Informatics in Medicine Unlocked 47 (2024) 101476

Contents lists available at ScienceDirect

Informatics in Medicine Unlocked

journal homepage: www.elsevier.com/locate/imu

EEG-based functional connectivity analysis of brain abnormalities: A systematic review study

Nastaran Khaleghi [a], Shaghayegh Hashemi [g], Mohammad Peivandi [b], Sevda Zafarmandi Ardabili [c], Mohammadreza Behjati [e], Sobhan Sheykhivand [a,f], Sebelan Danishvar [d,*]

[a] Biomedical Engineering Department, Faculty of Electrical and Computer Engineering, University of Tabriz, Tabriz, 51666-16471, Iran
[b] Department of Biomedical Engineering, Wayne State University, Detroit, MI, 48202, USA
[c] Electrical and Computer Engineering Department, Southern Methodist University, Dallas, TX, 75205, USA
[d] College of Engineering, Design and Physical Sciences, Brunel University London, Uxbridge, UB8 3PH, UK
[e] Faculty of Electronic and Computer Engineering, Azad University Tehran, Tehran, Iran
[f] Department of Biomedical Engineering, University of Bonab, Bonab, Iran
[g] Department of Computer Science and Engineering, Shahid Beheshti University, Tehran, Iran

ARTICLE INFO

Keywords:
Electroencephalogram
Functional connectivity
Brain abnormalities

ABSTRACT

Several imaging modalities and many signal recording techniques have been used to study the brain activities. Significant advancements in medical device technologies like electroencephalographs have provided conditions for recording neural information with high temporal resolution. These recordings can be used to calculate the connections between different brain areas. It has been proved that brain abnormalities affect the brain activity in different brain regions and the connectivity patterns between them are changed as a result. This paper studies the electroencephalogram (EEG) functional connectivity methods and investigates the impacts of brain abnormalities on brain functional connectivities. The effects of different brain abnormalities including stroke, depression, emotional disorders, epilepsy, attention deficit hyperactivity disorder (ADHD), autism, and Alzheimer's disease on functional connectivity of the EEG recordings have been explored in this study. The EEG-based metrics and network properties of different brain abnormalities have been discussed to present a comparison of the connectivities affected by each abnormality. Also, the effects of therapy and medical intake on the EEG functional connectivity network of each abnormality have been reviewed.

1. Introduction

Advances in brain recording technologies have shown that activity takes place in different parts of the human brain. These areas of activity are disparate in location but analogous and synchronous in context. A graph is a tangible representation of a network essentially consisted of nodes and edges between them. The functional connection networks approximated from brain activity recording technologies such as fMRI, magnetoencephalogram (MEG) and electroencephalogram (EEG) can be investigated by using the graph theory.

Preserving the temporal information would be possible with non-invasive brain recording methods with high temporal resolution. The EEG recordings are the most suitable technique for this aim. The EEG has been used extremely in studies related to understanding the brain reactions and interactions in several set of conditions; for example, studies concerning motor control, EEG-based driving safety monitoring, drowsiness in the brain, driver fatigue [1], movement intention detection [2], motor imagery [3], brain activities during sleep [4], visual decoding [5,6] and emotion recognition [7]. Several studies have examined synchronicity and functional connectivity of the brain activity using EEG technology [8,9].

Investigating the brain activities in healthy groups and abnormal individuals can help to recognize the effects of brain disorders on interactions between different brain areas. It is the capability of a healthy brain to adjust the synchronized oscillations by changing the strength, frequency and pattern of the activity in different brain regions. Accordingly, the disorders may interfere the brain function of adjusting the oscillations and consequently the functional connectivities would be

* Corresponding author.
E-mail addresses: khaleghi.nstr@tabrizu.ac.ir (N. Khaleghi), szafarmandiardabiliii@smu.edu (S.Z. Ardabili), sebelan.danishvar@brunel.ac.uk (S. Danishvar).

https://doi.org/10.1016/j.imu.2024.101476
Received 22 January 2024; Received in revised form 11 March 2024; Accepted 11 March 2024
Available online 21 March 2024

affected by brain abnormal activities. Investigating the non-invasive techniques for functional connectivity calculation can help to diagnose these abnormalities and would be a predictor of them. They can be used as a biomarker for predicting the recovery from the abnormality after a treatment process [10].

The review study in this paper consists of papers during the years between 1990 and 2023 corresponding to the EEG-based functional connectivity analysis of brain abnormalities. Process of selecting the articles to be reviewed is done by using EEG, functional connectivity and the name regarding the brain abnormality for the keywords.

The important issues disseminated in this review are as follows: the algorithms of calculating functional connectivity metrics, the effects of different brain abnormalities like stroke, depression, epilepsy, attention deficit hyperactivity disorder (ADHD), autism and alzheimer's disease on the EEG functional connections, emotional state recognition and its impact on EEG functional connectivities.

The contributions of this paper can be marked as.

(i) The review considers recent studies related with non-invasive functional connectivity analysis of brain abnormalities.
(ii) It summarizes the history of the most used functional connectivity techniques in order to analyze brain abnormalities.
(iii) It provides a framework for comparing the functional connected regions and the mostly affected regions by different brain disorders.
(iv) The connectivity network patterns, connectivity strength, graph properties including characteristic path length, clustering coefficient, local and global efficiencies and the number of connections affected by different abnormalities are represented in this review study.
(v) Some functional connectivity-based predictors of the abnormalities have been summarized and some medication responses have been presented to observe the effects of medical intake and treatment on the functional connectivity networks.

The remaining parts of this article are ordered as follows. In Section 2, the questions to be responded in this review, the specifications for selecting the articles and the article selection strategy are explained. Section 3 provides and presents the results. Discussions have been provided in Section 4. Conclusions are provided in Section 5.

2. Materials and methods

In this section, research question, article selection specifications and the strategy of selecting the articles are described.

2.1. The questions to be responded in this review

The main focus of this paper is to find the answers of the following questions.

Q1. What are the most used EEG functional connectivity techniques?
Q2. What are the differences in connectivity patterns according to the EEG-based functional connectivity analysis of brain abnormalities?
Q3. What are the suggestions for future studies on brain functional connectivity analysis related with brain abnormalities?

2.2. The specifications for selecting the articles

This review article includes papers with concentration on the following specifications.

1. Papers presented a brain functional connectivity method,
2. Papers focused on Electroencephalography signals,
3. Investigated brain abnormalities through functional connectivity,
4. Studies demonstrated numerical results for healthy subjects and other subjects with disorders.
5. Including applications to study the connectivities related with brain abnormalities.

2.3. The article selection strategy

The specifications considered in preferred reporting items for systematic reviews and meta-analyses (PRISMA) statement have been imposed to this review [11]. The works related to functional connectivity estimation techniques through EEG signals have been selected through a search of the Science Direct, PubMed, IEEE, Springer and Wiley online database. The studies published from the year 1990 until 2023 have been considered in this review study. The aim of this review paper is to focus on the articles meeting the specification criteria given in Section 2.2. The portions of articles in each decade of 1990–2000, 2001–2010 and 2011 until 2023 are illustrated in Fig. 1.

3. Results

The process of selecting papers corresponding to the specified criteria has been represented in Fig. 2. A total number of 130 articles has been collected. In this review, we are looking for articles in the field of EEG-based functional connectivity. In the collected studies, 31 number of papers have considered brain connectivity using single-photon emission computerized tomograph (SPECT), positron emission tomography (PET) scan and connectivity corresponding to the fMRI recordings in their studies. The aforementioned studies did not provide the specifications and have not been selected. Finally, 99 papers have been included in this review study. 11% of them have been published until the end of 2000.18% have been published by the end of 2010. Finally, 71% of studies have been available in the last decade until 2023. The EEG functional connectivity studies in this review study are clustered as follows.

- Functional connectivity methods and metrics (14.54%)
- EEG-based functional connectivity analysis of
  - stroke abnormality (12.72%)
  - depression abnormality (15.45%)
  - emotional processing (9.09%)
  - epilepsy (9.09%)
  - ADHD (9.09%)
  - autism spectrum disorder (3.63%)
  - Alzheimer's disease (4.54%)
  - Other brain abnormalities including OCD, psychotic disorder (9.09%)
- Related with treatment and medication of the abnormalities (11.81%)

A brief description has been dedicated to each study and has been presented in following sections. At first, we have brief overview of different methods of functional connectivity with respect to their

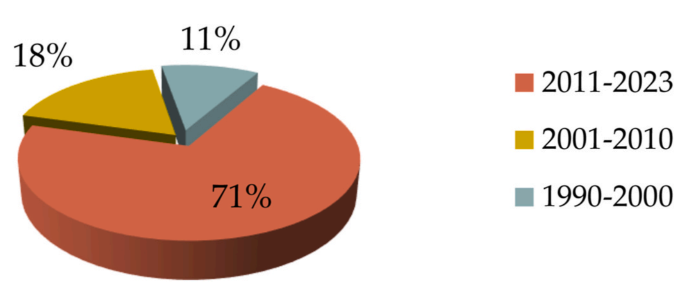

Fig. 1. Percentage of the papers considered in this review study: published during 1990–2000, 2001–2010 and 2011–2023.

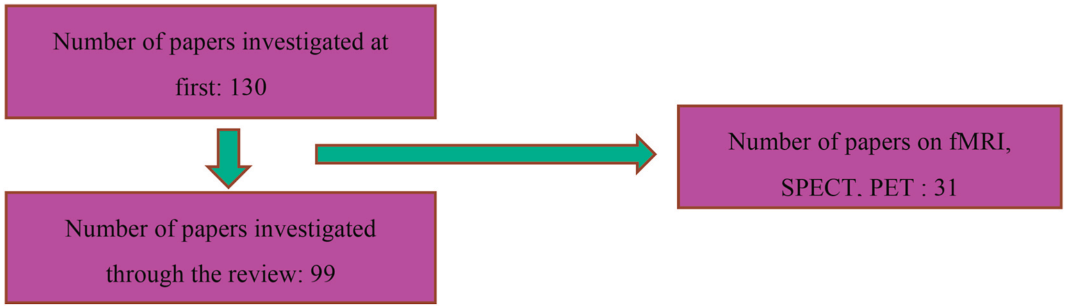

Fig. 2. Process of article selection [11].

historical background. Considering different methods of calculating the functional connectivity of brain activity, the applications of them to analyze the effects of various brain disorders on brain connectivities are explained. The brain abnormalities are described briefly and effects of the abnormalities on EEG functional connectivity are explained. In some cases like stroke disorder, the effects of treatment are evaluated through EEG-based functional connectivity and are reviewed briefly.

