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Multimodal-based machine learning approach to classify features of internet gaming disorder and alcohol use disorder: A sensor-level and source-level resting-state electroencephalography activity and neuropsychological study

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ABSTRACT

Objectives: Addictions have recently been classified as substance use disorder (SUD) and behavioral addiction (BA), but the concept of BA is still debatable. Therefore, it is necessary to conduct further neuroscientific research to understand the mechanisms of BA to the same extent as SUD. The present study used machine learning (ML) algorithms to investigate the neuropsychological and neurophysiological aspects of addictions in individuals with internet gaming disorder (IGD) and alcohol use disorder (AUD).

Methods: We developed three models for distinguishing individuals with IGD from those with AUD, individuals with IGD from healthy controls (HCs), and individuals with AUD from HCs using ML algorithms, including L1-norm support vector machine, random forest, and L1-norm logistic regression (LR). Three distinct feature sets were used for model training: a unimodal-electroencephalography (EEG) feature set combined with sensor- and source-level feature; a unimodal-neuropsychological feature (NF) set included sex, age, depression, anxiety, impulsivity, and general cognitive function, and a multimodal (EEG + NF) feature set.

Results: The LR model with the multimodal feature set used for the classification of IGD and AUD outperformed the other models (accuracy: 0.712). The important features selected by the model highlighted that the IGD group had differential delta and beta source connectivity between right intrahemispheric regions and distinct sensor-level EEG activities. Among the NFs, sex and age were the important features for good model performance.

Conclusions: Using ML techniques, we demonstrated the neurophysiological and neuropsychological similarities and differences between IGD (a BA) and AUD (a SUD).

1. Introduction

Addictions have recently been divided into two categories: substance use disorder (SUD, i.e., substance addiction) and behavioral addiction (BA, i.e., non-substance addiction). SUD is defined by patterns of symptoms produced by the use of a substance that an individual

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continues to consume, despite its adverse effects [1]. BA is defined as a set of behaviors on which the individual becomes dependent, such as gambling addiction [2]. BA is similar to SUD, with the exception that the individual is addicted to the behaviors or mood caused by the relevant activity, rather than substance [3]. There is substantial overlap between BA and SUD in many domains, including natural history, phenomenology, tolerance, comorbidity, overlapping genetic contributions, neurobiological processes, and therapeutic response [3–5]; in fact, in 2018, the World Health Organization (WHO) recognized gambling and gaming disorder as a significant public health issue and included it as "disorders due to addictive behaviors" in the 11th Revision of the International Classification of Diseases (ICD-11) [6]. The notion of BA has some scientific and clinical heuristic significance, but it is still debated [7]. In particular, previous studies emphasize the need for more research in the disciplines of neurobiology, including neuroimaging, to understand the BA mechanism to the same degree as that of SUD [4,8,9].

Internet gaming disorder (IGD), an emerging BA, is defined by the Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-5) as the persistent and frequent use of online games that causes clinically significant impairment or distress and withdrawal symptoms [1]. Individuals with internet addiction have a high prevalence of SUD, particularly alcohol use disorder (AUD) [10]. Furthermore, IGD shares several psychological features with AUD including dysfunctional impulsivity, limited capacity for self-control, excessive anxiety, and severe psychopathological impairment [11,12]. However, those studies are limited in that they mainly rely on self-report. To clarify the neurobiological mechanism underlying BA, objective and validated neurophysiological assessments are necessary.

Electroencephalography (EEG), an electrophysiological method for recording electrical activity emanating from the human brain, may offer the means of an objective measurement. The use of EEG for the evaluation of psychiatric disorders can enhance the spatial and temporal characterization of cortical circuits and systems involved in cognitive functions and behavioral planning, execution, and assessment [13]. Previous studies have attempted to compare the EEG activity of IGD with that of AUD to clarify the neurological underpinnings of BA. Son et al. [14] provided neurophysiological evidence to support the distinctive features of IGD separate from AUD. The authors demonstrated that reduced absolute beta power can be employed as a possible IGD characteristic marker, whereas higher absolute power in the delta band can be a risk factor for AUD. Another study showed that individuals with IGD and AUD have distinct coherence, which represents connectivity between two EEG sensors, and IGD may have a key neurophysiological characteristic of increased gamma coherence [15]. Nonetheless, the neurophysiological bases of both addictions have yet to be resolved.

Furthermore, the abovementioned studies examined only one or two dimensions of sensor-level EEG features, such as relative power, absolute power, or coherence. BA and SUD commonly involve changes in high-order brain networks [16]. The aim for researchers and clinicians is to identify the specific brain regions associated with EEG signals and to clarify the neural correlates of IGD and AUD. Although EEG is praised for its high temporal resolution, its spatial resolution is not as accurate as that of other neuroimaging tools. This limitation arises because sensor-level EEG recordings can become distorted or blurred because of volume conduction or shared sources [17]. However, it can be overcome by employing algorithms identified to locate the sources of these signals [18]. As a result, examining the network at the source-level is beneficial because it offers a more direct representation of the brain's connections, rather than focusing on the connections between EEG sensors [19]. A recent meta-analysis found that both BA and SUD share changes in resting-state functional connectivity (FC) between the frontoparietal network and various high-level neurocognitive networks, including the default mode network (DMN), affective network, and salience network (SN) [20]. Research on source-level EEG FC has focused primarily on the involvement of the DMN, reward network (RN), and SN during resting state, establishing links between these networks and observed neural patterns in IGD and AUD [21–24]. FC within DMN reflects the brain's resting neural activities and baseline mood states [25]. Addiction is associated with increased activity in the RN and SN, which is correlated with decreased cognitive control and impaired executive function [26]. However, there remains a lack of studies comparing source-level EEG connectivity between individuals with IGD and those with AUD. Therefore, further research is needed to investigate the neurophysiological activity within high-level neurocognitive networks in order to identify critical information about the underlying neurophysiological mechanism of both addictions.

A machine-learning (ML) method is particularly beneficial when there are a significant number of predictor variables compared to the number of samples, or when the focus is on the reliability and generalizability of measurements [27]. ML methods, due to their ability to handle complexity and high dimensions, are suitable for analyzing EEG data and enable the processing of integrated patterns compared to traditional analysis [28]. Recently, the integration of multimodal, multifeature ML applications has emerged as significant focus in medical research. These applications excel in disease classification and prediction, providing more in-depth insights into disease development and treatment outcomes surpassing traditional analytic methods such as regression analyses [29]. A magnetic resonance imaging (MRI) study demonstrated that a ML classifier, developed using a combination of structural, task-based, and resting-state MRI data, can effectively diagnose alcohol dependence. This novel multimodal approach outperforms a single imaging modality [30]. Another study suggested that the prediction accuracy for IGD was improved by using ML methods along with a combination of various types of data, such as clinical features, positron emission tomography scans, and EEG [31].

Several studies have attempted to detect IGD or AUD using unimodal EEG features via the application of ML techniques [21,32–35]. To the best of our knowledge, no previous research has leveraged multimodal data through ML methods to identify the neurobiological mechanisms of AUD and IGD yet. This study utilizes a range of ML algorithms, including the L1-norm support vector machine (SVM), random forest (RF), and L1-norm logistic regression (LR), to distinguish between IGD and AUD, IGD and healthy controls (HC), as well as between AUD and HCs. Our analysis includes three distinct sets of features: 1) a unimodal EEG feature set that includes sensor-level and source-level data; 2) a unimodal neuropsychological feature set (NFs); and 3) a multimodal feature set using a cross-validated deviance weighted probabilistic ensemble method. We hypothesize that there will be significant similarities and differences in the neurophysiological and neuropsychological patterns between individuals with IGD and AUD. Furthermore, we suggest that the use of a multimodal data approach would be more effective in distinguishing between IGD and AUD compared to using unimodal feature sets.

