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Review Article

The quantification of the effect of substance abuse on brain behavior based on electroencephalogram signals: A comprehensive review

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Abstract

Introduction: Substance abuse has become a significant health problem for individuals and society. This study aimed to investigate the effects of substance abuse on brain waves.

Materials and Methods: Articles used were systematically searched in Google Scholar, Scopus, Thomson Reuters, ScienceDirect, PubMed, and IEEE databases. The result of this search was 420 articles. Keywords [Substance-Related Disorders MESH) AND (EEG MESH)], ["substance-related disorder" AND "EEG"], ["drug dependence" AND "EEG"], ["Substance abuse" AND "EEG"], ["Opioid" AND "EEG"], ["Cannabis" AND "EEG"] and ["Methamphetamine" AND "EEG"] were used for the search. After removing irrelevant and duplicate articles, we included 22 full-text articles in the study.

Results: The articles examined the effects of substance abuse on brain waves with three approaches. The first approach is the event-related potentials technique. The second approach is to investigate the functional connections between different brain parts. The third approach analyzes EEG signals from various channels to select biomarkers to detect substance abuse.

Conclusion: According to the present findings, it is suggested that policymakers and community health managers increase public awareness of the harms of substance abuse. Researchers in health should also discover and develop new diagnostic methods and treatment strategies according to the damage caused to the brain of substance abusers.

Keywords: Brain, Diagnosis, Electroencephalogram, Substance abuse

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Introduction

Substance abuse as a global problem has provoked many theories and research. Substance abuse leads to severe physical and mental damage and includes social harm. According to the United Nations Office on Drugs and Crime, in 2017, 585,000 people died worldwide due to substance abuse (1). Thirty-five million people worldwide suffer from substance use disorders and need treatment services. According to this report, the number of substance-related deaths in 2017 in Iran was 3012. Among the types of substances, opioids and amphetamine-type stimulants were the most common cause of death due to substance abuse in Iran in 2017 (1). According to the DSM5 report, stimulants (like methamphetamine (Meth)), cannabis (Can), hallucinogenic, and opioids (Op) are among the

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substances. Abusing any of these substances can cause serious harm to a person's health (2).

Substance abuse is recognized as a disorder. The most critical place that substance affects is brain. The brain is one of the body's complex and vital tissues; it consists of billions of neurons. The correct functioning of the brain is due to healthy neurons and proper communication between neurons.

Addiction disrupts the neural circuits of brain which related to the reward system, motivation, and memory. Brain damage under the influence of substance abuse is divided into functional and structural. Brain structural damage can be investigated with Magnetic Resonance Imaging (MRI) (3,4) and Positron Emission Tomography (PET) (5).

Functional brain damage can be studied with Electroencephalogram (EEG), Near-Infrared Spectroscopy (NIFS) (6), Magnetoencephalography (MEG) (5), and functional Magnetic Resonance Imaging (fMRI) (7,8) technique. Most of the mentioned techniques for data recording require a place with unique and expensive equipment and have difficulties.

EEG, as a simple, low-cost, and non-invasive method, can express the activity of the brain cortex. Therefore, studies that have used EEG signals to quantify and change brain behavior and their proposed diagnostic systems in substance abuse have been reviewed.

Materials and Methods

Block diagram 1 showed the general structure of drug abuse detection systems based on EEG signals. The step-by-step process in drug abuse detection systems is as follows:

1) Signal acquisition: EEG signals are recorded from substance abusers and healthy control (HC) individuals with the same inclusion criteria and characteristics.

2) Data preprocessing: The recorded EEG signals are processed using conventional signal processing methods to minimize noise and artifacts.

3) Feature extraction: Different studies with three approaches try to find biological indicators for diagnosis.

Event-Related Potential (ERP) is the response of brain to visual and auditory stimuli.

Functional brain communication examines the connections between different parts of the brain.

Quantification of biological indicators is done by mathematical analysis of brain signals.

4) Evaluation of the extracted features: It is done for two purposes.

The statistical analysis of the indicators to check the significance of the changes in the extracted parameters, data classification is based on indicators using machine learning methods, artificial neural networks, or fuzzy methods.