3.1. Different functional connectivity methods

The functional connectivity metrics are divided into time-domain and frequency-domain measurements as it can be seen in Fig. 3. Time-domain metrics can be formulated considering the direction of the connections. The directed time-domain metrics can be divided into model-based or model-free versions of the functional connections. These categories of the functional connectivity metrics can be seen in Fig. 4. The left circular plot shows the categories of time-domain calculation of the connectivity metrics and the right circular plot illustrates the frequency domain calculation of the connections.

A distinction could be made between model-free and model-based methods in two types of directed and non-directed ones.

The dmodel-based and dmodel-free are for directed metrics in Fig. 4. Non-directed metrics consider interdependence between signals without referring to the direction of influence. Correlation is a time-domain model-based metric. Mutual information is another non-directed functional connectivity which is a model-based metric. Directed measures such as Granger causality and transfer entropy are based on the fact that causes precede their effects. The definitions of causality were developed by Wiener in 1956 and later implemented using auto-regressive models of Granger in 1969. The quantification of these neuronal interactions has been obtained using these approaches.

Measures including the coherence, phase locking value, pairwise phase consistency are model-based metrics that are calculated in frequency domain. Phase slope index, parametric and nonparametric Granger Causality are directed frequency domain metrics.

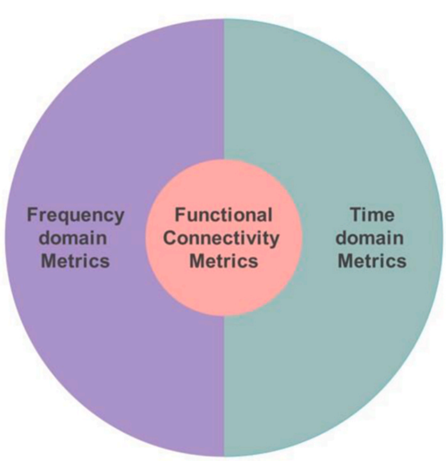

Fig. 3. Different categories of functional connectivity methods.

Granger Causality in the frequency domain can be calculated using parametric methods such as auto-regressive models or Fourier or wavelet-based methods such as non-parametric methods. Transfer matrices calculation and the covariance of the residuals in these methods are different. The non-parametric method of spectral factorization needs more data and a smooth shape of the cross-spectral density in order to converge to a stable result. Noise covariance matrix and spectral transfer function are used to calculate and estimate the Granger Causality.

3.1.1. The coherence coefficient

The spectral coherence is a method of determining the synchrony in EEG recordings. The coherence is the frequency range correspondent of the time-based cross-correlation. The length of the average vector of the cross-spectral densities of two signals at frequency domain constitutes the numerator. The square root of the average of trial power estimates of two signals at a specific frequency is needed to confine the absolute value of coherency to the range between zero and one.

This method of functional coupling of brain EEG activity first used in 1980 [12] to identify the interhemisferic functional coupling between mu waves in motor area and alpha waves of the same frequency range in the visual region of the brain. Furthermore, it has been used in 1988 [13] for analyzing the effect of tasks related to cognitive processes. A mental cube rotation study has been selected as the test procedure in the study and the local coherences have been analyzed for males and females and in the left and right hemisphere for different frequency ranges of brain activity.

Event-related coherence has been investigated for the first time in 1996 [14] in a right index finger movement procedure to see whether an information could be extracted corresponding to the EEG interaction of regionally separated brain lobes. Two years later Gerloff et al., in 1998 [15] studied the interaction of cortical motor regions in 3 stages of finger movement procedure. Task-related and movement-related EEG interactions of the motor areas for simple, internal paced and external paced extension of finger have been investigated. The mathematic formula of this metric is as equation (1). The numerator represents the length of the vector average of the cross-spectral densities between x and y. The denominator is the square root of the product of the average of the individual trial power estimates of signals x and y.

$$coh_{xy}(\omega) = \frac{\left|\frac{1}{n}\sum_{k=1}^{n} A_x(\omega,k)A_y(\omega,k)e^{i\left(\varphi_x(\omega,k)-\varphi_y(\omega,k)\right)}\right|}{\sqrt{\left(\frac{1}{n}\sum_{k=1}^{n} A_x^2(\omega,k)\right)\left(\frac{1}{n}\sum_{k=1}^{n} A_y^2(\omega,k)\right)}} \tag{1}$$

A single matrix is another way of representing the cross-spectral densities.

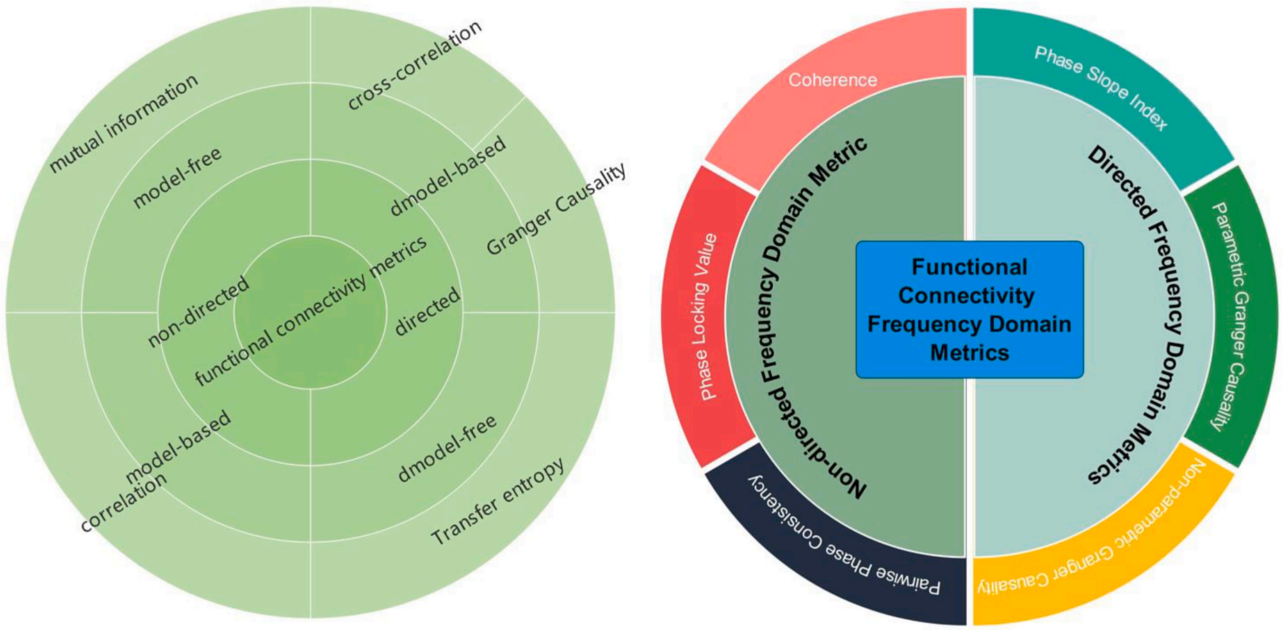

Fig. 4. The time-domain and frequency-domain categories of functional connectivity metrics, time-domain (left plot) and frequency-domain (right plot).

$$S(\omega) = \begin{bmatrix} S_{xx}(\omega) & S_{xy}(\omega) \\ S_{yx}(\omega) & S_{yy}(\omega) \end{bmatrix} \tag{2}$$

The coherence metric can be defined with equation (3).

$$coh_{xy}(\omega) = \frac{|S_{xy}(\omega)|}{\sqrt{S_{xx}(\omega)S_{yy}(\omega)}} \tag{3}$$

3.1.2. Phase-slope index (PSI)

This metric for measuring the orientation of information in multivariate time series has been proposed by Nolte et al. [16] for the first time in 2008. This functional connection metric is not sensitive to mixture of sources and to the nonlinearity of phase spectrum. The cause antecedes the effect and this fact constitutes the main idea of presenting this metric. Therefore, the gradient and incline of phase corresponding to the cross-spectrum between two time series reflects the directionality [17]. In the first application of this metric, the subjects were trained to close their eyes for 15 min and they were asked to open their eyes for 5 s every minute. 19-channel EEG recordings have been analyzed using the phase-slope index for all channel pairs. The results for all frequencies and all pairs of channels for flow of information from right to left and from frontal part of the brain to the back of the skull have been investigated in this research. Rana et al. [17] in 2012 used the phase slope index to propose a novel method for seizure detection. The increases in the spatio-temporal interactions between channel pairs have been identified by PSI metric. This identification has led to better distinguish interictal activity from seizure. For signals $z_i(n)$ and $z_j(n)$, the cross spectrum can be computed as in equation (4).

$$S_{ij}(f) = E\left[Z_i(f)Z_j^*(f)\right] \tag{4}$$

The complex coherence can be computed and the unnormalized phase slope index (PSI) can be defined as equation (5).

$$C_{ij}(f) = \frac{S_{ij}(f)}{\sqrt{S_{ii}(f)S_{jj}(f)}} \tag{5}$$

The formulation is defined using the f which is the frequency band of interest and the frequency resolution δf. A weighted sum of the slopes of the phase between $z_i(n)$ and $z_j(n)$ over the band f is defined as the phase slope index. This metric can be normalized by its standard deviation and can be used to determine the causal influence from $z_i(n)$ to $z_j(n)$.

$$\widetilde{P}_{ij} = \mathrm{Im}\left(\sum_{f\in B} C_{ij}^*(f)C_{ij}(f+\delta f)\right) \tag{6}$$

$$P_{ij} = \widetilde{P}_{ij} \,/\, \mathrm{var}\left(\widetilde{P}_{ij}\right) \tag{7}$$

3.1.3. Imaginary part of coherency

The unreal part of coherency metric is obtained through mapping the complex coherency on imaginary axis. It was the work by Nolte et al., in 2004 [18] reported that the complex coherency of the sources with no connectivity is real. Therefore, the imaginary part of coherency would be a good candidate for investigating brain interactions. The cross spectrum can be shown as (8):

$$D = \langle yy^\dagger \rangle = \begin{pmatrix} idm + iD_{AA}^I & D_{AB}^R + iD_{AB}^I \\ D_{AB}^R + iD_{AB}^I & idm + iD_{BB}^I \end{pmatrix} \tag{8}$$

