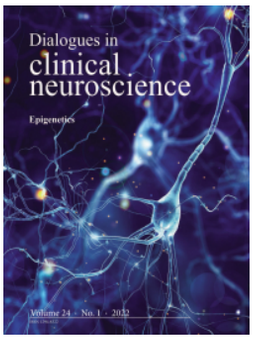

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Resting-state EEG microstate analysis of internet gaming disorder and alcohol use disorder

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ABSTRACT

Introduction: To investigate the neurophysiological aspects of addiction, the microstate characteristics of internet gaming disorder (IGD), alcohol use disorder (AUD), and healthy control (HC) groups were compared using resting-state electroencephalography (EEG).

Methods: In total, 199 young adults (75 patients with IGD, 57 patients with AUD, and 67 HCs) participated in this study. We conducted EEG microstate analysis among the groups and also compared the obtained parameters with the results of psychological assessments.

Results: The global explained variance, occurrence, and coverage of microstate C were significantly lower in the AUD group than in the IGD group. Additionally, rates of transition from microstates A, B, and D to C were significantly lower in the AUD group than in the IGD group, whereas rates of transition from microstate A to B were lower in the IGD group compared to HCs. Furthermore, the occurrence of microstate C and transition from microstate B to C were negatively correlated with the Alcohol Use Disorder Identification and Behavioural Inhibition Scale score.

Conclusion: There were significant differences in microstate characteristics among the groups, which correlated with the psychological scores. These findings suggest that microstate features can be used as neuromarkers in clinical settings to differentiate between addictive disorders and evaluate the pathophysiology of AUD and IGD.

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Electroencephalography; microstate analysis; internet gaming disorder; alcohol use disorder; microstate features

Introduction

Internet gaming disorder (IGD) is characterised by uncontrolled internet gaming activity that may lead to severe impairment in psychological and social functioning (Griffiths 1997). The Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-5) defined IGD as 'a pattern of excessive and prolonged internet gaming that results in a cluster of cognitive and behavioural symptoms, including progressive loss of control over gaming, tolerance, and withdrawal symptoms, analogous to the symptoms of substance use disorders' (American Psychiatric Association 2013). Its prevalence ranges from 0.5 to 9.9% (Petry et al. 2015). However, studies on IGD prevalence have been highly heterogeneous, and there are significant gaps in prevalence estimates by measurement and sampling issues. A most recent meta-analysis concerning various potential causes of heterogeneity reported that the overall prevalence of IGD was 3.3% (Kim et al. 2022). Although the prevalence of Internet Gaming Disorder (IGD) was variable, the DSM-5 included IGD as a condition necessitating further study due to its notable prevalence and significant public health concerns regarding the negative impact of gaming activity. Prior to the inclusion of IGD in Section III of the DSM-5, researchers used criteria for substance use disorders, gambling disorder, impulse-control disorder, or internet addiction to assess IGD (Petry et al. 2014).

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However, several studies have compared the clinical characteristics, conceptualisation, and neurobiological background of IGD with other addictive disorders in the DSM-5. The framework provided by the DSM-5 offers a basis for future research (Petry et al. 2015; Chew and Wong 2022). The DSM-5 pointed out that IGD is analogous to the symptoms of substance use disorders (SUD). It facilitates researchers in exploring the core pathophysiology of IGD. Previous study investigating risk factors of IGD by cluster analysis in adolescents reported that the cluster combined potential psychological factors such as depression and poor impulse control, and social issues showed higher degrees of IGD (Lin et al. 2015; Gervasi et al. 2017; Jeong et al. 2020). Within this framework, correlations between the psychological factors and the neurophysiologic markers can be studied in IGD patients to identify candidate markers that influence pathophysiology of IGD.

Numerous studies have demonstrated that IGD shares clinical features and comorbidities with SUD, such as tolerance, withdrawal, cravings, and relapse (Hwang et al. 2014; Park et al. 2017a), although IGD does not involve toxic agents. In a previous study of IGD and alcohol use disorder (AUD), a common SUD, we found similar emotional, temperamental, and personality traits between the two disorders (Hwang et al. 2014). Although IGD and AUD have similar properties, it remains unclear whether they share neurobiological features (Lee et al. 2024).

Multiple neuroimaging studies using magnetic resonance imaging (MRI), functional MRI, and positron emission tomography have evaluated the neurobiological characteristics of SUD and IGD (Baker et al. 2013; Meng et al. 2015; Kim et al. 2019a). Due to the costs associated with these methods, there is growing interest in using electroencephalography (EEG) to assess the neurobiological commonalities and differences between these disorders (Son et al. 2015; Kuss et al. 2018; Mumtaz et al. 2018). Several studies have used EEG, a non-invasive and effective tool for recording brain activity with excellent temporal resolution. Techniques such as quantitative EEG and analysis of ERPs have revealed significant correlations and differences in brain connectivity and coherence among patients with SUD and IGD (Park et al. 2017b). Notably, patients with IGD and AUD exhibit distinct neurophysiological patterns of brain connectivity, including an increase in the fast phasic synchrony of gamma coherence (Park et al. 2017b).

Our previous study (Park et al. 2017a) compared the N100 and P300 ERPs between patients with IGD and AUD, demonstrating reduced P300 amplitudes at the midline central and parietal areas in both groups compared to healthy controls (HCs). Compared to the SUD group and HCs, the IGD group exhibited reduced N100 amplitudes at the midline frontal area. Moreover, the reduced P300 amplitude in individuals with IGD was correlated with a higher spatial span error rate. Although these findings need to be replicated, various EEG methodologies have been used to explore the distinctive characteristics of patients with SUD and IGD.