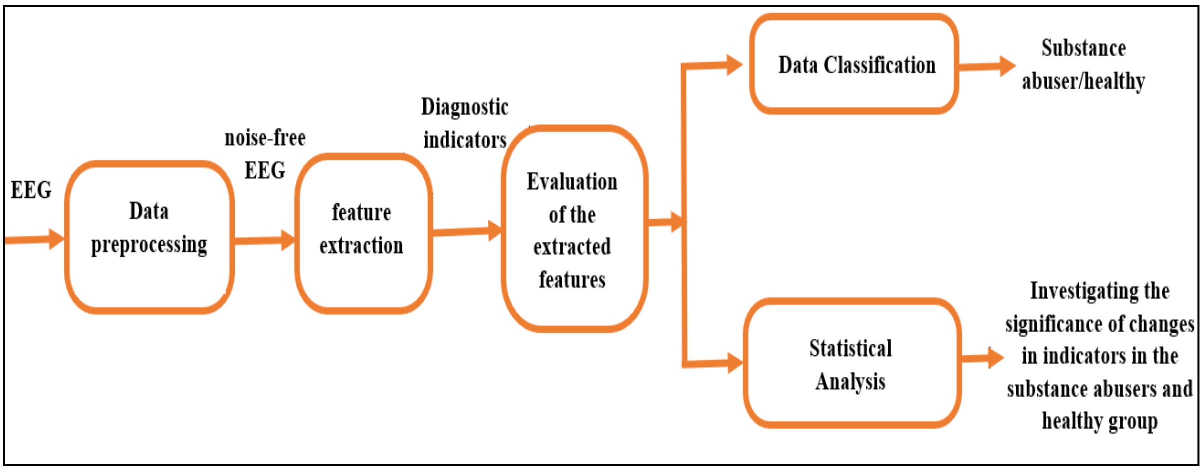

Figure 1. Block diagram of substance abuse detection system

We systematically searched Google Scholar, Scopus, Thomson Reuters (ISI), Science Direct, PubMed, and IEEE databases from 2012 to December 1, 2021. We found 420 articles. The search guide is based on the combination of English words and the Medical Subject Heading (MESH) modification, including [(Substance-Related Disorders MESH) AND (EEG MESH)]; ["substance-related disorder" AND "EEG"]; ["drug dependence" AND "EEG"]; ["Substance abuse" AND "EEG"]; ["Opioid" AND "EEG"];

["Cannabis" AND "EEG"] and ["Methamphetamine " AND "EEG"] were performed. Inclusion criteria: Comparative studies between healthy individuals and substance abusers, English studies, data of the EEG signal, and the availability of the full text.

Exclusion criteria: Studies investigated the effect of substance abuse with imaging techniques, studies used animal subjects, the dissertations, conference poster articles, abstract articles, systematic review studies, and meta-analyses.