In this matrix, the idm is the identity matrices. Considering weight vectors $\alpha \in \Re^{N\times 1}$ and $\beta \in \Re^{N\times 1}$ as column vectors for defining the $z_A = \alpha^T y_A$ and $z_B = \beta^T y_B$.

$$Coh_z = \frac{z_A z_B^\dagger}{\left(\langle z_A z_A^\dagger\rangle\langle z_B z_B^\dagger\rangle\right)^{1/2}} = \frac{\alpha\langle y_A y_B^\dagger\rangle\beta}{\left((\alpha^T\langle y_A y_A^\dagger\rangle\alpha)(\beta^T\langle y_B y_B^\dagger\rangle\beta)\right)^{1/2}} \tag{9}$$

To obtain the imaginary part of coherency as a connectivity metric which is robust to volume conduction phenomena, the substitution of the formula with (10) and (11), would result in equation (12) which is the formula for calculating the imaginary part of the coherency.

$$\left(\alpha^T\langle y_A y_A^\dagger\rangle\alpha\right) = \left(\alpha^T\langle id + iD_{AA}^I\rangle\alpha\right) = \alpha^T\alpha = \|\alpha\|^2 \tag{10}$$

$$\mathrm{Imaginary}\langle y_A y_B^\dagger\rangle = D_{AB}^I \tag{11}$$

$$\mathrm{Imaginary}(Coh_z) = \frac{\alpha^T D_{AB}^I \beta}{\|\alpha\|\|\beta\|} \tag{12}$$

3.1.4. The partial directed coherence

To calculate this metric, we need to compute the fourier domain transform of the multi-variate autoregressive model (MVAR) [19].

$$A(\omega)X(\omega) = V(\omega), A(\omega) = -\sum_{m=0}^{p} A(m)e^{-j\omega m}, A(0) = -I \tag{13}$$

The partial coherence C_{ij} can be defined as (14).

$$C_{ij}(f) = \frac{A_{ij}(f)}{\sqrt{A_{ii}(f)A_{jj}(f)}} \tag{14}$$

The partial directed coherence and the generalized partial directed coherence can be defined as follows:

$$P_{ij}(f) = \frac{A_{ij}(f)}{\sqrt{a_j^*(f)a_j(f)}}, GP_{ij}(f) = \frac{A_{ij}(f)}{\sum_{i=1}^{k} |A_{ij}(f)|^2} \tag{15}$$

3.1.5. Phase locking value (PLV)

Applying the coherence formula to the amplitude of the normalized Fourier transform of two signals, the phase locking value would be obtained. This metric measures the phase covariance between two signals and the significance of this metric would be obtained with a reasonable time resolution. Phase locking value was first introduced in the study by Lachaux et al. [20] in 1999. PLV in this study has been applied to analyze the epileptic EEG recordings of patients in response to visual discrimination task. Large scale connectivities between the frontal gyrus and hippocampus and local connections in limbic region have been reported in the gamma frequency band. The mathematic form of phase locking value is obtained via employing the coherence computation to amplitude normalized Fourier domain of signals.

$$plv_{xy}(\omega) = \frac{\left|\frac{1}{n}\sum_{k=1}^{n} 1_x(\omega,k)1_y(\omega,k)e^{i(\varphi_x(\omega,k)-\varphi_y(\omega,k))}\right|}{\sqrt{\left(\frac{1}{n}\sum_{k=1}^{n} 1_x^2(\omega,k)\right)\left(\frac{1}{n}\sum_{k=1}^{n} 1_y^2(\omega,k)\right)}} = \left|\frac{1}{n}\sum_{k=1}^{n} e^{i(\varphi_x(\omega,k)\varphi_y(\omega,k))}\right| \tag{16}$$

3.1.6. Phase lag index (PLI)

This metric is obtained by the average of the phase difference sign for each observation. PLI is a metric for evaluating the phase differences across observations. This metric has been introduced in the work by Stam et al. [21] in 2007. The problem of field spread and volume conduction in computing the functional connectivity has been addressed in this study and the novel PLI has been proposed to quantify the phase synchronization. A number of 15 alzheimer disease and control subject have been considered in the study. The mathematical formula for computing the phase Lag index metric is as in equation (17). It is an index of asymmetry of the phase differences $\Delta\varphi(t_k), k = 1, ..., N$ as in this equation. N is the number of observations.

$$PLI = |\langle sign[\Delta\varphi(t_k)]\rangle| \tag{17}$$

The PLI ranges between 0 and 1: 0≤PLI ≤ 1. A PLI of zero defines no coupling or coupling with a phase difference centered around 0 mod π. A PLI of 1 defines a perfect phase locking at a value of $\Delta\varphi$ different from o mod π. The stronger this phase locking results in larger index.

3.1.7. Pairwise phase consistency (PPC)

The quantification of the vector average of phase differences across observations is done using the pairwise phase consistency measure of functional connectivity. This connectivity measure has been first introduced in a work by Vinck et al. [22] in 2010. The practical experiment to use and propose this measure has been the orbitofrontal cortex EEG recordings of rats in a two-odour discrimination task. This metric is computed using the dot product between two unit vectors defined in (18).

$$f(\varphi,\omega) = \cos(\varphi)\cos(\omega) + \sin(\varphi)\sin(\omega)$$
$$\hat{\Upsilon} \equiv \frac{2}{N(N-1)}\sum_{j=1}^{N-1}\sum_{k=(j+1)}^{N} f(\theta_j,\theta_k) \tag{18}$$

3.1.8. Directed functional connectivity with granger causality

Granger causality solves the limitation of being consistently time-lagged and unidirectional interactions. The capability of this metric is quantifying the bi-directional connections and providing approximations of directional connections for pairs of signals. The first application of this concept has been in the field of economics in 1969 mentioned by Granger et al. [23].

Years later, Geweke [24] in 1982 extended the concept of granger causality to the frequency criteria and presented a novel formulation of the concept. The applications of Granger causality in neuroscience has been reviewed by Ding et al. [26] in 2006. Time domain granger [23,26] is formulated from autoregressive modeling. The frequency domain Granger causality have been presented in another study [24]. The approximation of the spectral transfer matrix and approximating the covariance of residual of the AR model is necessary for computing the frequency domain concept of this connectivity metric. The estimation process of the Granger causality is illustrated in Fig. 5. To obtain the formula, we need to define the spectral transfer matrix (H(ω)), which is frequency dependent, and the covariance of the autoregressive model's residual (∑) and the S(ω) being the cross-spectral density matrix.

$$GC_{x\rightarrow y}(\omega) = \ln\left(\frac{S_{yy}(\omega)}{S_{yy}(\omega) - \left(\sum_{xx} - \frac{\sum_{yx}^2}{\sum_{yy}}\right)|H_{yx}(\omega)|^2}\right) \tag{19}$$

$$S(\omega) = H(\omega)\sum H^*(\omega) \tag{20}$$

In multichannel EEG recording, the spectral transfer matrix can be obtained in two different ways of bivariate and multivariate modeling. The bivariate model considers the analysis for each pair of channels separately. The information from all channels are considered in the multivariate model and approximation of the interaction between any pair of sources is computed considering the information from other channels. The spectral transfer matrix obtained in the multivariate approach are used to calculate a set of connectivity metrics named directed transfer function (DTF) [25] and partial directed coherence (PDC) [19]. In another study in 2017, a robust Granger analysis-based method has been proposed to remove the ocular artifacts in resting-state EEGs [27].

History of the abovementioned connectivity metrics with respect to the year of representation are described in Table 1.

3.2. Applications

The applications of different EEG-based functional connectivity methods to analyze the effects of various brain abnormalities like stroke, depression, epilepsy, ADHD, autism and Alzheimer's disease as illustrated in Fig. 6 on brain connectivitieswill be explained in the following subsections.

3.2.1. Stroke disorder

Stroke is one of the brain disorders which happens when blood flow to part of the brain stops because of ischemia in veins. We have an overview on some works by researchers about the application of functional connectivity in EEG recordings for brain stroke detection. A brief introduction for these studies is described in Table 2. The objectives, subjects considered in them and the obtained results are available in this table corresponding to each study.

In 2009, brain functional networks were analyzed in Ref. [28] to detect differences in networks of stroke patients and healthy subjects.

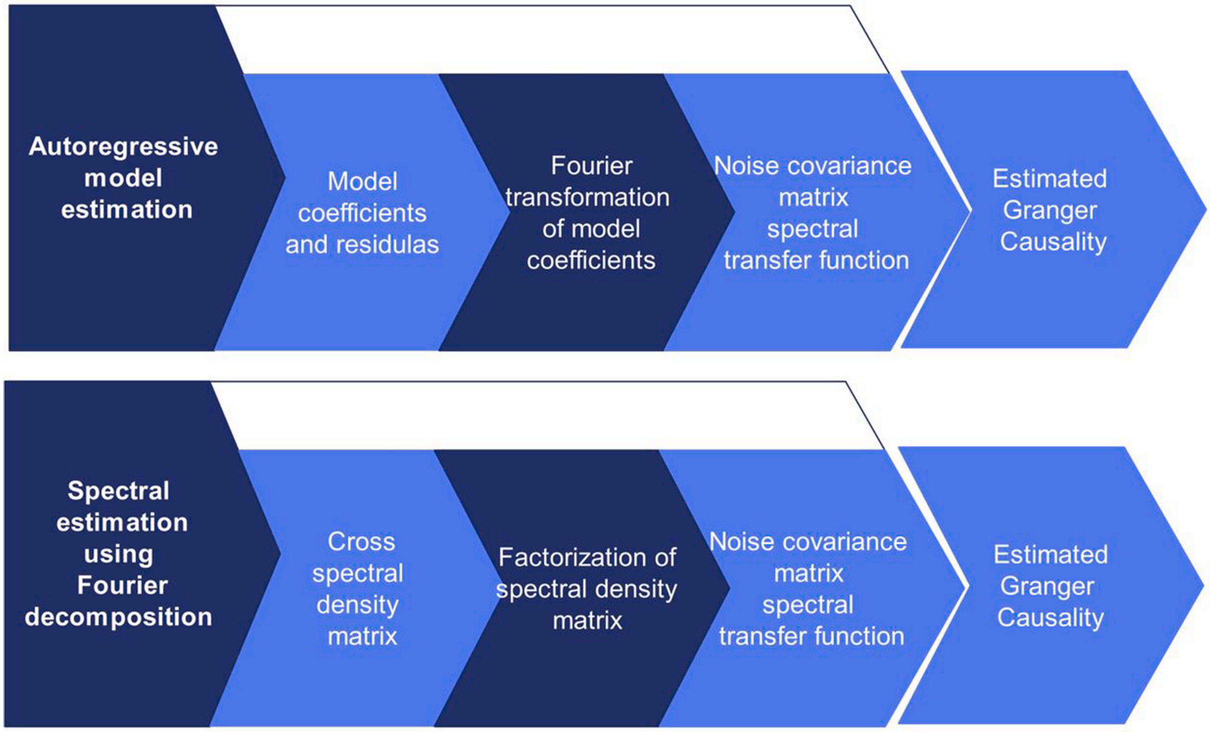

Fig. 5. Estimation process of Granger causality metric.