Resting-state EEG microstate analysis is used to evaluate the human brain state based on topographical configurations (Michel and Koenig 2018). It represents the dynamic spatial distribution of scalp electric potential over time. Using a clustering algorithm, microstates can be categorised into several groups based on topological similarity (Khanna et al. 2014). Although different cluster counts have been reported, analyses using four microstate maps have been widely adopted (Pascual-Marqui et al. 1995; He et al. 2021). These maps are typically labelled as classes A–D. A systematic review of the functional roles of each microstate revealed distinctive correlates between microstate A and auditory and visual processing, microstate B and self-related visual processing, microstate C and processing of personally significant information, and microstate D and executive functioning (Tarailis et al. 2024). Interestingly, these four microstates represent distinct topographies, including right frontal-to-left posterior, left frontal-to-right posterior, symmetric frontoposterior, and frontocentral maximum configurations (Michel and Koenig 2018; Tarailis et al. 2024). Therefore, these distinctive microstates have attracted attention as potential neurobiological markers for various psychiatric conditions associated with specific brain regions (Tarailis et al. 2024). Additionally, various features of microstates, such as the duration, occurrence, coverage, and transition probability (TP), are potential indicators of spontaneous mental states (Changeux and Michel 2006). For instance, duration reflects the temporal stability of underlying brain dynamics, whereas TP refers to the encoded sequential activation of neural assemblies generating microstates (Croce et al. 2020). Given their association with cognitive manipulation, EEG microstates may be used to evaluate mental states related to various cognitive functions (Kim et al. 2021).

To the best of our knowledge, no previous study has explored the characteristics of SUD and IGD using EEG microstate features. In this study, we compared microstate features among patients with SUD, those with IGD, and HCs. Based on the inconsistency in the results of prior studies, we hypothesised that patients

with SUD and IGD would exhibit unique microstate-related characteristics. This study aimed to determine the distinct microstate features in patients with SUD and IGD based on resting-state EEG.

Methods

Participants

In total, 75 patients with IGD (72 males and 3 females), 57 patients diagnosed with AUD (45 males and 12 females), and 67 HCs (57 males and 10 females) were included in this study. The study was conducted in accordance with the Declaration of Helsinki. The study protocol was approved by the Institutional Review Board of the SMG-SNU Boramae Medical Centre, Seoul, Republic of Korea. All participants provided written informed consent prior to participation, and all patients with IGD and AUD were recruited from the outpatient clinic of SMG-SNU Boramae Medical Centre. None of the patients had intellectual disability or psychotic, neurological, or seizure disorders. All participants were medication-naïve and right-handed. Furthermore, only participants with an intelligence quotient $>$ 70 were included. A clinically experienced psychiatrist diagnosed individuals with IGD or AUD based on the DSM-5 criteria. To determine the severity of IGD and AUD, the Young Internet Addiction Test (Young 1998; Lee et al. 2013) and the Alcohol Use Disorders Identification Test (AUDIT) (Saunders et al. 1993; Kim et al. 2008) were used. HCs were recruited from local communities and universities through public announcements. Recruitment efforts included posting flyers on university websites, as well as on student community platforms. All HCs played internet games for $<$ 2 h per day and consumed no more than 14 standard drinks per week and no more than four standard drinks per occasion. Additionally, there was no prior history of AUD in their lives. They had no documented history of psychiatric disorders (Choi et al. 2013; Son et al. 2015).

Psychological assessments

The age, sex, and educational level of participants were recorded. The self-reported Young Internet Addiction Test, comprising 20 items based on a total score ranging from 20–100, was used to assess IGD severity (Young 1998; Lee et al. 2013), with a higher score on the five-point scale (1, never; 5, very frequently) indicating more problematic internet game usage. The AUDIT was used to evaluate the degree of alcohol consumption (Saunders et al. 1993). The AUDIT consists of 10 items with the four-point Likert scale (0, never; 4, very frequently) indicating harmful drinking, and the total score ranges from 0 to 40. The Korean version of the Beck Depression Inventory (BDI)-2, a 21 items questionnaire, was used to assess the severity of depressive symptoms experienced during the past week (Beck et al. 1996; Sung et al. 2008). A higher score on the four-point Likert scale indicates more severe depression, with the total score ranging from 0 to 63. The Korean version of the Beck Anxiety Inventory (BAI), a 21 items questionnaire, was used to measure the level of anxiety during the previous week (Beck et al. 1988; Yook and Kim 1997). A higher score on the four-point Likert scale indicates a greater level of anxiety, with the total score ranging from 0 to 63. The degree of impulsivity was assessed using the Barratt Impulsiveness Scale (BIS)-11. An abbreviated Korean version with 23 items, scored using a four-point Likert scale with a total score range from 23 to 92, was used in this study (Lee 1992). The Behavioural Activation Scale (BAS) and Behavioural Inhibition Scale (BIS) were used to evaluate the dispositional sensitivity to rewards and punishments (Carver and White 1994). These scales contain 13 and 7 questions scored on a four-point Likert scale, and total scores range from 13 to 52 and 7 to 28, respectively. Verbal and physical aggression, hostility, and wrath were evaluated using the Aggression Questionnaire (AQ). The AQ consists of 29 items with higher scores on the five-point Likert scale indicating greater levels of aggression, and the total score ranges from 29 to 145 (Buss and Perry 1992). To assess the level of stress, the Psychosocial Well-Being Index (PWI), which contains 45 items, was used to assess the physical and psychological status during the previous few weeks (Kim 1999). This tool investigates the anxiety, self-confidence, social role performance, depression, sleep disruption, and well-being of participants with a total range from 0 to 135. Resilience was evaluated using the Connor-Davidson Resilience Scale (CD-RISC) (Connor and Davidson 2003), which evaluates the emotional state over the previous month; higher scores (range: 0–100) indicate increased resilience. CD-RISC includes 25 items rated on a five-point Likert scale. The quality of life was evaluated using the Korean version of the WHOQOL-BREF (Min et al. 2002), focusing on an individual's perception of their position within their culture, their value system, their expectations, and their concerns (Skevington et al. 2004). It contains 26 items, including two items in the overall quality of life and general health, seven items in the physical health domain, six items in the psychological domain, three items in the social relationship domain, and eight items in the environment domain. The responses are based on a

five-point Likert scale, and the conversion score for each sub-domain ranges from 0 to 100 points.