2. Material and methods

2.1. Participants

In all, 67 individuals with IGD (63 males and 4 females), 58 individuals with AUD (46 males and 12 females), and 66 HCs (56 males and 10 females), for a total of 191 participants, were recruited from the outpatient clinic of SMG-SNU Boramae Medical Center and the surrounding community. All of the participants were medication-naïve and right-handed. None of the participants had any comorbid psychiatric diagnoses, such as attention-deficit hyperactivity disorder, depressive disorders, or anxiety disorders. They also did not have a history of psychotic or neurological disorders, significant head injury, seizure, or intellectual disability (intelligence quotient [IQ] $<$ 80). Based on the DSM-5 criteria, a clinically experienced psychiatrist diagnosed individuals with IGD or AUD. Participants reported the severity of IGD and AUD via the Young Internet Addiction Test (IAT) [36,37], modified for

application to IGD [23,38] and the Alcohol Use Disorders Identification Test (AUDIT) [39,40]. All HCs were recruited from the local community and universities. None of the HCs had a history of any psychiatric disease, and they all played internet games for <2 h each day according to previous studies [14,41].

The Institutional Review Board of SMG-SNU Boramae Medical Center approved the study protocol, and the study adhered to the principles of the Declaration of Helsinki. Before taking part in the study, all participants were made aware of the procedure and each provided written informed consent.

2.2. EEG features

2.2.1. Data collection

The participants were situated in a sound-shielded room connected to the recording room through a one-way glass window in a resting position. EEG was recorded for 10 min: 5 min with eyes closed, and 5 min with eyes open, using a 64-channel (sensor) Quik-Cap (Compumedics Neuroscan, El Paso, TX, USA) following the modified International 10–20 system in conjunction with vertical and horizontal electrooculogram recordings and one bipolar reference electrode attached to the mastoid. All EEG recordings were obtained using SynAmps 2 (Compumedics, Abbotsford, Victoria, Australia) and the Neuroscan system (Scan 4.5; Compumedics). The EEG signals were amplified using a 0.1–100 Hz online bandpass filter and a 0.1–50 Hz offline bandpass filter at a sampling rate of 1000 Hz. The electrode impedance was maintained below 5 kΩ.

2.2.2. Data preprocessing

All acquired EEG data were processed using NeuroGuide software (NG; ver. 3.0.5; Applied Neuroscience, St. Petersburg, FL, USA). For the analysis, 19 of the 64 channels were chosen using the following montage of linked-ear references from NG: Fp1, Fp2, F3, F7, Fz, F4, F8, C3, Cz, C4, T3, T5, T4, T6, P3, Pz, P4, O1, and O2. Artifacts were eliminated using the NG artifact rejection toolbox, and artifact-free epochs with the eyes-closed condition were chosen for the analysis. The source- and sensor-level EEG features were computed for each of the following frequency bands: delta (1–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), beta (12–25 Hz), and gamma (30–40 Hz).

The source-level FC analysis using the standardized weighted low resolution electromagnetic tomography (swLORETA) was conducted via NeuroNavigator software (NG Deluxe 3.0.5; Applied Neuroscience). This technique, known as a three-dimensional electrical neuroimaging method, utilizes a real MRI with 12,270 voxels [42,43]. The NeuroNavigator software provides specific network nodes based on Brodmann areas (BA) [44,45]. The list below includes the twenty regions of interests (ROIs) for the DMN in both the left and right hemispheres: the prefrontal cortex (PFC, BA10), orbitofrontal cortex (OFC, BA11), medial temporal lobe and parahippocampal gyrus (MTL&PHG, BA35), postcentral gyrus (PCG, BA2), angular gyrus and inferior parietal lobe (AG&IPL, BA39), inferior parietal lobe (IPL, BA40), posterior cingulate and superior transverse temporal gyrus (PCC&STG, BA29), posterior cingulate and cuneus (PCC&Cnu, BA30), supramarginal gyrus (SMG, BA7), and occipital cortex (OC, BA19). The reward-salience network (RSN) is made up of edges from the RN and the SN, with duplicated edges removed. The twelve ROIs for the RN on the left and right sides are as follows on the left and right hemispheres: the inferior frontal lobe (IFL, BA47), inferior frontal and extra-nuclear gyrus of the prefrontal lobes (IFL&ENG, BA44), middle frontal gyrus (MFG, BA46), superior temporal gyrus and subcallosal gyrus-entorhinal area (STG&SGTA, BA34), anterior cingulate cortex (ACC, BA24), and insula (In, BA13). Fourteen ROIs for the SN are adopted as follows: the PFC (BA10), temporal lobe (TL, BA22), ACC (BA24), posterior cingulate cortex (PCC, BA23), PCC&STG (BA29), PCC&Cnu (BA30), and In (BA13).

The preprocessed EEG data were segmented into epochs and transformed into the frequency domain using fast Fourier transforms. Relative power is the amount of power within a specific frequency band in relation to the total power across all frequency bands. The coherence was calculated for each possible pair of19 sensors, resulting in 171 unique pairs for each frequency band. Detailed information regarding the sensor-level features has been previously discussed in other studies [14,15,46].

2.3. Neuropsychological features

The intensity of depression symptoms was assessed by the Korean version of the Beck Depression Inventory-2 (BDI) [47,48]. Items were scored on a 4-point Likert scale with higher scores indicating more severe depressive symptoms. The level of anxiety during the previous week was measured using the Korean version of the Beck Anxiety Inventory (BAI) [49,50]. The items were rated on a 4-point Likert scale, with higher scores indicating more intense anxiety symptoms. The degree of impulsivity was measured using the total score of the Barratt Impulsiveness scale-11(BIS-11) [51]. BIS-11 includes 23 questions, each scored from 1 to 4. To assess general cognitive functions, IQ levels were estimated with the Korean version of the Wechsler Adult Intelligence Scale fourth edition (K-WAIS- IV) [52].

The NFs were analyzed using the chi-square test and one-way analysis of variance using Python libraries. The effect size for group comparisons was calculated using the partial eta squared (η_p^2). $P < 0.05$ was considered indicative of statistical significance. The Bonferroni post-hoc test was also performed ($p < 0.0167$). Table 1 presents the features used for model training.

2.4. Algorithms

We used three algorithms for model training based on previous ML studies of EEG features [21,53]: L1-norm SVM, RF, and L1-norm LR. Notably, the L1-norm penalty used in SVM and LR works better for high-dimensional low-sample size data [54,55]. The statistical and ML analyses were conducted using Python 3.8 and its associated packages.

2.5. Evaluation of model performance for unimodal and multimodal feature sets

One of the main purposes of this study was to identify the benefits of using a multimodal feature set instead of a unimodal feature set. Therefore, we compared algorithm performance between unimodal and multimodal feature sets. Leave-one-out cross-validation (LOOCV; outer loop) was used to evaluate the performance of the unimodal feature sets. All samples (N_{sample}), except for one, were used to train the classification model, and one sample was used to obtain a prediction from the trained model. This procedure was repeated for all of the samples (N_{sample} times). The GridSearchCV method was utilized to perform 10-fold cross validation (CV; inner loop), which used to select the optimal

Table 1
Features used for model training.