Table 1
History of connectivity metrics.

Paper ref		Year	Objective and Abnormality	Method
[23]	Granger et al.	1969	economics	Granger causality
[12]	Schoppenhorst et al.	1980	mu waves in motor area and alpha waves of visual region	CC
[24]	Geweke et al.	1982	neuroscience	Frequency domain granger causality
[13]	Rappelsberger et al.	1988	tasks related to cognitive processes	CC
[25]	Kaminski et al.	1991	Spectral transfer matrix in multivariate modeling	directed transfer function (DTF)
[14]	Andrew et al.	1996	right index finger movement procedure	CC
[15]	Gerloff et al.	1998	motor regions in 3 stages of finger movement procedure	CC
[20]	Lachaux et al.	1999	Epileptic EEG	PLV
[18]	Nolte et al.	2004	–	Imaginary part of coherency
[26]	Ding et al.	2006	neuroscience	Frequency domain granger causality
[21]	Stam et al.	2007	15 alzheimer disease and control subject	PLI
[16]	Nolte et al.	2008	–	phase slope index
[22]	Vinck et al.	2010	EEG recordings of rats in a two-odour discrimination task	PPC
[17]	Rana et al.	2012	Seizure detection	phase slope index

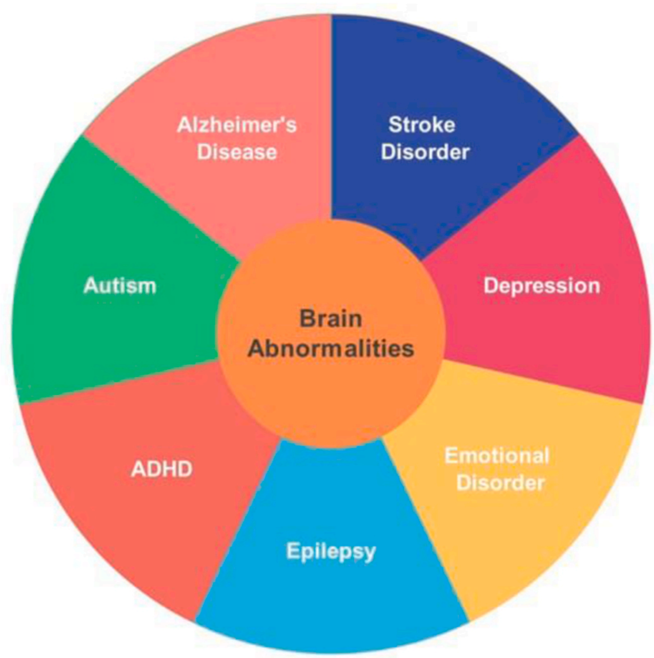

Fig. 6. Brain abnormalities considered in this study.

The synchronous activity of brain in motor cortex in order to percept or process cognitive content has been a vital subject in several studies and studied in case of stroke detection. Degree distribution, connectivity degree and efficiency parameters in all frequency bands were analyzed during the course of planning (PRE) and execution of movement (EXE) intervals. Activating the motor cortex is done through finger tapping paradigm. To characterize the spectral coherence related to finger tapping task, a theoretical graph approach has been evaluated. A decrease

Table 2
Studies about functional connectivity and stroke disorder.

Paper ref	objective	subjects	Functional connectivity method	result
[28] 2009	Activating the motor cortex through the finger tapping paradigm	stroke patients and healthy subjects with the course of planning (PRE) and execution of movement (EXE) intervals EEG	Coherence	decrease in global efficiency and local proficiency in EEG brain network connection in patients
[30] 2015	EEG-based biomarkers of the motor system function	12 hemiparetic patients in resting state after 7 month of the stroke during 28 days of therapy initialization for arm movement dysfunction	Coherence	connectivity in primary motor cortex (M1) was a biomarker of motor status; connectivity measures between M1 and premotor cortex
[31] 2016	sample entropy and Lempel-Ziv complexity features	healthy subjects and stroke patients in resting state condition with closed-eye state	Partial directed coherence	higher complexity in EEG recordings have been reported for stroke patients
[32] 2017	diagnosing the stroke through EEG connectivity using the generalized measure of association	Stroke patients in recovery state	Partial directed coherence	analyzing the recovery state of the stroke patients with local and global efficiency of graph
[33]	prediction of the upper limb function after post-stroke recovery	24 patients with stroke during the recovery phase	Generalized measure of association (GMA)	higher interhemispheric functional connectivity between M1 in every side of the brain during the ankle movement as well as higher motor-related recovery
[34] 2019	finding a possible predictive index of functional post-stroke recovery	a set of 110 patients suffering from 3 scales of stroke including NIHSS, Barthel and ARAT	Time-domain Amplitude envelope correlation	strong interdependence between small world index and NIHSS in the acute post-stroke period

in global efficiency and local proficiency in patient's networks reflected a lower capacity to incorporate and communicate with distant regions and a weak organization as a result. Furthermore, disconnected nodes as well as the links in some other crucial vertices have increased. Patterns according to degree values for stroke patients illustrated in Fig. 7.

The motor system in human brain comprises of areas with anatomical interaction and handles the function of motor-related tasks. Stroke would destroy and disrupt these connections. There is evidence of reorganization in the motor network as a contribution to motor recovery after stroke lesion construction with ischemia. How stroke influences brain connectivity in motor areas and investigating the relation between these harmed areas and functional recovery has been studied in a research [29] in 2013.

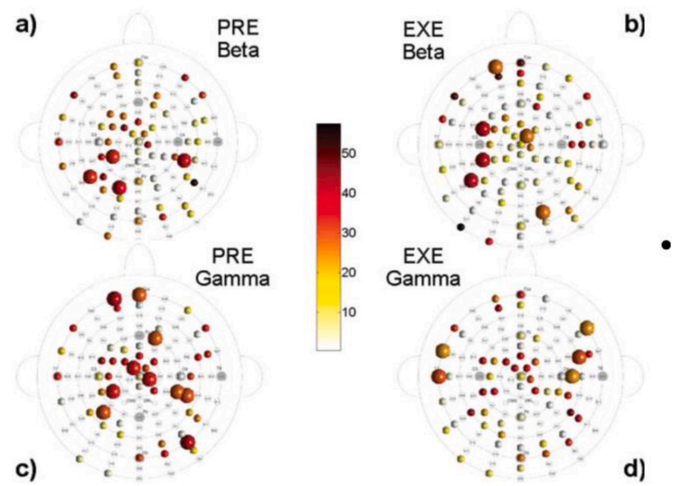

Fig. 7. Patterns according to degree values dedicated to the stroke patients [28]. The spheres illustrate the degree values. The larger circles represent the electrodes with large number of couplings. Degree values (a) in PRE interval. (b) In EXE stage. (c) During the PRE interval for the Gamma frequency. (d) Degree values during the EXE period for the Gamma frequency.

The connectivity metrics related to the dysfunction in motor-related tasks have been assessed during the 28 days of initial therapy in 2015 [30]. EEG records of 12 hemiparetic patients in the resting state for arm movement dysfunction have been analyzed. The signals have been recorded after 7 months of stroke event during 28 days of therapy initialization. According to this study, the connectivity in primary motor cortex (M1) was a biomarker of motor status. Baseline dysfunction is related with injuries of corticospinal tract and not the infarct volume. During the 28 days of therapeutic criteria, the changes in M1 connectivity patterns have been a good motor recovery biomarker. According to this study, it has been inferred that EEG measures of motor-related connectivity measures between M1 and premotor cortex are related to motor deficits and hence the connectivity improvement in these areas would be a valuable sign of motor recovery and cortical function and plasticity. These measurements play an important role in distinguishing different stages of stroke.

Liu et al. [31] in 2016, investigated the EEG recordings of healthy subjects and stroke patients in resting state condition with closed eyes. A vital tool for prediction of post-stroke motor recovery is biomarkers of neural activity. Brain network of recordings has been analyzed through calculating the sample entropy and Lempel-Ziv complexity features. Higher complexity in EEG recordings has been reported for stroke patients. According to brain network in stroke patients, transmission of information is done with functional impairment. Complexity of Lempel-Ziv (LZC) was applied in anesthesia depth, activity of brain in Alzheimer patients and sedative moments. The application of this parameter in stroke has been investigated in this research.

Researchers in 2017 [32] studied the process of diagnosing stroke through EEG connectivity. They used the generalized measure of association in order to assess the reorganization of brain networks into biomarkers. The graph properties such as local and global efficiency, as well as hemispheric intra and interdensity have been calculated to analyze the recovery state of the stroke patients. Finding a possible predictive index of functional post-stroke recovery is the objective of the research by Vecchio et al. [34] in 2019. For this purpose, a set of 110 patients considering 3 scales of stroke including the national institutes of health stroke scale (NIHSS), Barthel scale and action research arm test (ARAT) have been evaluated. A strong interdependence between the small world index and NIHSS has been found in the acute post-stroke period. The predictive index works based on correlation between functional deficiencies of brain networks measured by detecting the small world specifications in EEG resting state in early post-stroke clinical outcome.