EEG acquisition

Resting-state EEG data were collected using SynAmps 2 (Compumedics, Abbotsford, Victoria, Australia) and the Neuroscan system (Scan 4.5; Compumedics) with a 64-channel Quick-cap system (Neuroscan; Compumedics), based on the modified International 10–20 positioning scheme. The EEG was recorded for 5 min as participants closed their eyes in a sound-shielded room. The ground electrode was attached between FPz and Fz, with a bipolar reference electrode placed at the mastoid. Vertical and horizontal electrooculograms were obtained using electrodes placed above and below the left eye. Initially, the sampling rate for EEG recording was 250 or 500 Hz. However, we later changed it to 1000 Hz for a more sophisticated measurement of brain activity with no modification in EEG measurement or device settings. The EEG data was processed using a 0.1–100 Hz bandpass filter, and electrode impedance was kept below five kΩ.

EEG preprocessing

Raw EEG data were preprocessed using EEGLAB (Delorme and Makeig 2004) and MATLAB R2021b (MathWorks, Natick, MA, USA). First, we removed channels that were not used for the EEG analysis, including m1, m2, CB1, CB2, VEO, HEO, EKG, and Trigger. The EEG signals were downsampled to 250 Hz and subjected to baseline correction by subtracting the mean signal value for each channel. To remove the 60-Hz line noise, we used the CleanLine EEGLAB plugin (Mullen 2012). EEG signals were filtered using a bandpass of 1–55 Hz. We removed the noise artefacts in the EEG signal by applying mathematical methods. Artefact subspace reconstruction (Mullen et al. 2015) was performed to remove data components containing artefacts. Wavelet transform-based denoising was conducted to remove artefacts by decomposing the EEG signals (Safieddine et al. 2012; Mannan et al. 2018). Then, independent component analysis (Lee et al. 1999) was performed to separate the 60 components of the EEG signals and remove components with a probability of artefacts exceeding the threshold (0.5 for muscle artefacts and 0.9 for other artefacts) using the ICLabel EEGLAB plugin (Pion-Tonachini et al. 2019). The EEG data were re-referenced to a common average using an adapted version of the reference electrode standardisation technology (Yao 2001; Dong et al. 2017). For microstate analysis, we bandpass filtered the EEG data between 1 and 30 Hz using the same settings as numerous previous studies (von Wegner et al. 2018; Croce et al. 2020; Wang et al. 2021; Férat et al. 2022). EEG data were categorised into 2-s epochs, and epochs containing large physiological artefacts (amplitude $> \pm 75\ \mu V$) were excluded from the analysis.

Microstate analysis

For the microstate analysis, the first 60 2-s long artefact-free epochs were selected from each participant (Li et al. 2023). The microstate analysis was performed using the Microstate EEGLab Toolbox (Poulsen et al. 2018). First, the global field power (GFP) was calculated, and the local maximum peaks of GFP were determined for each participant. At each time point, the activity in the potential field was determined using the GFP, which is equivalent to the spatial standard deviation of all electrodes (Skrandies 1990; Murray et al. 2008). The local maximum peaks in the GFP indicate the moments with the largest field strength and highest signal-to-noise ratio. Additionally, the topographies observed at the maximum peaks of GFP indicate those at neighbouring time points due to the consistency between local minimum peaks (Lehmann et al. 1987; Khanna et al. 2014). We set the minimum peak distance to 10 ms and the number of peaks at 5,000, and we rejected peaks that exceeded 2 times higher than the standard deviation of all GFPs. If 5,000 peaks were not extracted from every participant, an equivalent number of peaks were extracted from each participant, with a focus on participants with the fewest number of peaks (Musaeus et al. 2019). Furthermore, an exclusion threshold was applied to peaks that exceed two times the standard deviation of the GFPs across all maps.

For clustering of the microstate topographic maps, the topographies at GFP peaks were entered into a modified K-means clustering algorithm with 50 repetitions, ignoring spatial polarity (Lehmann 1971; Pascual-Marqui et al. 1995). Based on previous research indicating that four clusters of microstate maps are commonly used, four was considered the optimal number to represent the measured brain activity. Therefore, we extracted four template maps for microstates A–D (Khanna et al. 2015; Michel and Koenig 2018; Schiller et al. 2021). Using the four grand mean template maps, representative template maps were backfitted into the EEG time point data for each participant. Based on the global map dissimilarity (GMD), microstate labels (A–D) were assigned through backfitting by determining the topographical similarity between the microstate topographic maps of the EEG data and template maps. GMD refers to the distance

measured by considering the similarity of topographical maps independent of the signal intensity (Poulsen et al. 2018; Ahmadi et al. 2020). A smaller GMD distance indicates that the two microstates are more similar.

Short segments of a microstate might appear after back-fitted labelling due to periods of unstable topography and residual artefacts in EEG data. To address this issue, a small-segment rejection algorithm was applied to smooth the microstates. To reject segments that were too short, the minimum duration of microstate segments was set to 30 ms. Then, microstate maps were switched until no microstate segment had a duration shorter than the specified one, as determined by the GMD (Poulsen et al. 2018). Finally, the labelled microstates were retrieved for all participants, and five microstate parameters were derived: global explained variance (GEV), duration, occurrence, coverage, and the transition probability (TP) between microstates. GEV uses a spatial correlation algorithm to determine how well each of the four templates maps can explain the original EEG data. Duration represents the average time that a specific microstate class is continuously present. Occurrence indicates the number of times a given microstate class occurs per second. Coverage is the proportion of time spent in a particular class. TP is the probability of conversion between certain classes of microstates. After extracting microstate parameters, outlier detection identified four IGD, six HC, three AUD values that were three-fold higher or lower than the interquartile range. An overview of the microstate analysis is shown in Figure 1.