EEG features		Neuropsychological features
Source-level	Sensor-level	
Connectivity within the default mode network	Absolute power	Sex
Connectivity within the reward-salience network	Relative power	Age
	Coherence	Level of depression
		Level of anxiety
		Level of impulsivity
		Intelligence quotient (IQ)

Note. Depression, anxiety, impulsivity, and IQ were assessed using the Beck Depression Inventory-2, Beck Anxiety Inventory, Barratt Impulsivity Scale (version 11; total score), and Korean version of the Wechsler Adult Intelligence Scale (fourth edition), respectively.

hyperparameters and train the model for each algorithm [56]. The range of candidate values is shown in Supplementary Table S1. Within the LOOCV, feature selection was conducted using wrapper methods (L1-norm and RF) to prevent overfitting from data leakage [57,58].

Calculation of the accuracy of each algorithm and the procedure used for merging distinct modality feature sets based on CV deviances, are described in Fig. 1. For the models using the multimodal feature set, we used a CV deviance weighted probabilistic ensemble method that was adapted from an earlier study [59]. This method combines models based on their CV performance while considering their contributions based on deviance and weighted probabilities. Training models on multimodal feature selection, including EEG and NFs, can lead to the exclusion of some features. However, using the CV-deviance weighted probabilistic ensemble method, we combined two modalities without excluding any features. We calculated the deviances (negative log loss) of the trained models with the trained samples and computed classification probabilities of the one test sample that was not used for training. We performed a weighted average of the probabilities based on the deviances and determined the class based on the weighted probabilities. This procedure was repeated N_{sample} times (LOOCV) and the accuracy of the models was calculated depending on the predicted and the actual classes. The sensitivity of the model, which is its ability to correctly identify individuals with addictions, and its specificity, which is its ability to recognize individuals without addictions, were assessed. IGD was labeled as 1 for distinguishing between IGD and AUD. To assess the significance of the accuracy of our best model and feature set, we performed a permutation test with 1000 iterations [60]. This involves comparing the observed data with a dataset that has randomly shuffled labels. The *p*-value was determined by comparing the frequency at which the permuted data's accuracy exceeded that of the original data [61].

2.6. Feature importance

Feature importance was assessed by conducting 100 permutations to consider the variability in CV. The computation of feature importance involved using the entire dataset, as well as an inner loop CV process. A threshold of 0.5 was set for the survival rate, and any feature that fell below this rate was discarded. The top 10 features with the highest importance were selected as key features.

3. Results

3.1. Neuropsychological features

The group differences in NFs are shown in Table 2. The chi-square test showed that there were no significant differences between males and females ($p = 0.052$). Patients with AUD were older than those with IGD and the HCs (IGD, 23.881 ± 5.401; AUD, 28.241 ± 5.417; HC, 24.939 ± 3.229; $p < 0.001$; $\eta_p^2 = 0.129$). The severity of IGD (IAT) was greater in the IGD group compared to the AUD and HC groups (IGD, 64.672 ± 15.828; AUD, 32.988 ± 10.911; HC, 29.766 ± 9.978; $p < 0.001$; $\eta_p^2 = 0.621$), whereas the severity of AUD (AUDIT) was greater in the AUD group compared to the IGD and HC groups (IGD, 5.660 ± 4.799; AUD, 25.491 ± 7.201; HC, 4.943 ± 3.403; $p < 0.001$; $\eta_p^2 = 0.759$). Patients with IGD and AUD had more severe depressive symptoms (BDI; IGD, 19.737 ± 11.398; AUD, 22.047 ± 15.157; HC, 4.263 ± 4.396; $p < 0.001$; $\eta_p^2 = 0.343$), anxiety symptoms (BAI; IGD, 15.830 ± 13.184; AUD, 20.090 ± 14.538; HC, 5.040 ± 5.458; $p < 0.001$; $\eta_p^2 = 0.230$), and impulsivity (BIS-11; IGD, 68.632 ± 11.060; AUD, 69.443 ± 11.673; HC, 55.460 ± 8.269; $p < 0.001$; $\eta_p^2 = 0.282$), and lower IQs (IGD, 108.065 ± 13.947; AUD, 105.197 ± 12.253; HC, 117.364 ± 11.790; $p < 0.001$; $\eta_p^2 = 0.144$), than HCs.

3.2. Model performances

The performance results for the model on the test set, as obtained through LOOCV, are presented in Table 3. The LR model with the multimodal feature set showed superior classification performance for IGD and AUD (accuracy: 0.712; $p < 0.001$) compared to the models with the other feature sets (EEG; accuracy: 0.672, NF; accuracy: 0.656). In addition, in the classification of IGD and HCs, the multimodal model had

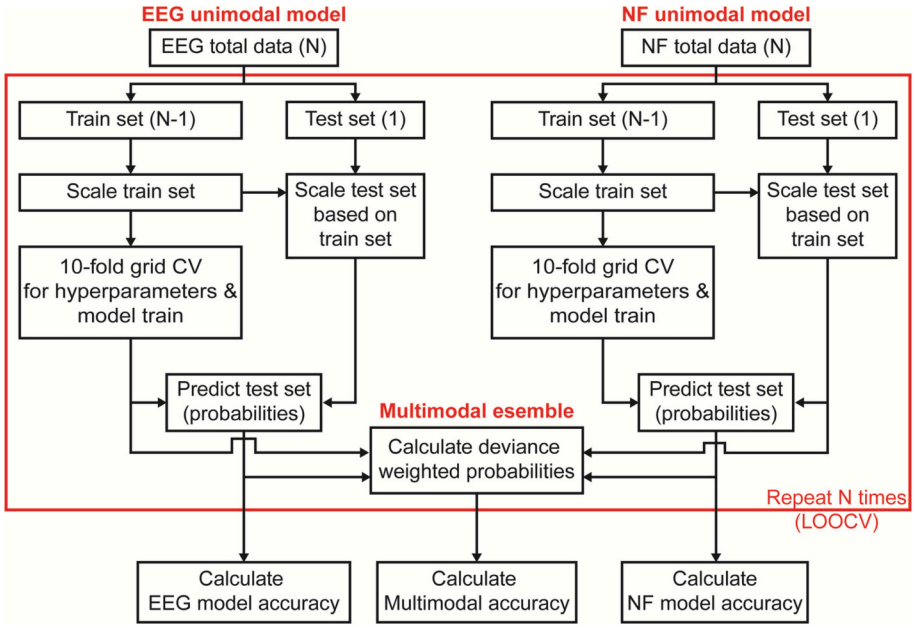

Fig. 1. Flowchart for calculating the accuracy of each algorithm and illustration of different feature set combinations based on cross-validation (CV) deviances. Using leave-one-out CV (LOOCV), individual algorithms, including L1-norm support vector machine, random forest, and L1-norm logistic regression, were trained on electroencephalography (EEG) or neuropsychological features (NF), and the accuracy of the models was calculated. Ten-fold CV was employed for hyperparameter selection and model training for each algorithm. To combine EEG and NF sets, the probabilities of a test set from each algorithm were weighted based on CV deviance. Then the weighted probabilities from the algorithms were integrated to calculate the multimodal ensemble accuracy.