The prediction of the upper limb function after post-stroke recovery has been done via neural connectivity [33]. Using the Fugl-Meyer assessment, the motor related function of the lower limb has been analyzed during the recovery phase in 24 patients with stroke. EEG signals at resting state and in time of moving the ankle have been recorded. The higher interhemispheric functional connectivity between M1 in every side of brain in time of moving the ankle is related to a higher motor-related recovery. Functional connectivity in motor-related areas after stroke might be related to the recovery of ability to move the lower limb. The relationship between amplitude envelope correlation (AEC) and Fugl-Myer assessment of the lower limb in resting state and in time of moving the ankle are illustrated in Figs. 8 and 9 respectively.

3.2.2. Depression

Depression is another brain disorder associated with neural deficit symptoms. Researchers used EEG functional connectivity to study the symptoms of the abnormal activity of brain that lead to this disorder. We have an overview on a number of studies related to depression detection through EEG recordings. The objectives, subjects used in these studies and the obtained results according to each study about depression disorder are available in Table 3.

The role of gender has been used in a research by Knott et al. [35] in 2001. The focus of the investigation has been on male depression and comparison of the power, power ratio indices in each hemisphere, coherence and mean frequency in the hemispheres between depressed males and healthy individuals. EEG recordings of resting state in closed eyes state from 70 male individuals with mild depressive disorder (MDD) and 23 normal individuals have been analyzed. The vigilancy of individuals has been controlled during the records. The asymmetry, absolute value, relative power of coherence and frequency measures derived from spectrally processed EEGs have been investigated for extracting discriminative features for classification. The relative and absolute beta power in bilateral anterior regions have been overally greater for patients compared with controls. Furthermore, mean total spectrum frequency has been faster in patients. Reduced left hemisphere activation in alpha power asymmetry index for healthy ones in each hemisphere has been recognized. Also, a reduction of coherence indices has been observed for delta, alpha and beta frequency bands. The power asymmetry has exhibited a decremental trend for theta band in patients at all regions bilaterally. Although, power asymmetry has been restricted unilaterally to the right hemisphere for beta frequency band.

In 2006, brain oscillations and the effects in ongoing EEG in patients with MDD has attracted the attention of the researchers [36]. The resting state EEG recordings of 12 patients have been assessed by the extracted short-term EEG spectral patterns. The results of this research insist on the effects of brain activity in nearly the whole brain regions. Representation of the effects is in the form of reestablishment of the brain oscillations in a frequency range between 0.5 and 30 Hz. The posterior cortex specifies the maximum effect in response to depression. The right hemispheric hyperactivity for MDD patients has been occurred in frontal, parietal and occipital regions of the brain.

Usually, there is an increase in brain functional connectivities of patients with major depression. Cenuet et al. [37] in 2007, used an EEG structural synchrony approach for 12 depressive patients and 10 control subjects. The EEG recordings have been investigated to extract difference in synchronized patterns of depressive and healthy groups. The strength and the number of functional connections in the case of depressive patients are different in the left and right hemispheres. They discovered larger long connections in the right hemisphere and larger short connections in the left one. The severity of depression has a positive correlation with some of the functionally connected activities of the brain. The connections in the left hemisphere, posterior and anterior for the alpha frequency band are in correlation with depression. The short connections in anterior region for the theta band are related with

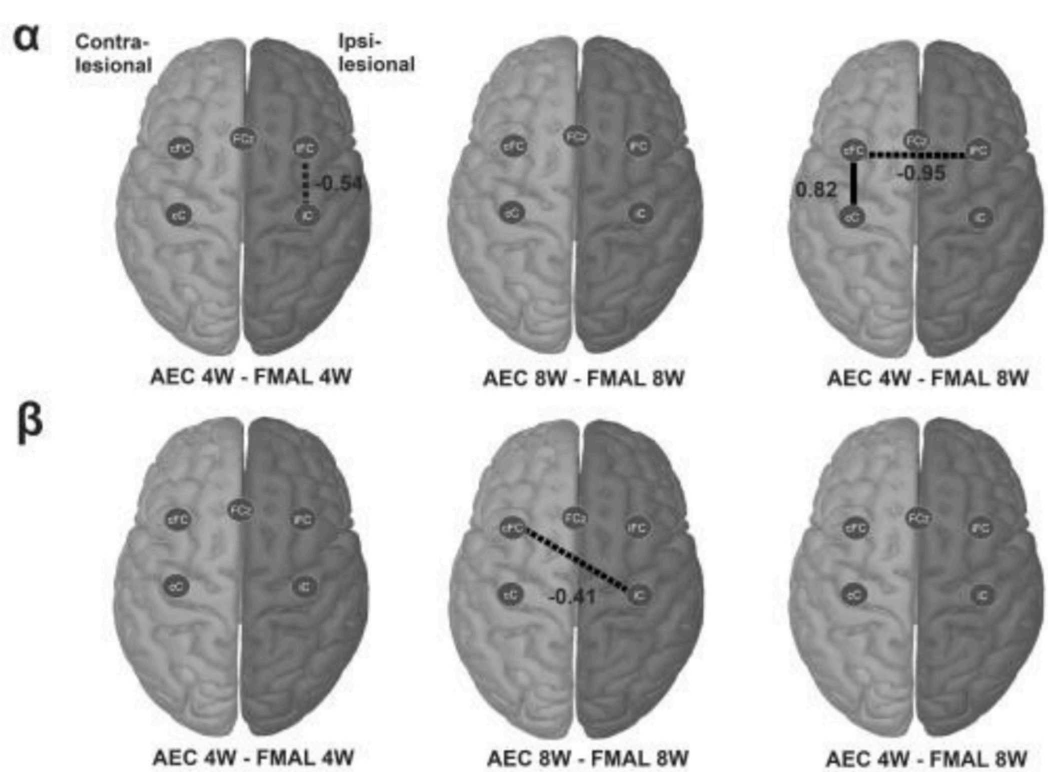

Fig. 8. The relationship between amplitude envelope correlation (AEC) and Fugl-Myer Assessment of the lower limb section (FMAL) in the resting state [33]. Solid lines indicate a positive correlation and dashed lines are for negative ones with a noticeable beta-coefficient between motor function, 4 W, fourth week after stroke onset; 8 W, eighth week after stroke onset.

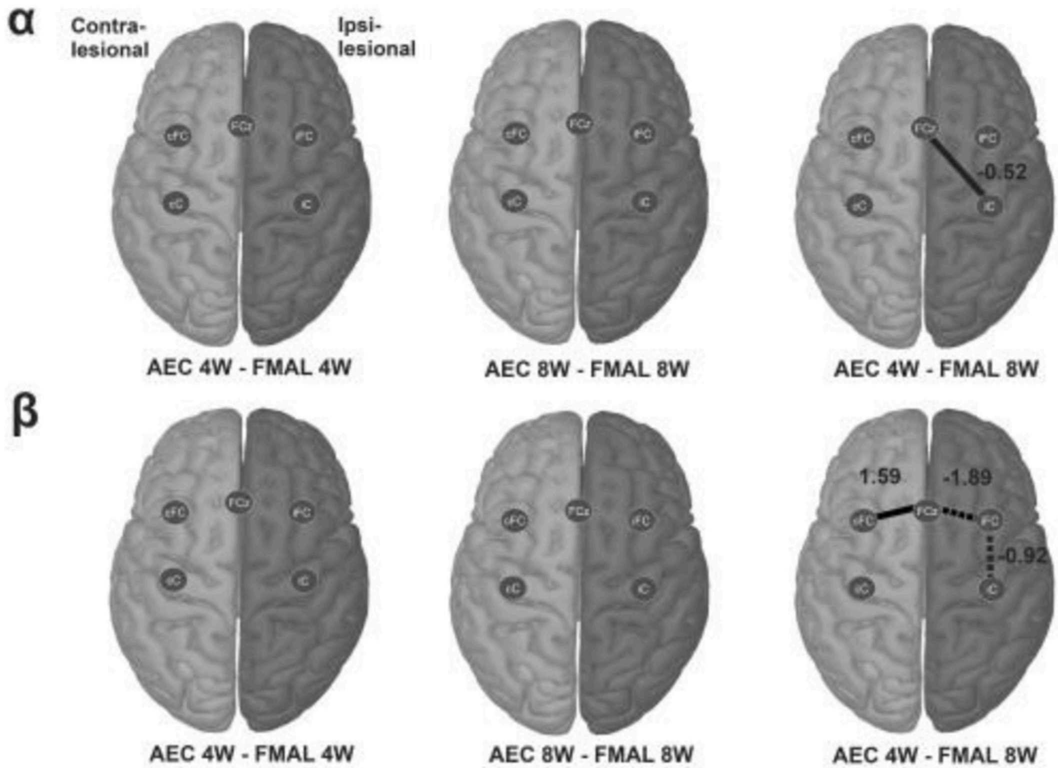

Fig. 9. The relationship between AEC and FMAL during the ankle movement [33]. Solid lines indicate a positive correlation and dashed lines are for negative ones with a noticeable beta-coefficient between motor function. 4 W, fourth week after onset of stroke; 8 W, eighth week after stroke onset.

depression. The representation of brain topomap corresponding to functional connectivities for depressed patients shows that discriminative signs are in the left posterior and the right anterior parts of the brain. The hypothesis about incremental trend for functional connections of depressed patients is observable in the obtained results.

For detecting the EEG-based biomarkers of response to treatment, researchers in 2011 [38] examined the resting state EEG connectivity strengths at 8 weeks after treatment initialization. A number of 108 depressed patients have been considered for EEG recording in resting state. The EEG records in 3 min with a closed-eye state have been studied for detecting the biomarkers of treatment. The power series correlation and coherence have been compared for patients with different states of responding and non-responding to treatment according to the Hamilton Depression Rating Scale. The connectivity strengths in predicting treatment responses have been evaluated though receiver operating characteristic (ROC) and pearson correlation. According to the evaluation, the stronger connectivity strengths, especially in frequency bands of delta and theta for the fronto-temporal network, indicate a poor response to treatment.