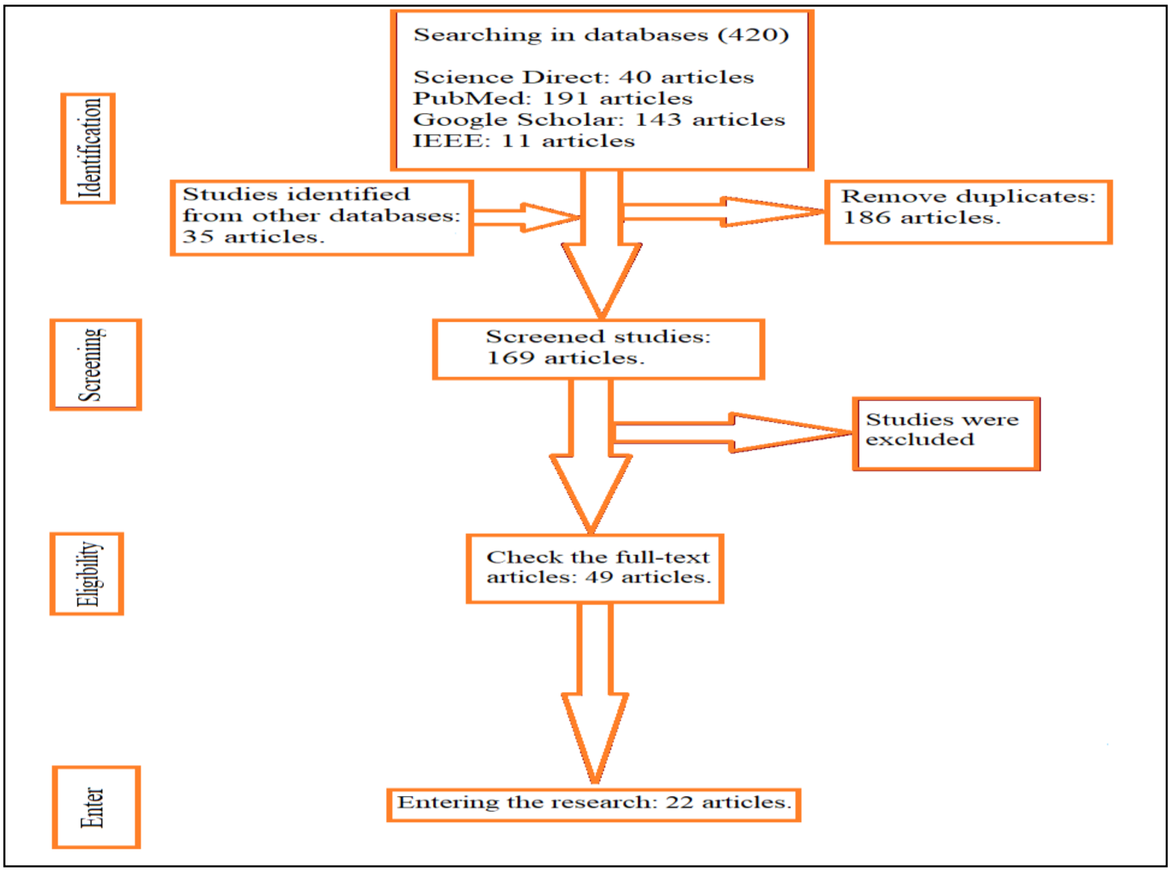

Figure 2. Flow chart of the articles selection process

The steps of selecting articles are shown in Figure 2. Also, the list of papers used, data collection technique, the sample size in abuse and control groups, type of substance consumed, and processing technique are given in Table 1.

Table 1. List of articles used in the research

Study	Publication year	Data collection technique	Abuser sample size	Control sample size	Type of substance consumed	Processing technique
(9)	2022	EEG	52	-	Meth	Event-Related Potential
(10)	2021	EEG	67	60	Can	Event-Related Potential
(11)	2019	EEG	105	-	61 Can users with high DI and 44 Can users with low DI	Event-Related Potential
(12)	2018	EEG	21	22	Meth	Event-Related Potential
(13)	2015	EEG	26	29	Meth	Event-Related Potential
(14)	2016	EEG	10	10	Meth	Event-Related Potential
(15)	2014	EEG	23	27	cocaine	Event-Related Potential

(16)	2016	EEG	-	123	Cocaine (53), Meth (51), Heroin (19)	Event-Related Potential
(8)	2019	EEG	36	24	Meth	Functional brain connection
(17)	2020	EEG	12	24	Can	Functional brain connection
(18)	2018	EEG	17	21	Can	Functional brain connection
(19)	2019	EEG	36	24	Meth	Functional brain connection
(20)	2013	EEG	36	36	Meth	Functional brain connection
(21)	2015	EEG	49	21	Op (17), methadone treatment subjects (32)	Functional brain connection
(22)	2016	EEG	49	21	Op (17), methadone treatment subjects (32)	Functional brain connection
(23)	2014	EEG	21	20	Substance	Functional brain connection
(24)	2017	EEG	39	26	25 Can users, 14 Can abusers	Quantification of biological indicator
(25)	2012	EEG	48	20	Meth	Quantification of biological indicator
(26)	2020	EEG	57	30	Meth	Quantification of biological indicator
(27)	2020	EEG	75	59	Heroin	Quantification of biological indicator
(28)	2021	EEG	58	20	Op(20), Meth(15), people with alcohol use disorder (23)	Quantification of biological indicator
(32)	2021	EEG& NIRS	45	-	Meth (mild:15; moderate:15;and severe:15)	Quantification of biological indicator

Results

Twenty-two studies included in the research examined the effects of substance abuse on brain function; some of these studies also developed substance abuse detection systems based on EEG signals. Figure 3 shows the number of articles related to substance abuse that were published in recent years and used in this research.

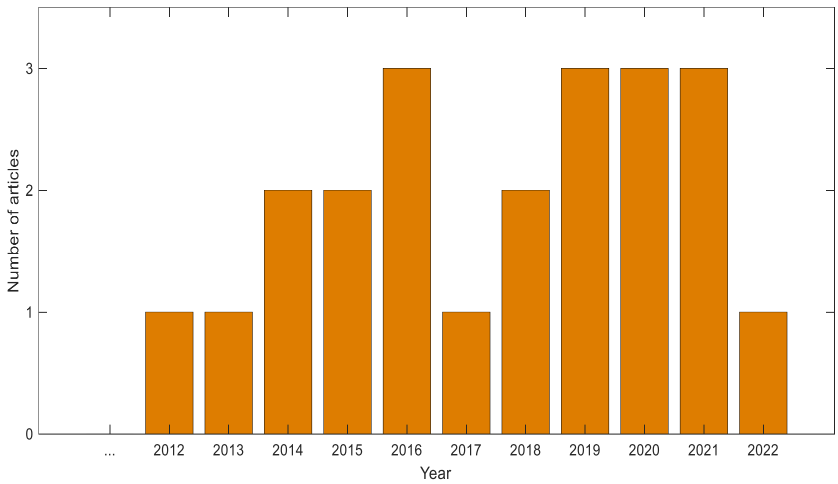

Figure 3. Articles published in 2012-2022 related to substance abuse

Figure 4 shows that 36% of the articles reviewed in the research were based on the Event-Related Potential (ERP), 36% were related to the study of functional brain connectivity, and 27% were associated with quantifying the biological indicators.