Statistical analysis

One-way analysis of variance and chi-squared tests were conducted to examine differences in demographic characteristics and psychological variables among the three groups. To evaluate the 28 microstate parameters across the three groups, a multivariate analysis of variance (MANOVA) was used, with age, sex, years of education, BDI score, and BAI score as covariates. An adjusted *P*-value was calculated using the false discovery rate to control for multiple comparisons (Benjamini and Hochberg 1995). Post hoc Bonferroni-corrected pairwise group comparisons were performed. Effect sizes were computed using partial eta squared (η^2). Pearson's correlation was used to evaluate the relationships between microstate parameters and psychological variables, with 5,000 bootstrap resamples to correct for multiple correlations. The bootstrap test, which is commonly used in EEG studies, has been demonstrated to be reliable and robust in numerous previous studies (Haukoos and Lewis 2005; Ruscio 2008; Pernet et al. 2011; Kim et al. 2019b). $p < 0.05$ was considered indicative of statistical significance. Statistical analyses were conducted using SPSS 27 (IBM Corp., Armonk, NY, USA).

Results

Demographic and psychological characteristics

Table 1 presents the demographic and psychological characteristics of the patients with IGD and AUD and HCs.

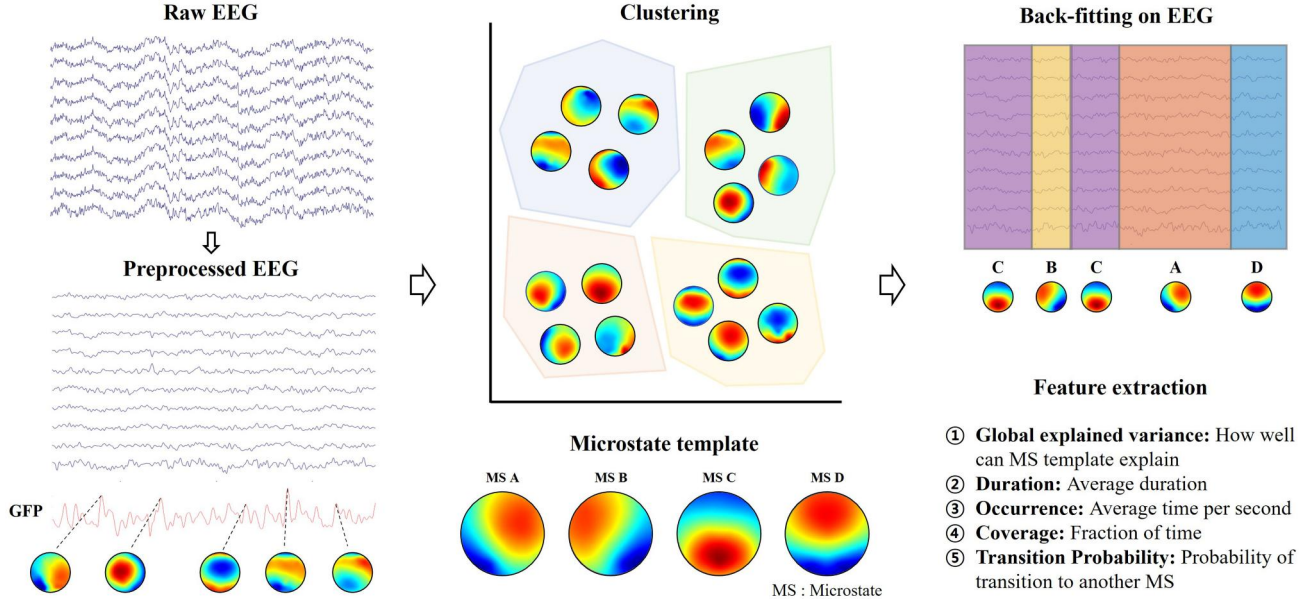


Figure 1. Overview of EEG microstate analysis.

Table 1. Participant demographic and psychological characteristics.

	IGD ($N = 75$)	AUD ($N = 57$)	HC ($N = 67$)	χ^2	p	Post hoc
Sex				9.087	0.011	
Male	72	45	57			
Female	3	12	10			
	Mean ± S. D	Mean ± S. D	Mean ± S. D	F	p	Post hoc
Age	23.65 ± 5.18	28.30 ± 5.39	24.94 ± 3.31	16.324	< 0.001	I, H < A
Education	12.88 ± 1.66	13.68 ± 2.22	14.60 ± 1.82	14.640	< 0.001	I < A < H
IAT	65.48 ± 15.89	33.00 ± 13.63	29.61 ± 9.02	156.920	< 0.001	A, H < I
AUDIT	4.86 ± 4.89	26.19 ± 6.37	4.96 ± 3.51	361.940	< 0.001	I, H < A
BDI	19.87 ± 11.38	23.32 ± 15.78	4.07 ± 4.14	54.282	< 0.001	H < I, A
BAI	16.39 ± 13.12	20.91 ± 15.49	4.81 ± 5.34	30.746	< 0.001	H < I, A
BIS-11	67.97 ± 11.22	70.18 ± 11.75	55.48 ± 8.14	37.488	< 0.001	H < I, A
BAS	34.25 ± 6.88	34.71 ± 7.71	33.01 ± 6.52	0.999	0.370	
BIS	21.83 ± 4.23	21.09 ± 3.99	17.70 ± 3.78	20.513	< 0.001	H < I, A
BIS/BAS	0.66 ± 0.17	0.63 ± 0.17	0.55 ± 0.11	9.698	< 0.001	H < I, A
AQ	72.99 ± 17.75	82.20 ± 21.66	55.18 ± 11.88	35.621	< 0.001	H < I < A
PWI	68.36 ± 25.38	72.00 ± 29.56	31.19 ± 14.91	59.113	< 0.001	H < I, A
CD-RISC	42.69 ± 19.86	47.11 ± 19.88	72.16 ± 10.82	53.355	< 0.001	I, A < H
QOL	71.12 ± 17.73	69.11 ± 17.37	97.64 ± 11.91	66.195	< 0.001	I, A < H

IGD (I): Internet gaming disorder; AUD (A): Alcohol use disorder; HC (H): Healthy control; S. D: Standard deviation; IAT: Young's Internet Addiction Test; AUDIT: Alcohol Use Disorder Identification; BDI: Beck Depression Inventory; BAI: Beck Anxiety Inventory; BIS-11: Barratt Impulsiveness Scale version 11; BAS: Behavioural Activation Scale; BIS: Behavioural Inhibition Scale; AQ: Aggression Questionnaire; PWI: Psychosocial Well-being Index; CD-RISC: Connor-Davidson Resilience Scale; QOL: Quality of life.