When depression is resistant to treatment, one of the therapy methods advised is deep brain stimulation (DBS). To evaluate the brain activity and extract the differences between the subjects who respond to DBS and those not affected by therapy, researchers in 2014 [39] recorded EEG signals of 12 patients after DBS surgery. The number of patients who do not respond to DBS is equal to 6 subjects. Power asymmetry and synchronization in hemispheres for all subjects have been compared. The differences have been represented with these two parameters for theta band in the frontal lobe and the alpha band activity in the parietal lobe. Asymmetries are calculated for healthy subjects and are similar to the parameters for responders and are opposite to others who do not respond to treatment. The characterization of power asymmetry is recognized by an increase in theta frequency band for right hemisphere frontal lobe relative to left frontal lobe in subjects not responding to the treatment. Also, in the case of this asymmetry, an increase has been detected in alpha frequency band for left parietal lobe in comparison to the right lobe. A difference in theta frequency band has been detected with analyzing the synchronization asymmetry. This asymmetry for subjects responding to the treatment was similar to the healthy subjects and opposite to the not responding subjects. Furthermore, the differences have been shown in connectivity patterns in the theta frequency band in frontal and parietal lobes of responders and non-responders.

Recognizing the brain activity differences in depressed and healthy subjects have been done through processing the emotional state in 2015 by Li et al. [40]. Identifying the brain activity in this study has been done through emotional face processing. The graph theory analysis of functional connectivity network has been done to detect the differences in networks of patients with depression and healthy subjects. Number of subjects with depression was 16 and 14 healthy subjects have been considered in the study. The coherency in all frequency bands was determined to calculate the correlation. The characteristic path length in addition to the clustering coefficient have been used to investigate the connectivity graph. In gamma frequency band, the EEG coherence is higher in subjects with depression disorder. In this frequency bands, the coherency for negative emotions for healthy subjects has been higher relative to positive emotions. The functional connectivity network for depressions were random in comparison to the network of healthy ones. This abnormal topology of the network for patients has occurred in occipital and prefrontal lobes. Another important point is that in gamma frequency bands, a negative bias occurs in normal state subjects and this bias disappeared for patients.

Another discriminative metric for diagnosing EEG signals of the depressive disorder patients is the EEG-derived synchronization likelihood (SL) studied in 2017 [41]. This feature performed better than mutual information and coherence. Different classification algorithms have been used in this study using the SL features and classification metrics have been calculated for these algorithms. According to this research, the likelihood of synchronization is a promising metric for

Table 3
Studies related with functional connectivity and depression disorder.

Paper ref	Objective	subjects	Functional connectivity method	Result
[35] 2001	male depression and comparison of traditional power, power ratio indices in each hemisphere, coherence and mean frequency in hemispheres have been done between the depressed males and the healthy individuals	70 male individuals with MDD and 23 normal individuals	Coherence	Decremental trend of theta power asymmetry has been observed in patients bilaterally at all regions and beta power asymmetry has been unilaterally restricted to the right hemisphere.
[36] 2006	brain oscillations and the effects in ongoing EEG in patients with MDD	12 patients	Assymetry analysis	Posterior cortex specifies the maximum effect in response to depression. The right hemispheric hyperactivity has been occurred in frontal, parietal and occipital regions of the brain.
[37] 2007	extracting the difference in synchronized patterns of depressive and healthy groups	12 depressive patients	Structural synchrony index	In alpha frequency band, connections in left hemisphere, posterior and anterior are correlated with depression. In theta band, short connections in anterior region is related with depression. The representation of brain topomap of functional connectivities for depressed patients shows that discriminative parts are the left posterior and the right anterior parts of the brain.
[38] 2011	detecting the EEG-based biomarkers of response to treatment	108 depressed patients; EEG records of 3 min of closed-eyes state	Coherence	The stronger connectivity strength in fronto-temporal network, specially in frequency bands of delta and theta, indicates the poorer treatment response.
[39] 2014	To evaluate the brain activity and extract the differences between the subjects who respond to DBS and those who not affected by therapy.	12 patients after deep brain stimulation (DBS) surgery; subjects who not respond to DBS is equal to 6 subjects	Phase coherence	The characterization of power asymmetry is recognized by an increase in theta frequency band in right hemisphere frontal lobe relative to the left frontal lobe in subjects not responding to treatment; An increase has been detected in alpha frequency band in left parietal lobe in comparison to the right lobe of these subjects.
[40] 2015	differences in depressed and healthy subjects have been done through processing of the emotional state	Number of subjects with depression was 16 and number of healthy ones is 14.	Coherence (cross-correlation between two signals)	The characteristic path length in addition to the clustering coefficient have been used to investigate the connectivity graph. In gamma frequency band, the EEG coherence is higher in subjects with depression disorder. In this frequency bands, the coherency for negative emotions for healthy subjects has been higher relative to positive emotions.
[41] 2017	EEG-derived synchronization likelihood (SL)	Depressed patients	Synchronization likelihood	The likelihood of the synchronization is a promising metric for EEG-based depression disorder detection.
[42] 2019	analyzing the functional connectivity networks of depression and healthy controls is the phase lag index	27 depression disorders and 28 number of healthy subjects	Phase lag index	Brain activity in nearly the whole brain was affected by abnormal condition in depression. The brain oscillation patterns in three frequency bands including delta, theta and beta are more important than the network patterns of the alpha frequency band.
[44] 2020	deep brain stimulation (DBS) for long-lasting depression	25 normal and 26 abnormal subjects	Partial Directed Coherence	Assessing the amygdala as a target for deep brain simulation would be an essential step for depression treatment; The partial Directed Coherence (PDC) for EEG in different brain regions including the amygdala and thalamus have been analyzed.
[43] 2020	diagnosing the depression during music perception	EEG recordings during music perception in diagnosing the depression	Phase lag index	The most discriminative frequency band in diagnosing the depression disorder has been the beta frequency band with the SVM classification method. A decreased connectivities for beta frequency band have been shown for depressed patients.
[45] 2021	Prediction of depression severity scores	60 patients	Phase lag index	In alpha and delta frequency bands, the depression severity score is in positive connection with the complexity measures.
[46] 2021	The connection between the major depressive disorder and the EEG features	30 healthy volunteers and 34 abnormal	Synchronization likelihood	The connection between major depressive disorder and the EEG features including spectral, statistical, functional connectivity, wavelet and nonlinear analysis methods has been represented in the study. The best performance has been achieved via 10-fold cross validation employing the SVM method with the use of RBF kernels.
[47] 2022	An automated EEG-based mild depression disorder (MDD) diagnosis framework.	34 MDD patients and 30 HC subjects	Pearson Correlation	An automated technique for mild depression disorder diagnosis via EEG signals has been proposed based on dictionary learning approaches and functional connectivity features.
[48] 2023	The intrinsic time-scale decomposition method for diagnosing the depression disorder.	the MODMA and EDRA databases	Pearson Correlation	EEG resting-state functional connecitivity analysis is an effective biomarkers for its clinical diagnosis and identification of the depression disorder.

EEG-based depression disorder detection.

Another metric considered for analyzing the functional connectivity networks of depression and healthy controls is the phase lag index. The construction of networks has been done using this metric in the study by Canuet et al., in 2019 [42]. The features with high discriminative power have been identified with the altered Kendall rank correlation coefficient. Classification algorithms have been employed to discriminate the features related to a group of patients and a set of normal subjects. A total number of 27 depression disorders and 28 number of healthy subjects have been studied. The SVM classifier with leave-one-out cross-validation has been employed and the classification accuracy has been reported to be equal to 92% and the area under the convergence curve was 0.98 for the whole frequency bands. According to the findings in this research, brain activity in nearly the whole brain was affected by abnormal conditions of depression. The brain oscillation patterns in three frequency bands including delta, theta and beta have more important discriminative features in comparison to the network patterns of alpha frequency band.

Deep brain stimulation is one of the treatments required for long-lasting depression. The amygdala has been detected as a target for DBS in 2020 [44]. It is an essential step for depression treatment according to this research. The resting state functional connectivity network has been explored for 25 normal and 26 abnormal subjects. The recurrent depressive, depressive and bipolar affective have been explored with calculating the partial directed coherence (PDC) for source EEG in different brain regions including the amygdala and thalamus. The role of amygdala seems important in depression detection.

In another study in 2020 [43], EEG recordings during music perception for diagnosing depression have been considered. The phase lag index has been analyzed in calculating the matrices of the functional connectivity networks. The topology of brain networks has been considered in different frequency bands and classification algorithms have been used according to the features of EEG signals in different frequency bands. The most discriminative frequency band in diagnosing depression disorder has been the beta frequency band with the SVM classification method. A decreased connectivities for beta frequency band have been shown for depressed patients. During music perception, the lateralization phenomenon in the left hemisphere has occurred in healthy cases and this connection has not happened for patients. The functional connectivity patterns have altered during music perception in delta and beta frequency bands. A significant alteration in the case of depressions in beta frequency during music perception has lead to the best classification accuracy via SVM method. The remarkable connections of brain network in delta and beta frequency bands of the healthy group and depression group are illustrated in Figs. 10 and 11.

Prediction of depression severity scores has been considered in 2020 [45] with the use of functional connectivity and intricacy of the EEG signal. The EEG data recordings with closed eyes for 60 patients have been analyzed in this study. Estimating of phase synchronization using the functional connectivity between EEG channels has been done for different frequency bands of brain activity. The functional connectivity has been quantified using graph theory metrics including degree and clustering coefficient (CC). The complexity of EEG recordings has been calculated using the fuzzy entropy and Lemple-Ziv measure. The modeling of the severity prediction with the use of EEG features has been done with linear regression. The depression severity score is affected by graph metrics negatively in alpha frequency band. The score is positively connected with the complexity measures in alpha and delta frequency bands.

The connection between major depressive disorder and the EEG features including spectral, statistical, functional connectivity, wavelet and nonlinear analysis methods has been represented in the study in 2021 [46] using a machine learning framework. The feature selection method used in this study was the sequential backward method. The number of subjects in the study has been 30 healthy volunteers and 34 abnormal ones. The best performance has been achieved via 10-fold cross validation employing the SVM method with the use of RBF kernels.