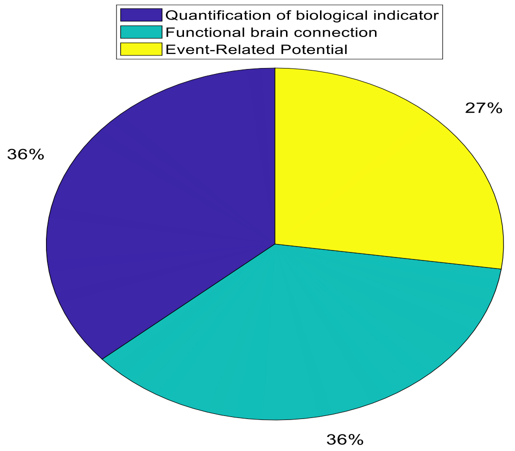

Figure 4. The percentage of published articles with different analytical approaches

In the following, first, the general approaches to investigating the effects of substances on brain function, then the systems of substance abuse detection are introduced.

The effects of substance abuse on the brain have been investigated with three approaches described below.

1) Examining ERP signals:

ERP is the examination of the response of brain to visual and auditory stimuli and enables the evaluation of brain function in patients with cognitive disorders. These studies aim to identify the nature and direction of reward processing disorders in substance abusers.

Research number 9 analyzed the reaction of Meth abusers to substance-related stimuli by examining people's responses to positive and negative stimuli and images related to Meth. Also, the self-report emotions and the person's reaction time were calculated. The results showed a decrease in brain activity in Meth abusers in response to substance-related stimuli. Analysis of the ERP response in Can abusers while playing the game was performed by calculating the parameters of positive reward, negative feedback, and time-frequency measures of reward and loss (10).

The results showed that "positive reward" increased in Can abusers' initial acquisition of monetary reward compared to others. Also, excellent responsiveness to neural reward was seen only transiently in Can abusers. Macatee et al. (11) investigated the relationship between Can abuse and high Distress Intolerance (DI), and recorded the ERP response of frequent Can abusers with high DI and low DI.

Results showed that the 1000-3000 ms modulation of the Late Positive PSotential (LPP) in high DI users was more significant only in the post-stress condition, this effect being only firm in the 1000-2000 ms window. In addition, the modulation in the high DI group with craving, stress reduction, and some indicators of Can abusers varied in the windows of 400 to 1000 ms and 1000 to 3000 ms, respectively. No significant effects of DI on LPP modulation induced by negative stimuli were found. Examining the ERP response in Meth abusers showed that Meth abusers had more risky choices in subsequent tests after experiencing loss compared to the HC group (12). They also showed an improvement in negativism of the preceding stimulus during the reward preliminary phase and an improvement in feedback-related negativity for losses versus gains during the reward outcome phase compared to the HC group. Overall, Meth abusers have a sensitive neural response to non-substance rewards. The impulsivity and motivational sensitization theories had proper for them. Examining ERP changes during consumption and six months of abstinence in the Meth group showed an increase in the P300 amplitude caused by methamphetamine-related words in the left anterior electrode sites (13). The abnormal P300 amplitude decreased to the normal levels at the end of three months of abstinence, and this reduction was maintained until the end of six months of abstinence. Shahmohammadi et al. (14) designed a non-invasive diagnostic system for Meth abuse based on the P300 response to the visual stimuli of the participants. Examining the ERP response in cocaine users showed that they performed weaker in inhibitory control than the control group (15).

At the same time, the level of executive dysfunction was not related to more intense substance use. ERP components of locked stimuli elicited by distractor stimuli in three VO-Distinct, VO-Repeated, Go/No Go tasks were investigated in a group of prisoners as treatment discontinuation predictors (16). The results showed that people who stopped treatment early showed lower P3a amplitude and less positive PC4 in the VO-D task. In the VO-R task, subjects who discontinued treatment early showed the more negative N200 amplitude than subjects hypothesized to have the smaller positive P3a amplitude. The group that stopped taking substances had less positive

PC4 amplitude. There were no differences in the time domain or principal component between groups on the Go/No Go task. Support vector machine models classified people who stopped treatment with 75% accuracy.

2) Examining the functional brain connections

The studies investigating functional brain connectivity quantify connectivity between different brain regions using different processing techniques.

Investigation of the functional connectivity of the triple network in Can abusers was carried out using low-resolution electromagnetic tomography (eLORETA) software (17).

The results showed that the delta band connections between the salient network and the central executive network, especially between the dorsal anterior cingulate cortex and the right posterior parietal cortex, increased in Can abusers. Cortical activity and functional communication in Can abusers were investigated by power spectrum density and spectral coherency in theta, delta, alpha, beta, and gamma frequency bands (18).