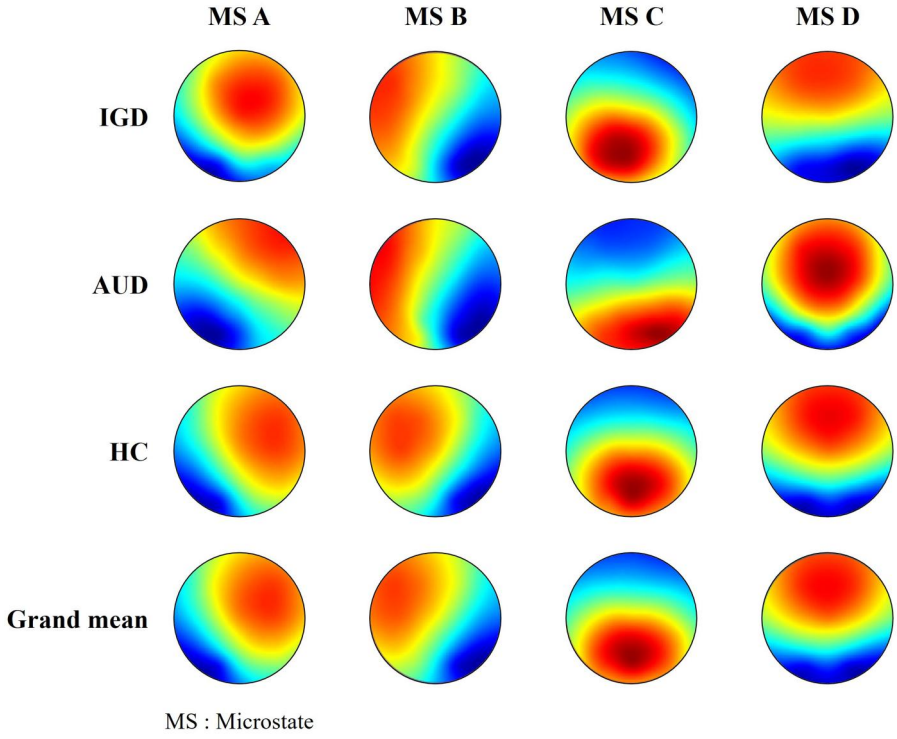


Figure 2. Microstate template maps obtained from IGD, AUD, HC, and grand mean among three groups.

Microstate analysis

Figure 2 presents the microstate template maps and grand means obtained from the IGD, AUD, and HC groups. The four topographies of microstate classes A–D were similar to those obtained in previous studies (Koenig et al. 2002; Michel and Koenig 2018; Schiller et al. 2021; Wang et al. 2021). Table 2 presents the means and standard deviations of microstate parameters in the IGD, AUD, and HC groups. The total average GEV value was not significantly different among the IGD (66.45 ± 6.93%), AUD (63.65 ± 8.33%), and HC (64.55 ± 8.01%) groups ($p = 0.103$). After Bonferroni correction, the GEV of microstate class C was significantly lower in the AUD group than in the IGD group ($p < 0.001$), whereas there were no significant differences between patients with IGD and HCs. However, the IGD and AUD groups exhibited higher GEV values in microstate class D compared to HCs.

Table 2. Mean and standard deviations value of microstate parameters, including GEV, duration, occurrence, and coverage among IGD, AUD, and HC group.

	IGD ($N = 75$)	AUD ($N = 57$)	HC ($N = 67$)	F	p	η^2	Post hoc
GEV (%)							
MS A	8.84 ± 3.21	8.86 ± 3.19	9.01 ± 2.77	0.136	0.873	0.002	
MS B	7.83 ± 2.75	8.00 ± 2.67	8.57 ± 2.90	0.790	0.455	0.009	
MS C	11.29 ± 4.30	8.40 ± 3.36	10.30 ± 3.55	9.552	< 0.001*	0.097	A < I
MS D	21.34 ± 8.73	20.61 ± 9.53	17.87 ± 5.59	3.305	0.039	0.036	
Duration (ms)							
MS A	80.07 ± 8.12	80.71 ± 8.53	79.29 ± 5.92	0.611	0.544	0.007	
MS B	77.65 ± 6.42	78.87 ± 6.82	79.48 ± 6.47	1.760	0.175	0.019	
MS C	83.94 ± 10.40	80.15 ± 10.13	82.66 ± 9.72	2.444	0.090	0.027	
MS D	98.16 ± 21.07	98.39 ± 23.08	90.12 ± 10.46	3.457	0.034	0.037	H < A
Occurrence (/s)							
MS A	2.74 ± 0.53	2.88 ± 0.54	2.92 ± 0.37	2.285	0.105	0.025	
MS B	2.64 ± 0.45	2.77 ± 0.44	2.86 ± 0.43	3.751	0.025	0.040	I < H
MS C	2.93 ± 0.45	2.70 ± 0.53	2.97 ± 0.37	5.494	0.005*	0.058	A < I, H
MS D	3.25 ± 0.32	3.27 ± 0.42	3.21 ± 0.33	0.202	0.817	0.002	
Coverage (%)							
MS A	22.24 ± 5.82	23.47 ± 5.86	23.23 ± 3.95	1.371	0.257	0.015	
MS B	20.68 ± 4.69	22.06 ± 4.87	22.92 ± 4.72	3.692	0.027	0.040	I < H
MS C	24.87 ± 6.21	21.96 ± 6.06	24.77 ± 5.50	4.733	0.010	0.050	A < I
MS D	32.21 ± 8.78	32.51 ± 9.79	29.08 ± 5.47	2.545	0.081	0.028	

GEV: Global explained variance; MS: Microstate; IGD (I): Internet gaming disorder; AUD (A): Alcohol use disorder; HC (H): Healthy control; *: Significant microstate parameters after FDR adjusting.