The features extracted from functional connectivity metrics have been used along with dictionary learning by Movahed et al. [47] in 2022 for depression detection. An automated technique for mild depression disorder diagnosis via EEG signals has been proposed based on dictionary learning approaches and functional connectivity features. A feature space of functional connectivity measures for depressed and normal participants has been constructed in this research and deep neural networks has been applied to classify the extracted features. The proposed technique for MDD diagnosis has employed a public dataset containing

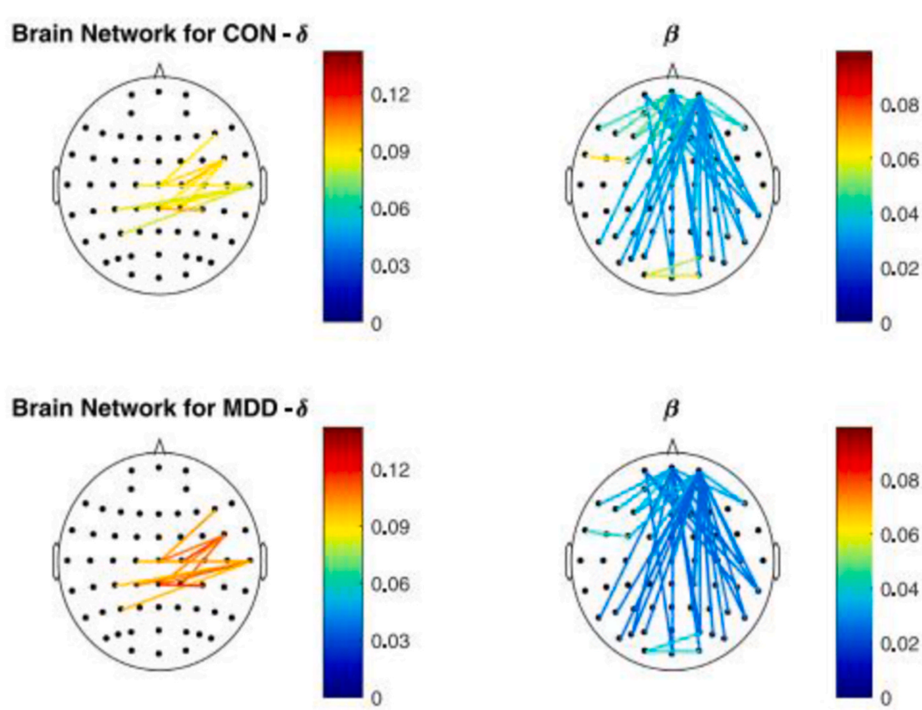

Fig. 10. The brain network connections in δ and β bands of the healthy group and depression group [43]. CON is for control; MDD is for major depression disorder.

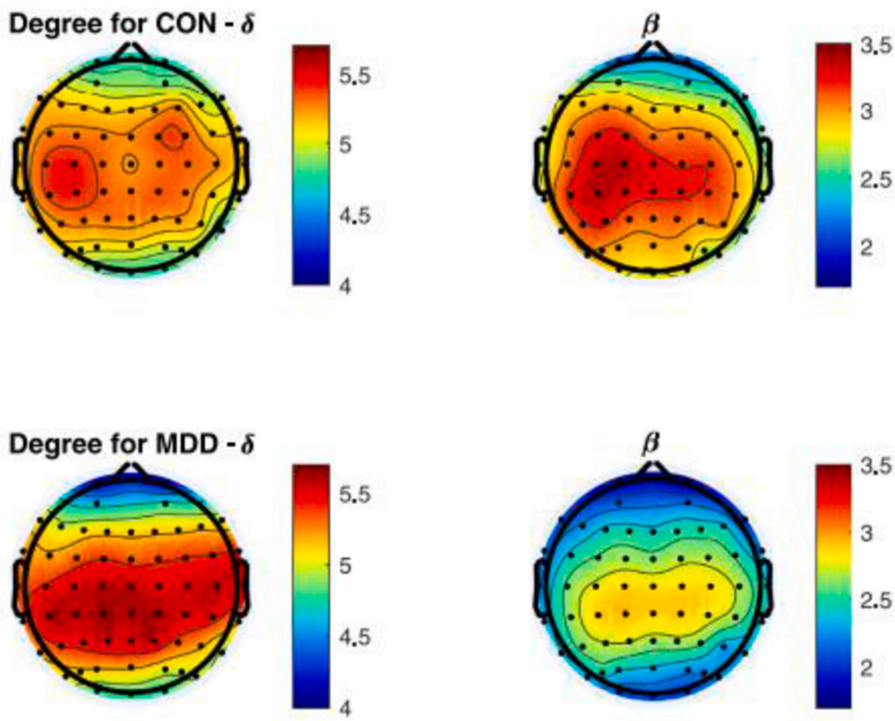

Fig. 11. The degree of each node for the healthy group and depression group in δ and β bands. CON, is for control group; MDD, is for major depression disorder [43].

EEG signals of 34 patients with depressive disorder and 30 normal subjects. The k-fold cross-validation technique has been employed to train the neural network and prevent overfitting. The efficiency of the proposed method has been evaluated with the provided accuracy, sensitivity, specificity and F1-score evaluation metrics.

The intrinsic time-scale decomposition (ITD) method in 2023 [48] has been introduced to mine the time and frequency related information simultaneously, instead of directly constructing the functional connection matrix. The Pearson correlation has been applied to measure the functional connectivity pattern between channel features extracted with ITD. A graph adaptive method based on least absolute shrinkage and selection operator has been proposed in this research to extract particular features of the obtained functional connectivity matrix. The simultaneous processing of discriminative weights corresponding to different features along with the connections between significant features with using the topology of graph nodes and edges has been the positive factor of the proposed method. The effectiveness of this technique for diagnosing the depression has been validated with the MODMA and EDRA databases. The experimental results of this study have elucidated the pathological structure of depression effects in the brain network. Furthermore, it could be inferred that EEG resting-state functional connecitivity analysis is an effective biomarkers for its clinical diagnosis and identification of the depression disorder.

3.2.3. *Application to emotional processing*

Functional connectivity of the EEG recordings has been employed in number of studies related with emotion recognition. We have a brief overview on this concept. In 2010 [49], audio-visual emotional stimulation has been involved in the EEG recordings of 26 healthy subjects to detect 4 different emotional states. The investigation of connectivity between 8 scalp regions has been done in this study calculating the magnitude squared coherence and mutual information. Processing the features extracted from connectivity patterns has been performed with KNN and SVM classification methods.

In another study in 2014 [50], classification of 3 different emotional states of positive, neutral and negative has been studied using the connectivity patterns of EEG recordings for 40 participants in response to representation of video clips. Correlation, phase synchronization and coherence have been calculated according to the connectivity patterns. Detection of the states via the connectivity patterns has been done in this study using the quadratic discriminant analysis. Another application of EEG functional connectivity has been investigated in classification of the effect of different emotional states in patients with Parkinson's disease. Deficits in emotional state recognition have been reported in Patients with Parkinson's disease and will cause problems in social relationships. Brain maps of correlation, coherence and phase synchronization index are illustrated in Figs. 12–14.

Researchers in 2016 [51] investigated the EEG recordings of 20 non-demented Parkinson's patients who had score above 24 in the Mini-Mental State Examination score and 20 Healthy controls to recognize six different emotional states including sadness, happiness, disgust, surprise, anger and fear. Phase Synchronization Index, correlation and coherence are the features related with functional connectivity considered in this study. Also, a new index feature of functional connectivity is proposed in the study using the bispectral analysis. Classification of the index features of functional connectivity patterns has been done using the SVM method. The best accuracy has been reported for the new proposed index feature. Classification performance for patients have been decreased as a result of emotional deficits. Functional disconnections between brain activity lobes have been reported as the result of decreased functional connectivity indices.

Emotion recognition has been reflected by the functional connectivity of EEG recordings in 2016 [52]. Brain network dynamics with high temporal information have been acquired with EEG-based functional connectivity. The resting state EEG recordings of 20 healthy volunteers and 20 number of people with anxiety disorder in response to emotion regulation tasks (ERT) have been recorded. The weighted phase lag index (WPLI) has been used to construct the EEG-based functional network connectomes. Characterizing the specifications of these connectomes has been done by calculating the characteristic path length (CPL) and clustering coefficients (CC). In theta frequency band, the network integration calculated with CPL has increased in response to the

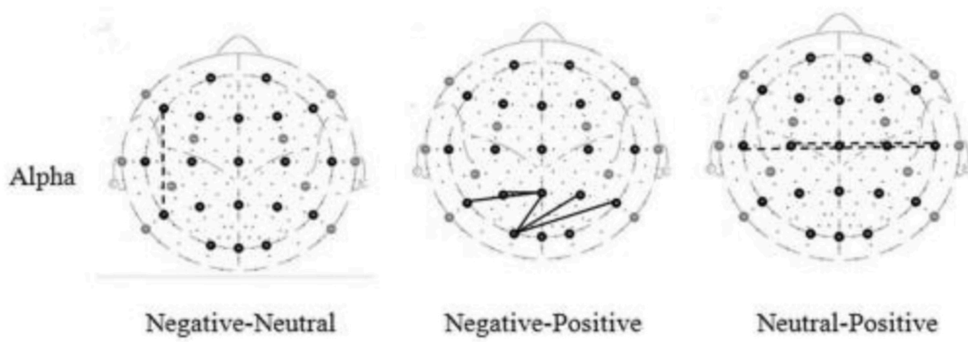

Fig. 12. Correlation brain maps. Solid lines for high correlation and dashed lines for low ones [50].

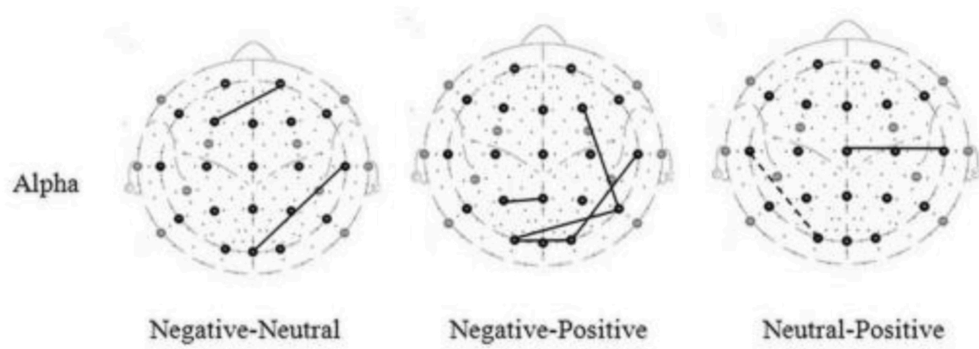

Fig. 13. Coherence Brain maps. Solid lines for high coherence and dashed lines for low ones [50].