Table 2
Differences in neuropsychological features among individuals with internet gaming disorder, individuals with alcohol use disorder, and healthy controls.

Features	IGD ($n = 67$)		AUD ($n = 58$)		HC ($n = 66$)		x^2	p	Post hoc.	η_p^2
	n		n		n					
Males / Females	63 / 4		46 / 12		56 / 10		5.931	0.052		
	Mean	(S. D)	Mean	(S. D)	Mean	(S. D)	F	p		
Age	23.881	(5.401)	28.241	(5.417)	24.939	(3.229)	13.881***	<0.001	IGD, HC < AUD	0.129
IAT	64.672	(15.828)	32.988	(10.911)	29.766	(9.978)	154.099***	<0.001	AUD, HC < IGD	0.621
AUDIT	5.660	(4.799)	25.491	(7.201)	4.943	(3.403)	296.191***	<0.001	IGD, HC < AUD	0.759
BDI	19.737	(11.398)	22.047	(15.157)	4.263	(4.396)	49.166***	<0.001	HC < IGD, AUD	0.343
BAI	15.830	(13.184)	20.090	(14.538)	5.040	(5.458)	28.082***	<0.001	HC < IGD, AUD	0.230
BIS-11	68.632	(11.060)	69.443	(11.673)	55.460	(8.269)	36.838***	<0.001	HC < IGD, AUD	0.282
IQ	108.065	(13.947)	105.197	(12.253)	117.364	(11.790)	15.864***	<0.001	IGD, AUD < HC	0.144

Note. IGD, internet gaming disorder; AUD, alcohol use disorder; HC, healthy control; η_p^2, partial eta squared; S. D, standard deviation; IAT, Young Internet Addiction Test; AUDIT, Alcohol Use Disorders Identification Test; BDI, Beck Depression Inventory-2; BAI, Beck Anxiety Inventory; BIS-11, Barratt Impulsivity Scale (version 11); IQ, intelligence quotient; ***$p < 0.001$ (Bonferroni-corrected, $p < 0.0167$).

Table 3
Model performances for the test set according to leave-one-out cross-validation.

IGD versus AUD									
	EEG			NFs			EEG + NFs		
	Acc.	Sens.	Spec.	Acc.	Sens.	Spec.	Acc.	Sens.	Spec.
SVM	0.560	0.687	0.414	0.648	0.731	0.552	0.608	0.687	0.517
RF	0.600	0.716	0.448	0.616	0.627	0.552	0.624	0.701	0.534
LR	0.672	0.672	0.672	0.656	0.731	0.569	**0.712**	**0.746**	**0.672**
Best model / feature set				*p*-value					
LR / multimodal (EEG + NFs)				< 0.001					
IGD versus HC									
	EEG			NFs			EEG + NFs		
	Acc.	Sens.	Spec.	Acc.	Sens.	Spec.	Acc.	Sens.	Spec.
SVM	0.571	0.537	0.636	0.850	0.791	0.909	0.850	0.791	0.909
RF	0.481	0.448	0.591	0.850	0.806	0.879	**0.865**	**0.821**	**0.924**
LR	0.518	0.418	0.621	0.850	0.806	0.894	0.850	0.806	0.894
Best model / feature set				*p*-value					
RF / multimodal (EEG + NFs)				< 0.001					
AUD versus HC									
	EEG			NFs			EEG + NFs		
	Acc.	Sens.	Spec.	Acc.	Sens.	Spec.	Acc.	Sens.	Spec.
SVM	0.589	0.379	0.773	0.863	0.828	0.894	0.863	0.793	0.924
RF	0.669	0.517	0.742	**0.887**	**0.862**	**0.924**	0.863	0.810	0.894
LR	0.581	0.569	0.591	0.863	0.828	0.894	0.863	0.845	0.879
Best model / feature set				*p*-value					
RF / unimodal (NF)				< 0.001					

Note. IGD, Internet gaming disorder; AUD, alcohol use disorder; EEG, electroencephalography; NFs, neuropsychological features; Acc, accuracy; Sens, sensitivity; Spec, specificity; HC, healthy controls; SVM, L1-norm support vector machine; RF, random forest; LR, L1-norm logistic regression; P-value was computed with a permutation test with 1000 iterations.

greater accuracy (RF; accuracy: 0.865; $p < 0.001$) than the unimodal EEG (SVM; accuracy: 0.571) and NF (RF; accuracy: 0.850) models. However, in terms of AUD and HCs, the RF model with the unimodal NF set was more accurate (accuracy: 0.887; $p < 0.001$) than the unimodal EEG (RF; accuracy: 0.669) and multimodal model (SVM, RF, and LR; accuracy: 0.863).

3.3. Features to distinguish between IGD and AUD

The importance of features, as indicated by the estimated beta coefficients for the LR model (the best-performing model), is shown in Fig. 2. Among source-level EEG features, the LR model showed that individuals with IGD exhibited that decreased delta connectivity between the right OFC and the right AG&IPL in the DMN. In addition, increased beta connectivity in the IGD group was observed between the right PFC and the right TL in the RSN. Moreover, increased delta connectivity was found between the right TL and the right PCC&Cnu. However, the beta connectivity between the right PFC and the right ACC was reduced compared to the AUD group. Distinctly, source-level FC only showed a group difference in the right interhemispheric region. Regarding sensor-level EEG features, the increased absolute delta power of the parietal (Pz) region was selected in the IGD group only in the LR model. The beta coherence between the right parietal (P4) and right temporal (T6) regions, as well as the gamma coherence between frontal (Fz) and right central (C4) regions, were higher in the IGD group than in the AUD group. Conversely, delta and alpha coherence between right