After Bonferroni correction, the duration of microstate class D was significantly longer in the AUD group than in HCs ($p = 0.045$), whereas there was no significant difference between the AUD and IGD groups. Furthermore, no significant difference in the duration of microstate class C was observed among the three groups.

After Bonferroni correction, the occurrence of microstate class B was significantly less common in the IGD group than in HCs ($p = 0.022$). Additionally, the occurrence of microstate class C was significantly less common in the AUD group than in the IGD and HC groups ($p = 0.005$ and $p = 0.041$, respectively).

In the IGD group, similar to the occurrence, the coverage of microstate class B was significantly lower compared to HCs after Bonferroni correction ($p = 0.023$). In the AUD group, the coverage of microstate class C was lower than that in the IGD group ($p = 0.008$).

Table 3 presents the mean microstate TP values in various microstate classes. The TP from A to B was significantly lower in the IGD group than in HCs after Bonferroni correction ($p = 0.025$). There were significant differences in the TPs between class C and all other microstate classes C (for A → C, B → C, and D → C). The AUD group exhibited significantly lower TP values in microstates A to C ($p = 0.020$) and D to C ($p = 0.004$) compared to the IGD group after Bonferroni correction. Additionally, the TP from microstate B to C was significantly lower in the AUD group than in the IGD and HC groups ($p = 0.003$ and $p = 0.036$, respectively).

In Tables 2 and 3, asterisks (*) indicate significant differences between groups at a *P*-value adjusted based on the false discovery rate to control for multiple comparisons.

Relationship between microstate parameters and psychological variables

In HCs, the TP from microstate A to C was significantly positively correlated with the Aggression Questionnaire score ($r = 0.279$, $p = 0.037$). However, there were no significant correlations between microstate parameters and psychological variables in the IGD group.

In the AUD group, the occurrence and coverage of microstate class C were significantly negatively correlated with the AUDIT score ($r = -0.400$, $p = 0.003$ and $r = -0.359$, $p = 0.008$, respectively) and BIS score ($r = -0.346$, $p = 0.011$ and $r = -0.298$, $p = 0.030$, respectively). Additionally, the TP from microstate B to C was significantly negatively correlated with the AUDIT and BIS scores ($r = -0.311$, $p = 0.022$ and $r = -0.346$, $p = 0.011$, respectively). Furthermore, the TP from A to C was significantly correlated with the AUDIT ($r = -0.383$, $p = 0.004$), BIS ($r = -0.360$, $p = 0.008$), PWI ($r = -0.308$, $p = 0.023$), and CD-RISC ($r = -0.319$, $p = 0.035$) scores. Figure 3 presents the correlations between microstate parameters and psychological variables in the AUD group.

Discussion

In this study, we compared microstate features among patients with AUD, those with IGD, and HCs. As expected, various psychological characteristics differed

Table 3. Mean and standard deviation values of microstate transition probabilities (%) among IGD, AUD, and HC group.

	IGD ($N = 75$)	AUD ($N = 57$)	HC ($N = 67$)	F	p	η^2	Post hoc
MS A → B	28.47 ± 6.34	30.49 ± 6.30	31.42 ± 6.14	3.782	0.025	0.041	I < H
MS A → C	32.82 ± 6.70	29.24 ± 6.95	31.96 ± 6.09	3.808	0.024	0.041	A < I
MS A → D	38.71 ± 7.60	40.27 ± 9.45	36.61 ± 6.68	1.890	0.154	0.021	
MS B → A	29.88 ± 7.41	32.28 ± 7.39	31.73 ± 5.26	2.584	0.078	0.028	
MS B → C	31.61 ± 6.82	28.40 ± 7.26	32.24 ± 5.70	5.874	0.003*	0.062	A < I, H
MS B → D	38.50 ± 8.58	30.49 ± 6.30	31.42 ± 6.14	1.607	0.203	0.018	
MS C → A	30.02 ± 6.50	31.11 ± 7.28	31.35 ± 4.82	1.010	0.366	0.011	
MS C → B	28.86 ± 5.98	29.61 ± 5.79	31.21 ± 5.35	1.767	0.174	0.019	
MS C → D	41.12 ± 8.49	39.28 ± 9.15	37.43 ± 6.54	2.828	0.062	0.031	
MS D → A	32.58 ± 7.39	34.65 ± 7.34	33.25 ± 5.27	1.973	0.142	0.022	
MS D → B	30.83 ± 6.20	32.85 ± 5.88	31.72 ± 5.79	1.860	0.159	0.020	
MS D → C	36.60 ± 7.88	32.50 ± 7.35	35.03 ± 6.74	5.495	0.005*	0.058	A < I