Average degree, clustering coefficient, and local efficiency were used to quantify functional communication. The results showed a decrease in the delta band power spectrum, an increase in the theta, beta, and gamma bands power spectrum, an increase in coherency between the hemispheres and within the hemisphere, and a decrease in communication indices in some areas. These factors indicate the loss of brain nerve function. The studies investigated functional communication in Meth abusers with sLORETA software (19), weighted phase delay index (8), and visual graph similarity methods and coherency methods (20).

The abnormal inter-regional connectivity and network hub changes were shown in all frequency bands, especially in delta and gamma bands (19). In addition, it was proved that the topology of brain functional communication is disturbed in Meth abusers, especially in the gamma band (20). Neucube's spiking neural network framework examined the brain's functional communication in Op abusers, methadone-treated subjects, and the HC group (21,22). The result showed that the communication of brain in the resting state with eyes closed is utterly different from the resting state with eyes open. Also, more connections were observed in the left frontal, central and occipital-occipital regions in the open eye state. In comparing people treated with high and low doses with the HC group, it was observed that the brain connections in the group treated with high doses decreased compared to the low (21). Also, the brain activity pattern of healthy subjects differed from Op abusers during Go/No Go task, and this difference was less compared to the treated subjects. During the Go/No Go task, the functional pathways of the healthy person's brain were larger and broader than in the other two groups. Also, the brain communication patterns of high and low-dose users were completely different (22). The synchronization probability algorithm evaluates the brain communication network in multi-substance-dependent individuals. Results showed that substance abusers had higher levels of synchronization in the theta frequency between frontal and posterior cortical areas at resting state and performing a simple counting task (23). Patients showed increased coordination in beta and gamma frequency bands during the counting task in anterior-posterior and interhemispheric temporal regions. The two factors of "slowness" at rest and "excessive scramble" during work indicate that substance abusers' brains suffer from a type of premature aging.

3) Finding biomarkers of biological indicators

"Biomarkers" are indicators obtained from EEG signal analysis that can differentiate between substance abusers and HC groups.

Analyzing EEG signals in acute Can abusers showed that the Limpel-Ziv complexity index could distinguish these people from the HC group (24). The Kruskal-Wallis ANOVA nonparametric test proved that the increase in Limpel-Ziv index values in acute Can abusers is significant compared to the HC group. The increase in complexity in Can-dependent individuals may reflect a random increase in neural activity in these individuals. The approximate entropy index, as a measure of chaotic information theory, was introduced as a biomarker for the diagnosis of Meth abuse in Yun K et al.'s research (25).

Approximate entropy values in Meth abusers were significantly lower than in HC in most areas of the cerebral cortex, which indicated a decrease in the complexity of the cerebral cortex in Meth subjects. Chen et al. (26) quantified brain network dynamics in Meth abusers by microsatellite analysis. The results showed that Meth abusers are utterly different from the HC group in A, B, C, and D classes, which depend on phonological processing, optical network, salience network, and attention. The Meth group was unstable in the A and B classes. Also, intracranial current sources were destroyed in Meth patients. Erguzel et al. (27) introduced the entropy characteristic as a quantitative indicator of heroin abuse. The results showed that the entropy values in heroin users were higher than in the HC group. EEG data and theta frequency band could differentiate two groups based on entropy biomarkers. In the research conducted by Minnerly C et al., the power spectrum of EEG signals was introduced as a biomarker for diagnosing Op abuse, Meth, and alcohol consumption (28). According to block diagram 1, biomarkers are classified by data classification block with Support Vector Machine (SVM) algorithms, neural networks, and fuzzy systems. Accuracy assessment methods check the accuracy of drug abuse detection systems. Substance abuse diagnostic systems, diagnostic accuracy, and system characteristics are summarized in Table 2.

Table 2. The substance abuse diagnostic systems

Study	Extractive index	Classifier	Number of classes	Accuracy (%)
(8)	Weighted phase delay index, in the beta band	Support Vector Machine (SVM)	2 (Meth-HC)	93
(15)	ERP components	Support Vector Machine (SVM)	3	75
(20)	Small global network characteristics,	Improved probabilistic neural network	2 (Meth-HC)	82.8
(21)	Neucube model based on spiking neural network	Spiking neural network	2 (people under methadone treatment - Op users)	86
(22)	Neucube model based on spiking neural network	Spiking neural network	2(Op-HC)	90
(27)	Entropy	Perceptron neural network	2 (Heroin user - HC)	97