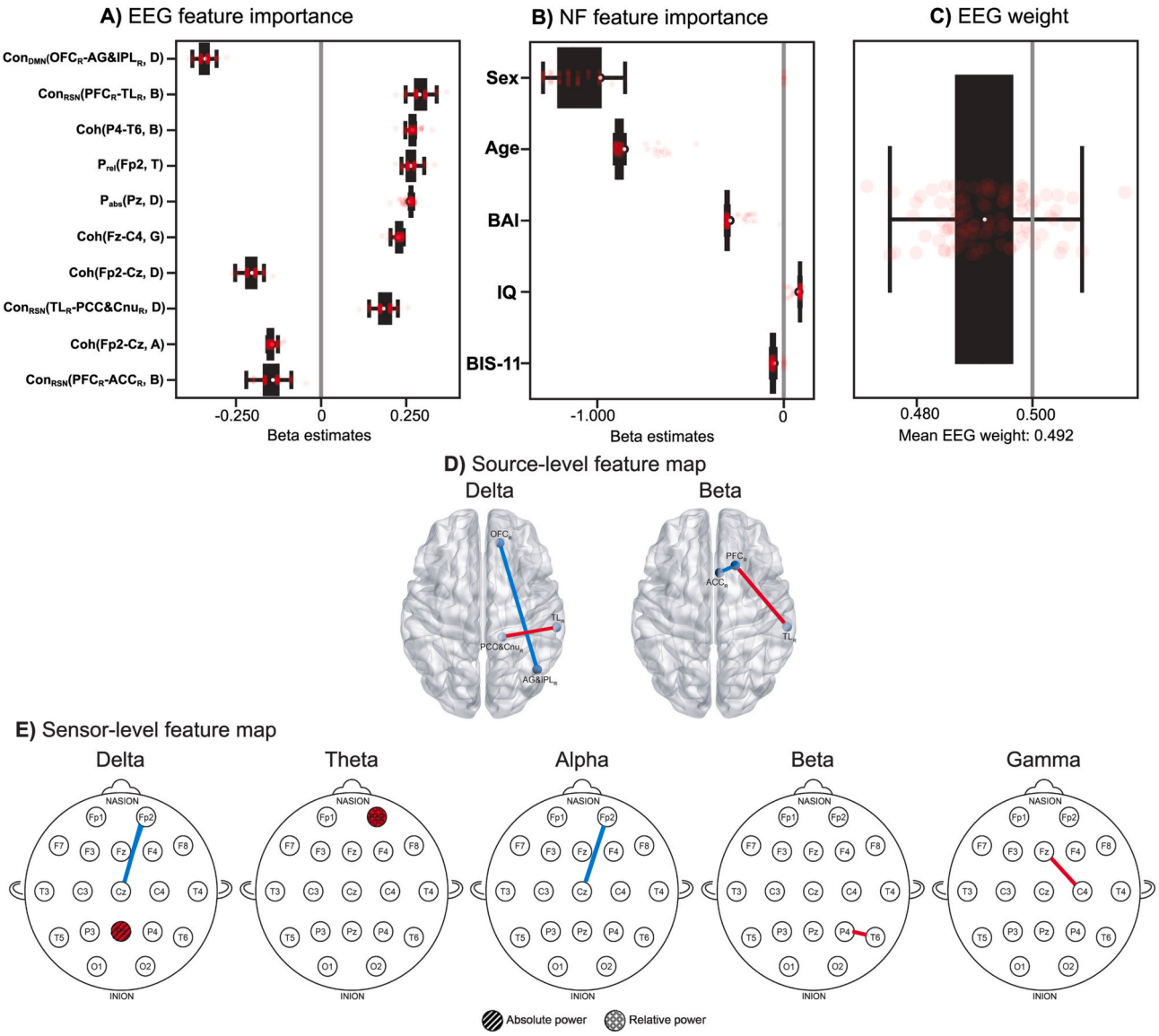

Fig. 2. Feature importance according to beta coefficients: comparison between internet gaming disorder (IGD) and alcohol use disorder (AUD). Features were selected by L1-norm logistic regression (LR). (A) and (B) The highest feature importance of NF and EEG features. (C) Weights of the EEG feature set used for the cross-validation deviance-weighted probabilistic ensemble between EEG and NF features. (D) Source-level features are represented on brain surface maps. The red color represents increased brain activity of IGD, whereas the blue color represents decreased brain activity of IGD compared to AUD. (E) Sensor-level features (absolute power, relative power, and coherence) are represented on scalp topographic maps. In addition, diagonal and circle patterns indicate absolute and relative power, respectively. BAI, Beck Anxiety Inventory; IQ, Intelligence Quotient; BIS-11, Barratt Impulsivity Scale version 11 total score; $Con_{Network}$ (node 1-node 2, and frequency), connectivity between node 1 and node 2 for the frequency band; Coh (sensor 1-sensor 2, and frequency): coherence between sensor 1 and sensor 2 for the frequency band; P_{type} (sensor and frequency): power type of the sensor for the frequency band; OFC_R: right orbital frontal cortex; TL_R: right temporal lobe; $PCC\&Cnu_R$: right posterior cingulate cortex and cuneus; $AG\&IPL_R$: right angular gyrus and inferior parietal lobe; PFC_R: right pre-frontal cortex; ACC_R: right anterior cingulate cortex. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

prefrontal (Fp2) and central (Cz) regions was lower in the IGD group compared to the AUD group.

Among the NFs, sex, age, IQ, and BAI were selected by the LR model; sex and age were the highest important features. Lastly, based on the "trained deviances" for the classification of IGD and AUD, the EEG feature set had an average weight of 0.486 ± 0.008 (SVM: 0.482 ± 0.005; LR: 0.492 ± 0.008; RF: 0.482 ± 0.006). The detailed features of each model, the weights for the EEG feature set, and details regarding model performance in distinguishing AUD from HCs, as well as IGD from HCs, can be found in the Supplementary Material.

4. Discussion

The present study investigated the neurophysiological and neuropsychological similarities and differences among individuals with IGD, individuals with AUD and HCs using ML techniques. Consistent with our hypothesis, the findings revealed that the model with the multimodal (EEG + NF) feature set performed better in distinguishing IGD from AUD, and IGD from HCs than the other models. For AUD individuals and HCs, however, the model using the unimodal NF set performed better than the other models.

The LR model with the multimodal feature set distinguished IGD from AUD more accurately than the other models. With regard to important source-level EEG features, compared to individuals with AUD,

those with IGD had lower delta FC between the right OFC and the right AG&IPL, lower beta FC between the right PFC and the right ACC, higher delta FC between the right TL and the right PCC&Cnu, and higher beta FC between the right PFC and the right TL. These results disagree with those related to the differentiation of IGD and HCs, which relied on alpha and gamma source FC, and those related to the differentiation of AUC and HC, which relied on delta source FC. The findings indicate that individuals with addiction may struggle to process rewards and are more likely to suffer from reduced cognitive abilities. Our previous study showed that individuals with IGD have increased theta, alpha, and beta FC within the DMN between the OFC and parietal regions, and increased alpha and beta FC within RSN between the ACC and TL within the RSN, compared to HCs. The altered FC patterns potentially reflect the dysfunction of cognitive and reward-related processes [23]. A previous ML study revealed increased FC within the DMN between the parahippocampal and other regions in patients with AUD. These finding suggest the presence of neural hyperexcitability and compensatory mechanisms [21]. Huang et al. [62] suggested that altered beta and theta EEG source-level FC in patients with AUD was related to deficiency in suppressing substance-related craving, described as the "unified percept of incentive salience related to reward". Consequently, altered delta and beta FC within the DMN and RSN between individuals with IGD and AUD may be linked to their impaired reward processing and or cognitive function.

The present model emphasized the important of source-level FC within the right hemisphere, although the highest feature importance regions differed by addiction type. Patients with IGD showed increased FC in the PCC&Cnu, PFC, and TL, whereas those with AUD showed increased FC in the OFC, PFC, ACC, and AG&IPL. These findings disagree with those of a previous study [23]. In this study, to distinguish the IGD and HC, greater left or interhemispheric source FC across theta, alpha, beta, and gamma frequency bands was more important. Other studies have emphasized the involvement of the right hemisphere in both addiction types [63,64]. Therefore, changes in delta and beta source-level FC within the right hemisphere can serve as distinct neurophysiological indicators for differentiating between BA and SUD. Additional research is needed to compare the potential hemispheric and regional effects between the two addiction types.

Our LR model identified several important sensor-level EEG features. Previous studies have revealed that patients with AUD have increased delta absolute power, reduced theta absolute power, and increased intrahemispheric theta coherence [14,15,33]. Lower delta and beta absolute power, higher gamma absolute power, and higher intrahemispheric gamma coherence have been linked to IGD [65]. While the application of sensor-level EEG features is limited by technical issues, these features can still play a crucial role in classifying both addiction types and distinguishing such individuals from HCs. Therefore, the integration of sensor- and source-level EEG activities is useful for diagnosis. Furthermore, this approach can enhance our understanding or underlying neurophysiological mechanisms and facilitate the identification of addictive disorders using ML techniques.