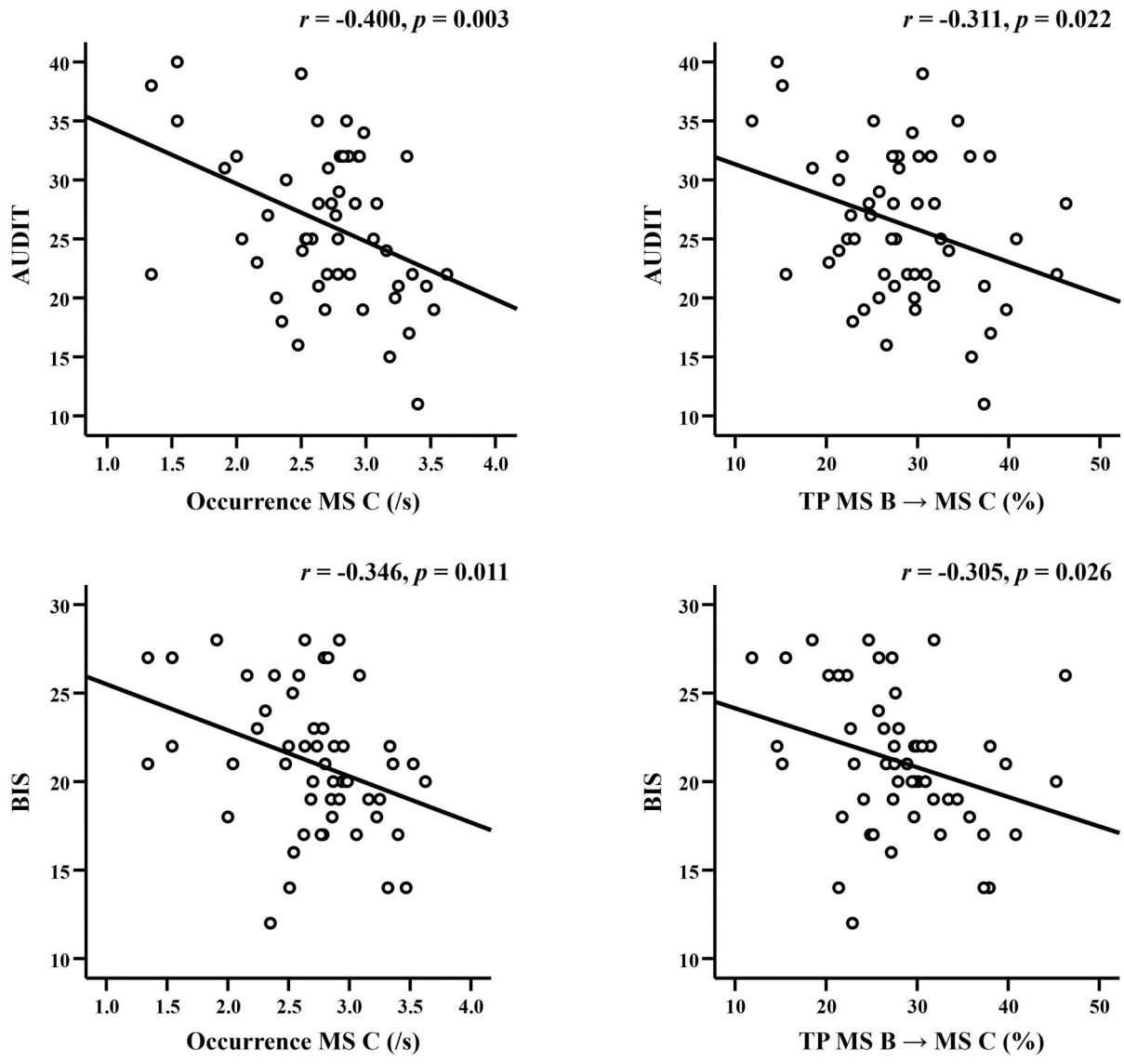
MS: Microstate; IGD (I): Internet gaming disorder; AUD (A): Alcohol use disorder; HC (H): Healthy control; *: Significant microstate parameters after FDR adjusting.

between patients with AUD or IGD and HCs. Additionally, we hypothesised that patients with AUD, those with IGD, and HCs would exhibit distinct microstate-related characteristics. There were significant differences in microstate values among the three groups. In particular, the AUD group demonstrated significantly lower TPs from other microstate classes to microstate C compared to the IGD group. Additionally, reduced TPs and microstate components (occurrence and coverage) were significantly associated with related psychological characteristics, such as the severity of alcohol addiction and impulsivity, in the AUD group. To the best of our knowledge, this study is the first to compare EEG microstate dynamics between substance and behavioural addictions.

IGD is characterised by cognitive and emotional deficits (Liu et al. 2018). Previous studies have reported the co-occurrence of IGD and emotional dysregulation, such as depression and poor impulse control (Kaess et al. 2014; Lin et al. 2015). Studies on IGD reported higher depressive tendencies in individuals with IGD, as well as a reduction in depression during remission from IGD (King and Delfabbro 2016). At the neural level, individuals with IGD exhibited enhanced resting state functional connectivity between the left amygdala and right dorsolateral prefrontal cortex, inferior frontal, and precentral gyrus, compared with control participants (Connolly et al. 2013; Zhang et al. 2016). Moreover, the amygdala-frontoparietal connectivity at the baseline negatively predicted a reduction in depression symptoms following a psychotherapy intervention for IGD (Winkler et al. 2013). The proposed DSM-5 criteria for IGD require ongoing and recurrent internet gaming causing clinically significant impairment or distress. In addition, the medications studied so far for IGD are typically used to treat depression and poor impulse control, such as antidepressants and methylphenidate (Sá et al. 2023). The place of emotion regulation in the pathophysiology of IGD is currently unclear, but symptoms associated with emotion regulation difficulties may be important in the diagnosis and treatment of IGD. In addition, the emphasis on the importance of independent diagnosis and treatment may be an important factor in the need for distinct diagnostic criteria.

In the present study, the TPs from all microstate classes to class C differed significantly between the AUD and IGD groups. This suggests the presence of a direct interaction between two networks, where the inhibition or activation of regions belonging to one network affects the activity of the other one. In the AUD group, microstate class C exhibited a significantly lower GEV value than that in the IGD group even after adjusting for multiple comparisons. These findings suggest that the brain functional connectivity (FC) between microstate C and other microstates was significantly weakened. Considering that microstate C is associated with the default mode network (DMN), which plays a crucial role in addiction (Bae et al. 2018), and that the DMN is a unique brain region that is activated during rest and deactivated during task completion (Buckner et al. 2008), our findings suggest that, compared to IGD, AUD is associated with reduced resting-state FC between DMN-related regions (Wang et al. 2017; Bae et al. 2018). Alcohol intoxication and addictive states have a potentially significant impact on the DMN, delaying activity therein compared to behavioural addiction.

