiction display abnormal brain networks associated with impulsivity. These findings suggest that impulsivity may be a critical factor in the development and maintenance of addiction and that targeting these irregular brain networks could be a potential. The correlation findings between impulsivity and atypical brain network characteristics in individuals with addiction provide valuable insight into the intricate relationship between psychological traits and neurological attributes. These call for further investigations into these associations' causal pathways and developmental trajectories. Moreover, future research should consider other analyses to explore additional potential information revealed from rest-state EEG or combining advanced neuroimaging techniques to elucidate these abnormal brain networks' structural and functional connectivity.

CRediT authorship contribution statement

Qianlan Yin: Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Tianzhen Chen:** Validation, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Yan Long:** Project administration, Investigation, Data curation. **Jing Zhai:** Project administration, Investigation, Data curation. **Xinru Liu:** Project administration, Investigation. **Weizhi Liu:** Writing – review & editing, Validation, Supervision, Resources. **Min Zhao:** Writing – review & editing, Validation, Resources, Project administration, Methodology, Conceptualization. **Jiang Du:** Writing – review & editing, Visualization, Validation, Resources, Project administration, Methodology, Investigation, Funding acquisition, Data curation, Conceptualization.

Ethical declarations

This study was reviewed and approved by The Shanghai Mental Health Center research ethics boards, with the approval number: 2022-18C1. All participants provided informed consent to participate in the study.

Data availability statement

Data will be available on request.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2024.e40212.

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