Discussion

By combining different studies, the present study sought to understand the effect of drug abuse on brain function and introduce automatic drug abuse detection systems based on EEG signals. Drug abuse causes many brain disorders by damaging the brain's structure and function. A study of 17 long-term Can users compared to the HC group with two MRI techniques showed an increase in the gray matter volume in the basal ganglia and nucleus accumbens (29). The brain images of 18 heroin-addicted people compared to 20 HC people examined with MRI and voxel-based morphometry (VBM) (3). The reduction of gray matter volume in the prefrontal, frontal, temporal, and cingulate cortices in heroin-addicted people is proved. In a case-control study, brain structural differences in 25 Meth-dependents were compared with 20 HC subjects using the VBM technique to find volume differences in MRI images. The results showed decreased brain volume in the hippocampus, para-hippocampus, frontal lobe, temporal lobe, caudate, and amygdala in Meth abusers. These studies investigated structural brain damage under the influence of substance abuse (4).The next group of studies examines functional brain damage from substance abuse. Neural reward responsiveness was investigated in 67 Can abusers compared to 60 HC individuals with the ERP technique, calculating the positive reward, negative feedback, and frequency domain measurements. The results showed more responsiveness to reward in the initial acquisition of non-substance rewards of Can abusers; also, after experiencing loss, these people made more risky choices in subsequent choices (10). Several studies investigated neurological responses to stimuli in Meth abusers (9,12-14). One study examined the EEG signal of 21 Meth abusers and 22 HC individuals while playing a simple gambling game. The results showed increased P300 amplitude in winning conditions and improved feedback-dependent negativity in losing conditions. Meth abusers had sensitive neural responses to non-drug rewards (12). The another study examined the changes in the P300 amplitude during the Stroop test in 26 people using Meth compared to 29 HC people during use and 3 and 6 months after abstinence. An increase in P300 amplitude was observed in Meth users and a decrease in damages after abstinence (13). Another study assessed the response to stimuli in 10 Meth-dependent and 10 HC individuals using the time window analysis method. The results reported significant changes in P300 amplitude in meth abusers (14). Also, one study measured the reaction of 52 Meth abusers to substance-related stimuli, emotion expression index, and reaction time. The results showed a decrease in the brain activity of Meth abusers (9). Sensitive neural response and risky choices can be due to having the higher P300 amplitude in Meth abusers (12-14). Another study investigated the performance of cocaine-dependent people in inhibitory control and their level of anhedonia by calculating the response to external stimuli in 23 cocaine abusers compared to 27 HC people. The results showed weakness in inhibitory control in cocaine abusers (15).

One study examined functional brain connections in 12 Can abusers compared to 24 HC individuals with eLORETA software and showed increased connections in the delta band in Can abusers (17). Also, the cortical activity and functional communication in 17 Can abusers compared to 21 HC individuals were investigated by power spectrum density and spectral coherency in five frequency bands (18). Communication indices were used to quantify functional communication. The results showed a decrease in the power spectrum in the delta band and an increase in the power spectrum in the theta, beta, and gamma bands, inhibiting inhibitory functions that can disrupt cognitive activities. The researchers investigated changes in brain communication patterns of Meth abusers in three studies (8,19,20). The functional brain connections of 36 Meth dependent and 24 HC people were assessed using the graph theory method (8) and sLORETA software (19). In contrast, 36 Meth abusers and 36 HC were assessed using the graph theory method (20). The results of three above studies showed changes in the functional communication of the brain, especially in the gamma band (8,19,20). The analysis of brain communication in studies was done by considering the groups of 17 Op abusers, 32 treated people, and 21 HC by the spiking neural networks method. The results showed decreased brain communication in high-dose users (21). Analyzing the brain connections during the Go/No Go task showed that Op abusers have smaller and more limited communication pathways (22). EEG signals were analyzed to find biomarkers. The researchers conducted EEG signal analysis in 39 Can abusers compared to 26 HC individuals and showed increased signal complexity in 24 Can abusers (24). In another study, the EEG signal of 48 Meth abusers were compared to 20 HC individuals and introduced the entropy index as a biomarker of Meth abuse. It showed a reduction in complexity in Meth abusers. Also, the researchers performed microstate analysis on 55 Meth abusers and 27 HC individuals. This study showed instability in the sound processing class and the optical class in Meth abusers compared to HC subjects (26). In a study, EEG signal of 75 heroin-addicted was analyzed, and the entropy index was introduced as a determining biomarker of heroin abusers (27). The researchers examined the EEG signal in 20 OP abusers, 15 Meth abusers, and 23 people with alcohol use disorder groups using the power spectrum method. They investigated the spectral changes of the signal in delta, theta, alpha, beta, and gamma frequency bands (28). The cognalyzer device detects the consumption of Can based on the EEG signal. The studies investigated the accuracy and sensitivity of the device for the correct diagnosis of Can consumption by testing 75 Can abusers; also, quantified the amount of Meth consumption by analyzing EEG and NIRS indicators (30-32). The correct diagnosis of the substance used by the patient referring to the treatment centers is a great help to the treatment staff and physicians, especially for primary and emergency treatments, where there is often insufficient clinical information about the patient. The treatment method and prescription medicines for substance abuse are diverse in different groups. Substance abuse detection methods include blood, urine, scalp hair, and oral saliva tests. The main advantage of the substance abuse detection system based on the EEG signal compared to conventional methods is that the abuser will not be able to manipulate the test results. Therefore, the development of these systems with appropriate diagnostic accuracy can help physicians in medical centers. In addition, these diagnostic systems can also help test the abuse of people who want to enter sensitive jobs.This study investigated the effect of substance abuse on brain function only with the EEG technique. Studies that used MEG and fMRI techniques were not considered. We did not investigate the impact of abuse of hallucinogens and sleeping pills. In future studies, the effect of substance abuse should be suggested with meta-analysis tools and considering all techniques of examining brain function and all categories of substances.