Among the NFs in this study, age and sex had a significant impact on model performance, whereas depression, anxiety, impulsivity, and IQ played relatively minor roles. Patients with IGD and AUD may share certain psychological symptoms. Previous study indicated that they had similar emotional, temperamental, and personality features [66]. Individual with IGD also show similar levels of impulsivity to those with AUD and gambling disorder [11]. In summary, our ML model suggest that IGD and AUD share certain neuropsychological characteristics, despite differences in underlying neuropsychological mechanisms. Evaluating neurophysiological mechanisms is a crucial for the treatment and intervention of both BA and SUD.

Our multimodal model was more accurate in identifying IGD than the models using unimodal feature sets. The multimodal approach can help clinicians diagnose patients with IGD by incorporating both subjective neuropsychological (self-report) and objective neurophysiological (EEG) data. Hence, our ML model will only enhance our understanding of the neural basis of IGD and could also improve diagnostic accuracy for IGD. To further improve model performance, it is essential to incorporate a variety of ML and deep learning algorithms. On the other hands, the RF model with the unimodal NF set showed better performance in classifying AUD and HCs compared to the other models. The role of age is significant in assessing brain impairments in individuals with AUD. A review study suggested that the aging brain has a greater susceptibility to alcohol-related damage compared to the impact of alcohol consumed throughout one's lifetime [67]. Additionally, younger individuals exhibit significantly better brain recovery ability during prolonged abstinence. In our research, we found that participants with AUD were under 30 years old, suggesting that younger brains may experience less damage from alcohol and have a greater chance of recovery compared to older adults with AUD. As such, their intense NFs may have a stronger effect on model performance with respect to AUD and HC classification compared to other features. Thus, conducting additional research with larger participant groups that include older individuals is necessary to clarify the influence of age.

The present study had several limitations. First, the generalizability of our findings is limited due to the small sample size, which is insufficient to represent the entire population of individuals with both IGD and AUD. Therefore, further studies with larger sample sizes are required. Second, the causal effects of medication and comorbidities were not evaluated. Third, the limited results of source connectivity were due to the analysis being conducted with only 19 channels extracted from a total of 64 channels. We cannot entirely eliminate bias due to the inclusion of a small number of channels, such as those associated with mislocalization and/or blurring. In a previous study, it was found that utilizing swLORETA with specific techniques produces comparable levels of accuracy in localizing the lead field using both 19 and 128 EEG channels, similar to magnetoencephalography [45]. However, further studies using a large number of channels are needed. Finally, the study was based on cross-sectional data, and the models were not validated prospectively.

5. Conclusions

Despite its limitations, this study is the first to use ML methods in distinguishing among patients with IGD, patients with AUD, and HCs. The study utilizes multimodal feature sets, including sensor- and source-level EEG and NFs. In particular, the changes in delta and beta source-level FC within the right hemisphere can serve as a neurophysiological indicator for distinguishing between IGD and AUD. Notably, individuals with IGD and AUD have similar neuropsychological symptoms despite their dissociable neurophysiological mechanisms. Furthermore, the multimodal ML model for distinguishing IGD from HCs emphasizes the potential utility of ML models for diagnosing IGD. EEG offers unique advantages over other neuroimaging modalities, including lower costs, mobility, and ease of use. This makes it particularly suitable for diagnosis purposes, neurofeedback therapy, as well as non-invasive brain stimulation. Continued investigation of these findings could enhance diagnostic precision and therapeutic approaches for individuals with both IGD and AUD. Overall, the findings enhance the value of ML techniques in identifying IGD through neurophysiological and neuropsychological patterns, distinguishing it from AUD and advancing our understanding of both as IGD (a BA) and AUD (a SUD).

Supplementary data to this article can be found online at https://doi.org/10.1016/j.comppsych.2024.152460.

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Code availability

Python code used in the present paper is publicly available at https://github.com/CCS-Lab/project_addiction_classification_with_EEG_and_NFs.

CRediT authorship contribution statement

Ji-Yoon Lee: Writing – original draft, Formal analysis. **Myeong Seop Song:** Writing – original draft, Funding acquisition, Formal analysis. **So Young Yoo:** Validation. **Joon Hwan Jang:** Validation. **Deokjong Lee:** Validation. **Young-Chul Jung:** Validation. **Woo-Young Ahn:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Jung-Seok Choi:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization.

Declaration of competing interest

The all of the authors declare that they have no financial interests or conflicts of interest.