The aforementioned hypothesis appears more plausible considering our correlation results. The higher the AUDIT score, the lower the occurrence and coverage of microstate C, and the lower the TP from microstates A and B to C. This indicates that more severe alcohol addiction is associated with a greater functional reduction in microstate C and a decrease in brain FC from A and B to C. Interestingly, similar



MS: Microstate, TP: transition probability, IGD (I): Internet gaming disorder, AUD (A): Alcohol use disorder, HC (H): Healthy control, AUDIT: Alcohol use disorder identification, BIS: Behavioral inhibition scale

Figure 3. Correlation between microstate parameters and scores of psychological measures in AUD group.

correlations were observed for impulsivity scale scores. In the AUD group, the worse the impulse control, the greater the decline in microstate C and the lower the brain FC with microstate C. In AUD, trait impulsivity correlates with alcohol consumption, cue-induced alcohol craving, and early onset alcohol consumption (Papachristou et al. 2013; Jasinska et al. 2014; Sanchez-Roige et al. 2019). Impulsivity and alcohol use are highly correlated, with impulsivity being a potential endo-phenotype for these disorders (Burnette et al. 2019; Sanchez-Roige et al. 2019). The dynamic interplay between the DMN and other neural networks impacts cognitive processes and emotional states, thereby influencing impulsivity (Shannon et al. 2011). This interplay may contribute to craving and relapse in addiction (Zhang and Volkow 2019). Additionally, some neuroimaging studies have demonstrated that impulsivity scores were significantly correlated with altered DMN (Zhu et al. 2017; Burnette et al. 2019). Stronger cue-elicited alcohol craving is linked to higher impulsivity, which predicts both tonic and phasic cravings upon cue exposure (Papachristou et al. 2014). Individuals with AUD scored higher on trait measures of impulsivity and demonstrated increased self-reported craving, skin conductance, and heart rate when exposed to alcohol cues. This supports the notion that interactions between impulsivity and cue reactivity may characterise alcohol use motivation in dependent drinkers (Subotic et al. 2014). A recent study demonstrated that individuals with higher

impulsivity have a stronger Pavlovian reaction to visual alcohol cues (Sommer et al. 2017). Additionally, impaired alcohol cue processing in AUD emerges early, at the stage of sensory processing. This deficient initial processing is crucial for understanding cue reactivity processes in the brain and the subjective experience of craving (Rohde et al. 2020). Considering that microstate A is linked to auditory and visual processing, whereas microstate B is associated with self-related visual processing, the reduced FC from microstate A and B to DMN-associated microstate C that we observed in the AUD population could impact functions related to impulse control and sensory processing associated with alcohol cues in AUD. In turn, this could contribute to alcohol craving and difficulty in controlling it.

Meanwhile, the TP from microstate A to B was reduced in the IGD group compared to HCs. These findings suggest a significant reduction in brain FC between microstates A and B in individuals with IGD compared to HCs. According to functional MRI studies, microstate A is associated with auditory and visual processing, whereas microstate B is associated with self-related visual processing (Tarailis et al. 2024). A previous study found that, in patients with IGD, the brain activation in the inferior occipital cortex induced by gaming-related cues was greater compared to that in HCs (Qian et al. 2008; Zhang et al. 2016). In this study, metabolic activation of the occipital lobe was enhanced in the IGD group after playing games, indicating a different activation pattern of regional brain metabolism compared to HCs. Similarly, other studies demonstrated that the FC of the occipital lobe after playing games was significantly lower in the IGD group than in HCs (Chen et al. 2016). Considering that addictive traits in IGD are associated with visual cues and occipital lobe metabolism, which is linked to visual processing (Uysal 2023), the decreased TP from microstate A to B reflects altered brain FC in related brain circuits. It could be that a reduced ability to control and handle visual stimuli may affect the craving for games and related addictive traits. Further studies are needed to investigate brain connectivity, metabolism, and clinical characteristics in relation to gaming addiction.

This study had several limitations. First, the three groups had significant differences in age, sex, and educational level. The AUD group was older than the IGD and HC groups, and the educational level was lower in the IGD group than in the AUD and HC groups. However, we statistically controlled for the effects of age, sex and education, and the microstate yielded group effects were not correlated with age, sex, and education. Second, although previous studies have identified the brain regions and networks predominantly involved in microstate clusters, this study did not involve before-and-after comparison of functional MRI tasks, limiting interpretability. Future studies with more sophisticated designs are needed to support our results. Third, the causal effects of comorbidities were not assessed. Fourth, the total average GEV of the IGD ($66.45 \pm 6.93\%$), AUD ($63.65 \pm 8.33\%$), and HC ($64.55 \pm 8.01\%$) groups were relatively small compared to previous studies (Michel and Koenig 2018). However, there was no significant difference in the total average GEV among the three groups ($p = 0.103$), and a smaller total average GEV value was associated with a significantly lower value of microstate C in the AUD group. Finally, nicotine addiction is another representative substance abuse. Future studies should include comparisons with other types of substance abuse, such as nicotine addiction, which may have a different neurobiological basis.

Despite these limitations, this study is the first to compare IGD, AUD, and HC groups using microstate analyses. We observed significant differences in microstate characteristics among the groups, which correlated with psychological scores. Our results suggest that microstate features may serve as potential neuromarkers in clinical settings, offering a means to differentiate between distinct addictive disorders. We demonstrated the potential utility of microstate features as biomarkers of AUD and IGD pathophysiology in clinical settings. Large-scale studies are warranted to validate and broaden the applicability of these findings.

Authors' contributions

Ji Sun Kim contributed to the study design, conceptualisation, interpretation of the findings, and writing of the original draft. Young Wook Song contributed to the study design, formal analysis, and writing of the original draft. Sungkean Kim and Ji-Yoon Lee contributed to the study design and reviewed the draft and editing. So Young Yoo and Joon Hwan Jang contributed to the collection of data and interpretation of the findings. Jung-Seok Choi contributed to the overall study, conceptualisation, interpretation of the findings, and reviewed the draft.

Disclosure statement

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