Conclusion

Substance abuse causes structural and functional damage to the brain. Substance abuse detection systems based on EEG signals provide the ability to detect substance abuse by finding biomarkers. The main advantage of these diagnostic methods compared to conventional methods is the impossibility of changing the results by the individual.

References

1. World Drug Report 2021_Annex 2021. [cited 2021]. Available from: https://www.unodc.org/unodc/en/data-and-analysis/wdr2021_annex.html.
2. American Psychiatric Association. Diagnostic and statistical manual of mental disorders. Am J Psychiatry 2013; 21(21): 591-643.
3. Keihani A, Ekhtiari H, Batouli SAH, Shahbabaie A, Sadighi N, Mirmohammad M, et al. Lower gray matter density in the anterior cingulate cortex and putamen can be traceable in chronic heroin dependents after over three months of successful abstinence. Iran J Radiol 2017; 14(3): e41858.
4. Farnia V, Farshchian F, Farshchian N, Alikhani M, Pormehr R, Golshani S, et al. A voxel-based morphometric brain study of patients with methamphetamine dependency: A case controlled study. NeuroQuantology 2018; 16(12): 57-62.
5. Vuletic D, Dupont P, Robertson F, Warwick J, Zeevaart JR, Stein DJ. Methamphetamine dependence with and without psychotic symptoms: A multi-modal brain imaging study. Neuroimage Clin 2018; 20: 1157-62.
6. Huhn A, Meyer R, Harris J, Ayaz H, Deneke E, Stankoski D, et al. Evidence of anhedonia and differential reward processing in prefrontal cortex among post-withdrawal patients with prescription opiate dependence. Brain Res Bull 2016; 123: 102-9.
7. Sadeghi AZ, Jafari AH, Oghabian MA, Salighehrad HR, Batouli SAH, Raminfard S, et al. Changes in effective connectivity network patterns in drug abusers, treated with different methods. Basic Clin Neurosci 2017; 8(4): 285.
8. Khajehpour H, Mohagheghian F, Ekhtiari H, Makkiabadi B, Jafari AH, Eqlimi E, et al. Computer-aided classifying and characterizing of methamphetamine use disorder using resting-state EEG. Cogn Neurodyn 2019; 13(6): 519-30.
9. Li X, Zhou Y, Zhang G, Lu Y, Zhou C, Wang H. Behavioral and brain reactivity associated with drug-related and non-drug-related emotional stimuli in methamphetamine addicts. Front Hum Neurosci 2022; 16: 894-911.
10. Crane NA, Funkhouser CJ, Burkhouse KL, Klumpp H, Phan KL, Shankman SA. Cannabis users demonstrate enhanced neural reactivity to reward: An event-related potential and time-frequency EEG study. Addict Behav 2021; 113: 106669.
11. Macatee RJ, Okey SA, Albanese BJ, Schmidt NB, Cougle JR. Distress intolerance moderation of motivated attention to cannabis and negative stimuli after induced stress among cannabis users: An ERP study. Addict Biol 2019; 24(4): 717-29.
12. Wei S, Zheng Y, Li Q, Dai W, Sun J, Wu H, et al. Enhanced neural responses to monetary rewards in methamphetamine use disordered individuals compared to healthy controls. Physiol Behav 2018; 195: 118-27.
13. Haifeng J, Wenxu Z, Hong C, Chuanwei L, Jiang D, Haiming S, et al. P300 event-related potential in abstinent methamphetamine-dependent patients. Physiol Behav 2015; 149: 142-8.
14. Shahmohammadi F, Golesorkhi M, Kashani MMR, Sangi M, Yoonessi A, Yoonessi A. Neural correlates of craving in methamphetamine abuse. Basic Clin Neurosci 2016; 7(3): 221.
15. Morie KP, De Sanctis P, Garavan H, Foxe JJ. Executive dysfunction and reward dysregulation: A high-density electrical mapping study in cocaine abusers. Neuropharmacology 2014; 85: 397-407.
16. Fink BC, Steele VR, Maurer MJ, Fede SJ, Calhoun VD, Kiehl KA. Brain potentials predict substance abuse treatment completion in a prison sample. Brain Behav 2016; 6(8): e00501.
17. Imperatori C, Massullo C, Carbone GA, Panno A, Giacchini M, Capriotti C, et al. Increased resting state triple network functional connectivity in undergraduate problematic cannabis users: A preliminary EEG coherence study. Brain Sci 2020; 10(3): 136.
18. Prashad S, Dedrick ES, Filbey FM. Cannabis users exhibit increased cortical activation during resting state compared to non-users. Neuroimage 2018; 179: 176-86.
19. Khajehpour H, Makkiabadi B, Ekhtiari H, Bakht S, Noroozi A, Mohagheghian F. Disrupted resting-state brain functional network in methamphetamine abusers: A brain source space study by EEG. PloS One 2019; 14(12): e0226249.
20. Ahmadlou M, Ahmadi K, Rezazade M, Azad-Marzabadi E. Global organization of functional brain connectivity in methamphetamine abusers. Clin Neurophysiol 2013; 124(6): 1122-31.
21. Capecci E, Kasabov N, Wang GY. Analysis of connectivity in NeuCube spiking neural network models trained on EEG data for the understanding of functional changes in the brain: A case study on opiate dependence treatment. Neural Netw 2015; 68: 62-77.