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References

[1] American Psychiatric Association. Diagnostic and statistical manual of mental disorders. 5th ed. Washington, DC: American Psychiatric association; 2013.
[2] Tolomeo S, Yu R. Brain network dysfunctions in addiction: a meta-analysis of resting-state functional connectivity. Transl Psychiatry 2022;12:1–11. https://doi.org/10.1038/s41398-022-01792-6.
[3] Alavi SS, Ferdosi M, Jannatifard F, Eslami M, Alaghemandan H, Setare M. Behavioral addiction versus substance addiction: correspondence of psychiatric and psychological views. Int. J Prev Med 2012;3:290 [PubMed PMID: 22624087; PubMed Central PMCID: PMC3354400].
[4] Grant JE, Potenza MN, Weinstein A, Gorelick DA. Introduction to behavioral addictions. Am J Drug Alcohol Abuse 2010;36:233–41 [PubMed PMID: 20560821; PubMed Central PMCID: PMC3164585].
[5] Holden C. 'Behavioral' addictions: do they exist? Science 2001;294:980–2. https://doi.org/10.1126/science.294.5544.980.
[6] World Health Organization. The ICD-11 classification of mental and behavioral disorders: Diagnostic criteria for research. Geneva: World Health Organization; 2019.
[7] Griffiths MD. Disorders due to addictive behaviors: further issues, debates, and controversies •: commentary to the debate: "behavioral addictions in the ICD-11". J Behav Addict 2022;11:180–5. https://doi.org/10.1556/2006.2022.00025.
[8] Choi JS, King DL, Jung YC. Neurobiological perspectives in behavioral addiction. Front. Psychiatry 2019:3. https://doi.org/10.3389/fpsyt.2019.00003.
[9] Karim R, Chaudhri P. Behavioral addictions: an overview. J Psychoactive Drugs 2012;44:5–17. https://doi.org/10.1080/02791072.2012.662859.
[10] Ko CH, Yen JY, Yen CF, Chen CS, Chen CC. The association between internet addiction and psychiatric disorder: a review of the literature. Eur Psychiatry 2012;27:1–8. https://doi.org/10.1016/j.eurpsy.2010.04.011.
[11] Choi SW, Kim H, Kim GY, Jeon Y, Park S, Lee JY, et al. Similarities and differences among internet gaming disorder, gambling disorder and alcohol use disorder: a focus on impulsivity and compulsivity. J Behav Addict 2014;3:246–53. https://doi.org/10.1556/JBA.3.2014.4.6.
[12] Na E, Lee H, Choi I, Kim DJ. Comorbidity of internet gaming disorder and alcohol use disorder: a focus on clinical characteristics and gaming patterns. Am J Addict 2017;26:326–34. https://doi.org/10.1111/ajad.12528.
[13] McLoughlin G, Makeig S, Tsuang MT. In search of biomarkers in psychiatry: EEG-based measures of brain function. Am J Med Genet B Neuropsychiatr Genet 2014;165:111–21. https://doi.org/10.1002/ajmg.b.32208.
[14] Son KL, Choi JS, Lee J, Park SM, Lim JA, Lee JY, et al. Neurophysiological features of internet gaming disorder and alcohol use disorder: a resting-state EEG study. Transl Psychiatry 2015;5. https://doi.org/10.1038/tp.2015.124. e628-e.
[15] Park SM, Lee JY, Kim YJ, Lee JY, Jung HY, Sohn BK, et al. Neural connectivity in internet gaming disorder and alcohol use disorder: a resting-state EEG coherence study. Sci Rep 2017;7:1333. https://doi.org/10.1038/s41598-017-01419-7.
[16] Darnai G, Perlaki G, Zsidó AN, Inhóf O, Orsi G, Horváth R, et al. Internet addiction and functional brain networks: task-related fMRI study. Sci Rep 2019;9:15777. https://doi.org/10.1038/s41598-019-52296-1.
[17] Shim M, Hwang HJ, Kim DW, Lee SH, Im CH. Machine-learning-based diagnosis of schizophrenia using combined sensor-level and source-level EEG features. Schizophr Res 2016;176:314–9. https://doi.org/10.1016/j.schres.2016.05.007.
[18] Imperatori C, Fabbricatore M, Innamorati M, Farina B, Quintiliani MI, Lamis DA, et al. Modification of EEG functional connectivity and EEG power spectra in overweight and obese patients with food addiction: an eLORETA study. Brain Imaging Behav 2015;9:703–16. https://doi.org/10.1007/s11682-014-9324-x.
[19] van Mierlo P, Höller Y, Focke NK, Vulliemoz S. Network perspectives on epilepsy using EEG/MEG source connectivity. Front Neurol 2019:10. https://doi.org/10.3389/fneur.2019.00721.
[20] Han X, Jiang P, Yuan Z, Zeng X, Zheng D. Similarity and difference in large-scale functional network alternations between behavioral addictions and substance use disorder: a comparative meta-analysis. Psychol Med 2023:1–15. https://doi.org/10.1017/S0033291723003434.
[21] Kamarajan C, Ardekani BA, Pandey AK, Chorlian DB, Kinreich S, Pandey G, et al. Random forest classification of alcohol use disorder using EEG source functional connectivity, neuropsychological functioning, and impulsivity measures. Behav Sci 2020;10:62. https://doi.org/10.3390/bs10030062.
[22] Padula CB, Tenekedjieva LT, McCalley DM, Al-Dasouqi H, Hanlon CA, Williams LM, et al. Targeting the salience network: a mini-review on a novel neuromodulation approach for treating alcohol use disorder. Front Psych 2022:13. https://doi.org/10.3389/fpsyt.2022.893833.
[23] Lee JY, Choi CH, Park M, Park S, Choi JS. Enhanced resting-state EEG source functional connectivity within the default mode and reward-salience networks in internet gaming disorder. Psychol Med 2022;52:2189–97. https://doi.org/10.1017/S0033291722000137.
[24] Marco-Pallarés J, Münte TF, Rodríguez-Fornells A. The role of high-frequency oscillatory activity in reward processing and learning. Neurosci Biobehav Rev 2015;49:1–7. https://doi.org/10.1016/j.neubiorev.2014.11.014.
[25] Dong G, Li H, Wang L, Potenza MN. The correlation between mood states and functional connectivity within the default mode network can differentiate internet gaming disorder from healthy controls. Prog Neuropsychopharmacol Biol Psychiatry 2017;77:185–93. https://doi.org/10.1016/j.pnpbp.2017.04.016.
[26] Christensen E, Brydevall M, Albertella L, Samarawickrama SK, Yücel M, Lee RSC. Neurocognitive predictors of addiction-related outcomes: a systematic review of longitudinal studies. Neurosci Biobehav Rev 2023;152:105295. https://doi.org/10.1016/j.neubiorev.2023.105295.
[27] Ahn WY, Ramesh D, Moeller FG, Vassileva J. Utility of machine-learning approaches to identify behavioral markers for substance use disorders: impulsivity dimensions as predictors of current cocaine dependence. Front Psych 2016;7:34. https://doi.org/10.3389/fpsyt.2016.00034.
[28] Jaworska N, de la Salle S, Ibrahim MH, Blier P, Knott V. Leveraging machine learning approaches for predicting antidepressant treatment response using electroencephalography (EEG) and clinical data. Front Psych 2019:9. https://doi.org/10.3389/fpsyt.2018.00768.
[29] Kinreich S, McCutcheon VV, Aliev F, Meyers JL, Kamarajan C, Pandey AK, et al. Predicting alcohol use disorder remission: a longitudinal multimodal multi-featured machine learning approach. Transl Psychiatry 2021;11:166. https://doi.org/10.1038/s41398-021-01281-2.
[30] Guggenmos M, Schmack K, Veer IM, Lett T, Sekutowicz M, Sebold M, et al. A multimodal neuroimaging classifier for alcohol dependence. Sci Rep 2020;10:298. https://doi.org/10.1038/s41598-019-56923-9.
[31] Jeong B, Lee J, Kim H, Gwak S, Kim YK, Yoo SY, et al. Multiple-kernel support vector machine for predicting internet gaming disorder using multimodal fusion of PET, EEG, and clinical features. Front Neurosci 2022;16. https://doi.org/10.3389/fnins.2022.856510.
[32] Kinreich S, Meyers JL, Maron-Katz A, Kamarajan C, Pandey AK, Chorlian DB, et al. Predicting risk for alcohol use disorder using longitudinal data with multimodal biomarkers and family history: a machine learning study. Mol Psychiatry 2021;26:1133–41. https://doi.org/10.1038/s41380-019-0534-x.
[33] Mumtaz W, Vuong PL, Malik AS, Rashid RBA. A review on EEG-based methods for screening and diagnosing alcohol use disorder. Cogn Neurodyn 2018;12:141–56. https://doi.org/10.1007/s11571-017-9465-x.
[34] Sun S, Yang J, Chen YH, Miao J, Sawan M. EEG signals based internet addiction diagnosis using convolutional neural networks. Appl Sci 2022;12:6297. https://doi.org/10.3390/app12136297.
[35] Gross J, Baumgartl H, Buettner R. A novel machine learning approach for high-performance diagnosis of premature internet addiction using the unfolded EEG spectra. In: Proceedings of 25th Americas conference on information systems, (AMCIS); 2020. http://www.prof-buettner.de/downloads/gross2020a.pdf; [accessed 12 Jan 2024].
[36] Young KS. Caught in the net: How to recognize the signs of internet addiction–and a winning strategy for recovery. New York: John Wiley & Sons; 1998.
[37] Lee K, Lee HK, Gyeong H, Yu B, Song YM, Kim D. Reliability and validity of the Korean version of the internet addiction test among college students. J Korean Med Sci 2013;28:763–8. https://doi.org/10.3346/jkms.2013.28.5.763.
[38] Park M, Jung MH, Lee J, Choi AR, Chung SJ, Kim B, et al. Neurophysiological and cognitive correlates of error processing deficits in internet gaming disorder. Cereb Cortex 2020;30:4914–21. https://doi.org/10.1093/cercor/bhaa083.
[39] Saunders JBAO, Babor TF, De La Fuente JR, Grant M. Development of the alcohol use disorders identification test (AUDIT): WHO collaborative project on early detection of persons with harmful alcohol consumption-II. Addiction 1993;88:791–804. https://doi.org/10.1111/j.1360-0443.1993.tb02093.x.