22. Doborjeh MG, Wang GY, Kasabov NK, Kydd R, Russell B. A spiking neural network methodology and system for learning and comparative analysis of EEG data from healthy versus addiction treated versus addiction not treated subjects. IEEE Trans Biomed Eng 2015; 63(9): 1830-41.
23. Coullaut-Valera R, Arbaiza I, Bajo R, Arrúe R, López ME, Coullaut-Valera J, et al. Drug polyconsumption is associated with increased synchronization of brain electrical-activity at rest and in a counting task. Int J Neural Syst 2014; 24: 1450005.
24. Laprevote V, Bon L, Krieg J, Schwitzer T, Bourion-Bedes S, Maillard L, et al. Association between increased EEG signal complexity and cannabis dependence. Eur Neuropsychopharmacol 2017; 27(12): 1216-22.
25. Yun K, Park H-K, Kwon D-H, Kim Y-T, Cho S-N, Cho H-J, et al. Decreased cortical complexity in methamphetamine abusers. Psychiatr Res Neuroimag 2012; 201(3): 226-32.
26. Chen T, Su H, Zhong N, Tan H, Li X, Meng Y, et al. Disrupted brain network dynamics and cognitive functions in methamphetamine use disorder: insights from EEG microstates. BMC Psychiatry 2020; 20(1): 1-11.
27. Erguzel TT, Uyulan C, Unsalver B, Evrensel A, Cebi M, Noyan CO, et al. Entropy: A promising EEG biomarker dichotomizing subjects with opioid use disorder and healthy controls. Clin EEG Neurosci 2020; 51(6): 373-81.
28. Minnerly C, Shokry IM, To W, Callanan JJ, Tao R. Characteristic changes in EEG spectral powers of patients with opioid-use disorder as compared with those with methamphetamine-and alcohol-use disorders. PloS One 2021; 16(9): e0248794.
29. Moreno-Alcázar A, Gonzalvo B, Canales-Rodríguez EJ, Blanco L, Bachiller D, Romaguera A, et al. Larger gray matter volume in the basal ganglia of heavy cannabis users detected by voxel-based morphometry and subcortical volumetric analysis. Front Psychiatry 2018; 3(9): 175.
30. Bosnyak D, McDonald AC, Gasperin Haaz I, Qi W, Crowley DC, Guthrie N, et al. Use of a novel EEG-based objective test, the Cognalyzer®, in quantifying the strength and determining the action time of cannabis psychoactive effects and factors that may influence them within an observational study framework. Neurol Ther 2022; 11(1): 51-72.
31. McDonald AC, Gasperin Haaz I, Qi W, Crowley DC, Guthrie N, Evans M, et al. Sensitivity, specificity and accuracy of a novel EEG-based objective test, the Cognalyzer®, in detecting cannabis psychoactive effects. Adv Ther 2021; 38(5): 2513-31.
32. Gu X, Yang B, Gao S, Yan LF, Xu D, Wang W. Application of bi-modal signal in the classification and recognition of drug addiction degree based on machine learning. Math Biosci Eng 2021; 18: 6926-40.