[40] Kim SS, Gulick EE, Nam KA, Kim SH. Psychometric properties of the alcohol use disorders identification test: a Korean version. Arch Psychiatr Nurs 2008;22:190–9. https://doi.org/10.1016/j.apnu.2007.07.005.
[41] Choi JS, Park SM, Lee J, Hwang JY, Jung HY, Choi SW, et al. Resting-state beta and gamma activity in internet addiction. Int J Psychophysiol 2013;89:328–33. https://doi.org/10.1016/j.ijpsycho.2013.06.007.
[42] Koberda JL. QEEG as a useful tool for the evaluation of early cognitive changes in dementia and traumatic brain injury. Clin EEG Neurosci 2020;52:119–25. https://doi.org/10.1177/1550059420914816.
[43] Palmero-Soler E, Dolan K, Hadamschek V, Tass PA. swLORETA: a novel approach to robust source localization and synchronization tomography. Phys Med Biol 2007;52:1783. https://doi.org/10.1088/0031-9155/52/7/002.
[44] Thatcher RW. Symptom check list and functional specialization in the brain. https://www.appliedneuroscience.com/PDFs/Symptom_Check_List-Functional_Specialization_in_the_Brain.pdf;; 2010.
[45] Robert WT, Carl JB, Ernesto Palermero S, Joel L, Koberda JL. Advances in electrical neuroimaging, brain networks and neurofeedback protocols. In: Edward Da-Yin L, editor. Smart biofeedback. Rijeka: IntechOpen; 2020. https://doi.org/10.5772/intechopen.94326.
[46] Thatcher RW, North D, Biver C. EEG and intelligence: relations between EEG coherence, EEG phase delay and power. Clin Neurophysiol 2005;116:2129–41. https://doi.org/10.1016/j.clinph.2005.04.026.
[47] Beck AT, Steer RA, Brown G. Beck depression inventory–II. San Antonio: Psychological Corporation; 1996.
[48] Sung H, Kim J, Park Y, Bai D, Lee S, Ahn H. A study on the reliability and the validity of Korean version of the Beck depression inventory-II (BDI-II). J Korean Soc Biol Ther Psychiatry 2008;14:201–12.
[49] Beck AT, Epstein N, Brown G, Steer RA. An inventory for measuring clinical anxiety: psychometric properties. J Consult Clin Psychol 1988;56:893–7. https://doi.org/10.1037//0022-006x.56.6.893.
[50] Yook S, Kim Z. A clinical study on the Korean version of Beck anxiety inventory: comparative study of patient and non-patient. Korean J Clin Psychol 1997;16:185–97.
[51] Patton JH, Stanford MS, Barratt ES. Factor structure of the barratt impulsiveness scale. J Clin Psychol 1995;51:768–74. https://doi.org/10.1002/1097-4679(199511)51:6<768::AID-JCLP2270510607>3.0.CO;2-1.
[52] Hwang S, Kim J, Park G, Chey J, Hong S. K-WAIS-IV administration and scoring manual. Daegu: Korean Psychology; 2012.
[53] Park SM, Jeong B, Oh DY, Choi CH, Jung HY, Lee JY, et al. Identification of major psychiatric disorders from resting-state electroencephalography using a machine learning approach. Front Psych 2021:12. https://doi.org/10.3389/fpsyt.2021.707581.
[54] Lee SI, Lee H, Abbeel P, Ng AY. Efficient L1 regularized logistic regression. In: Proceedings of association for the advancement of artificial intelligence (AAAI); 2006. https://www.aaai.org/Papers/AAAI/2006/AAAI06-064.pdf; [accessed 12 Jan 2024].
[55] Zhu J, Rosset S, Tibshirani R, Hastie T. 1-norm support vector machines. In: Proceedings of advances in neural information processing systems (NIPS); 2003. https://proceedings.neurips.cc/paper_files/paper/2003/file/49d4b2faeb4b7b9e745775793141e2b2-Paper.pdf; [accessed 12 Jan 2024].
[56] Hosseini M, Powell M, Collins J, Callahan-Flintoft C, Jones W, Bowman H, et al. I tried a bunch of things: the dangers of unexpected overfitting in classification of brain data. Neurosci Biobehav Rev 2020;119:456–67. https://doi.org/10.1016/j.neubiorev.2020.09.036.
[57] Kuncheva LI, Rodríguez JJ. On feature selection protocols for very low-sample-size data. Pattern Recognit 2018;81:660–73. https://doi.org/10.1016/j.patcog.2018.03.012.
[58] Shim M, Lee SH, Hwang HJ. Inflated prediction accuracy of neuropsychiatric biomarkers caused by data leakage in feature selection. Sci Rep 2021;11:7980. https://doi.org/10.1038/s41598-021-87157-3.
[59] Large J, Lines J, Bagnall A. A probabilistic classifier ensemble weighting scheme based on cross-validated accuracy estimates. Data Min Knowl Discov 2019;33:1674–709. https://doi.org/10.1007/s10618-019-00638-y.
[60] Ojala M, Garriga GC. Permutation tests for studying classifier performance. J Mach Learn Res 2010:11. https://www.jmlr.org/papers/volume11/ojala10a/ojala10a.pdf [accessed 12 Jan 2024].
[61] Noirhomme Q, Lesenfants D, Gomez F, Soddu A, Schrouff J, Garraux G, et al. Biased binomial assessment of cross-validated estimation of classification accuracies illustrated in diagnosis predictions. NeuroImage Clin 2014;4:687–94. https://doi.org/10.1016/j.nicl.2014.04.004.
[62] Huang Y, Mohan A, De Ridder D, Sunaert S, Vanneste S. The neural correlates of the unified percept of alcohol-related craving: a fMRI and EEG study. Sci Rep 2018;8:923. https://doi.org/10.1038/s41598-017-18471-y.
[63] Hong YN, Hwang H, Starcevic V, Choi TY, Kim TH, Han DH. Which is more stable and specific: DSM-5 internet gaming disorder or ICD-11 gaming disorder? A longitudinal study. Psychiatry Clin Neurosci 2023;77:213–22. https://doi.org/10.1111/pcn.13522.
[64] Tessner KD, Hill SY. Neural circuitry associated with risk for alcohol use disorders. Neuropsychol Rev 2010;20:1–20. https://doi.org/10.1007/s11065-009-9111-4.
[65] Burleigh TL, Griffiths MD, Sumich A, Wang GY, Kuss DJ. Gaming disorder and internet addiction: a systematic review of resting-state EEG studies. Addict Behav 2020;107:106429. https://doi.org/10.1016/j.addbeh.2020.106429.
[66] Hwang JY, Choi JS, Gwak AR, Jung D, Choi SW, Lee J, et al. Shared psychological characteristics that are linked to aggression between patients with internet addiction and those with alcohol dependence. Ann Gen Psychiatry 2014;13:1–6. https://doi.org/10.1186/1744-859X-13-6.
[67] Bühler M, Mann K. Alcohol and the human brain: a systematic review of different neuroimaging methods. Alcohol Clin Exp Res 2011;35:1771–93. https://doi.org/10.1111/j.1530-0277.2011.01540.x.