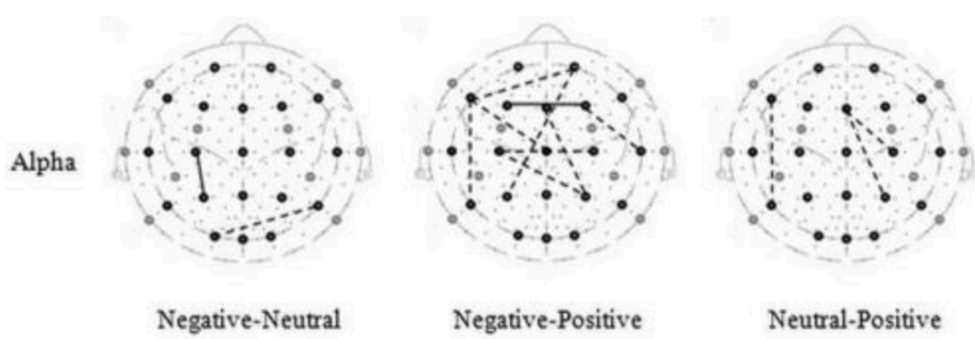

Fig. 14. Phase synchronization index brain maps. Solid lines for high phase synchronization index and dashed lines for low ones [50].

ERT.

Sharghi et al. [53] in 2019 have proposed a Burg autoregressive model to estimate brain activities using the power spectral density. Estimation of the functional connectivity networks has been done with calculating the phase locking value. Patterns according to three different emotional states for all EEG frequency bands have been shown as the result of fusion in brain activities and the connectivity networks. The classification accuracies have been improved as affected by this fusion. The average improvement in the proposed method is 6.84% compared to PSD alone and is 4.1% in comparison to the PLV alone.

In another work by Xun et al., in 2019 [54], different connection networks according to EEG recordings of the SEED emotion dataset have been investigated with analyzing the strength, eigen vector centrality and clustering coefficient of the connectivity networks. The connectivity patterns corresponding to different emotion states have specific coherence in various brain lobes. Also, the frequency bands according to the emotion states are different. For the happy state, higher coherence connectivity in gamma, beta and alpha bands can be seen at frontal lobe. The coherence connectivity for the sad emotion is in delta frequency band at occipital and parietal lobes. For the neutral state of emotion, higher coherence can be seen in delta frequency band at frontal lobe. These connectivity features outperform the traditional power spectral density.

A dominant factor of illustrating the differences in EEG activity in brain regions is the spectral power density. A higher performance have been obtained by fusion of this feature with the phase locking value in functional network on three public EEG emotional datasets in the study by Li et al. [55] in 2019. The fusion method has shown that the common specifications of connectivity patterns and brain activation have been involved in detecting the three different emotional states. The crucial part in making use of human-computer interaction (HCI) in real-world is personality profile recognition. EEG-based recognition of the personality profile will make the HCI applications more real and adaptable.

The study by Klados et al. [56] in 2020 have considered the neurobiology of personality prediction. The resting state EEG would not have valuable data for personality profile identification. EEG recordings provoked emotionally would be useful for this study. The AMIGOS database is a set of emotionally stimulated EEG signals of 37 number of healthy volunteers. 10 number of features of the AMIGOS dataset have been selected and imposed to the support vector machine to classify the EEG samples. The classification accuracies via this method have been reported for 5 number of personality groups including conscientiousness, extraversion, neuroticism, openness and agreeableness.

Another effective method has been proposed by Cao et al. [57] in 2020 for EEG-based emotional signal processing. In this study, the weighted brain connectivity network has been extracted and illustrated with the information flow using the minimum spanning tree algorithm (MST). The limitations of traditional methods of power spectrum analysis have been avoided in an effective way. The DEAP database has been analyzed for classifying 4 groups of emotional states corresponding to high arousal and valence (HAHV), low arousal and valence (LALV), low arousal with high valence (LAHV) and high arousal with low valence (HALV). In this study, the phase lag index (PLI) has been calculated for five different frequency bands. Configurations in low arousal state are line-shaped in comparison to high arousal states of emotion. In high arousal emotion state, the illustration of MST trees for low valence is starshaped in comparison to the trees in high valence emotional state. This trend of MST trees confirms the randomness of functional connectivity network in negative emotional states. Also, it can be deduced that brain activity has increased when faced with negative emotions.

A phase locking and distance-based method have been proposed in in 2023[58]. The matrices of phase locking value corresponding to different frequency bands have been constructed. Three distance metrics including the Frobenius norm, the log-Euclidean and the spectral norm have been considered to calculate three distance matrices of phase locking value. Corresponding to results of this study, the right temporal and anterior lobes of the brain are linked inextricably to emotional state. The best classification accuracy according to the Frobenius norm has been obtained for alpha band between neutral and positive emotional states. The classification accuracy for beta frequency band according to the classification of positive and negative emotional states has been achieved for the log-Euclidean distance. Also, the best recognition between negative and neutral emotional states has been obtained with Frobenius norm metric for delta frequency band.

3.2.4. *Epilepsy*

Another brain abnormality characterized by repeated seizures and sudden changes in brain electrical activity is epilepsy. A number of studies have been dedicated to analyzing this brain disorder using the functional connectivity of the EEG recordings [59]. The objectives, subjects used in these studies and the obtained results according to each study about epilepsy disorder are available in Table 4.

The effect of epilepsy on the small-world networks has been studied by Ponten et al. [60] in 2007. The EEG signals of mesial temporal lobe seizure type have been collected during seizure event. The small-world feature connectivity has been displayed with EEG analysis. The likelihood of synchronization in intra-cerebral EEG recordings has been calculated corresponding to 7 patients for 5 periods of interest including interictal, before, during and after the occurrence of rapid discharges. The graphs have been constructed based on the SL matrix. The clustering coefficient and the shortest path length have been obtained measuring the local connectedness and calculating the overall network integration.

Table 4
Studies related with functional connectivity and epilepsy disorder.

Paper ref	Objective	subjects	method	result
[60] 2007	investigating the EEG signals of mesial temporal lobe seizure type collected in seizure	7 patients for 5 periods of interest including interictal, before, during and after the occurrence of rapid discharges	Synchronization likelihood	An ordered configuration with higher clustering coefficient and higher path length have been observed during the seizure in comparison to the more randomly structured of network during the interictal phase.
[61] 2008	interictal intracerebral EEG records in temporal brain lobe	two groups of patients with different involvement of epileptogenic structures of the brain; 21 drug-resistant epileptic patients	Correlation	A decrease of power spectral density in theta frequency has been recognized in patient group whom EEG start from the mesial temporal lobe.
[62] 2011	pathologic regions of the brain as well as regions without the epileptic discharges	5 patients with epilepsy in temporal lobe of brain	Correlation	tangible effect of epilepsy on coupling alteration in pathological and other regions without epileptic discharges
[63] 2011	epileptic patients without schizophrenia deficit	21 psychotic schizophrenia epileptic patients as well as 21 focal epileptic patients without schizophrenia	Lagged phase synchronization	The lateral and medial part of parietal cortex of brain involved in the default mode network have represented increased oscillations for psychotic patients in the theta frequency band; Positive symptoms of increased connectivity have been reported in tempro-prefrontal region for psychotic schizophrenia patients
[65] 2014	the classification of pediatric volunteers with epilepsy and normal ones	pediatric volunteers with epilepsy and normal ones	Phase distance	The classification of pediatric volunteers with epilepsy and normal ones has been studied. Three sets of topological features have been used and the general linear model has been employed for clustering these two groups
[66] 2016	use of granger causality to see the alterations in EEG epochs without IEDs of epileptic patients	20 number of left temporal lobe epilepsy, 20 number of patients with epilepsy sourced right temporal lobe and 20 number of healthy controls	Granger Causality	Longer duration for disease has been detected in RTLE patients with driving from ipsilateral mediolimbic and contralateral regions; A lower outflow in patients with depression or learning losses from the anterior cingulate cortex has been detected compared to healthy controls.
[68] 2018	measuring the effects of functional connectivity measures on post-surgical prognosis	59 patients with cortical development of epilepsy	Non-linear correlation	The larger alterations of functional connectivity have related with weak post-surgical prognosis and the connectivities have been needed for modeling the spatiotemporal specifications of seizure disease.
[69] 2020	the network of functional connections have been constructed to infer and verify the alterations due to the epilepsy	Number of 6 patients with childhood absence epilepsy	correlation	The enhanced synchronicity during epileptic episodes have been observed and specific spatial changes have been revealed.
[70] 2021	resting state EEG evaluation of Psychogenic Non-Epileptic Seizures (PNES)	20 number of PNES individuals along with 19 healthy	Phase locking index	The pathophysiological mechanisms of PNES could be inferred from the fact that the dysfunctional in interaction across brain areas have been in relation with the intrinsic organization of functional connections

These two parameters have increased during seizure prominently in alpha, theta and delta frequency bands. An ordered configuration with higher clustering coefficient and higher path length have been observed during the seizure in comparison to more randomly structured network during the interictal phase.

In the research by Bettus et al. [61] in 2008, spectral properties have been compared and the connections of interictal intracerebral EEG records in temporal brain lobe have been analyzed for two groups of patients with different involvement of the epileptogenic structures of brain. Interictal EEG of 21 drug-resistant epileptic patients have been compared with healthy group. A healthy control group along with number of patients in whom seizure EEG records do not start from the mesial temporal lobe (non-MTLE), has been considered in the study. A decrease of power spectral density in theta frequency has been recognized in patient group whom EEG start from the mesial temporal lobe. Nonlinear correlation values have been reported in this study are higher in the patient in comparison to the non-MTLE group. According to this study, a decrease of oscillations has been recognized in epileptogenic zone for theta frequency band and an increase has been illustrated in signal interdependencies. The epileptogenic zone according to this research is affected by functional connectivity reinforced to the neuronal network assemblies in the brain.

In another study in 2011 [62], spontaneous oscillations in the blood oxygen level dependent (BOLD) from fMRI recordings of resting state have been studied to recognize whether these fluctuations reflect spontaneous brain activity in pathologic regions of brain as well as regions without epileptic discharges. The EEG signals in this study are intracerebral EEG (iEEG) from 5 patients with epilepsy in temporal lobe of brain. Cross correlation of EEG signals as well as fMRI in resting state have been calculated. The quantification of both brain signal modalities has been done for interictal period for both epileptic and non-epileptic regions. The iEEG functional connectivity has been reported higher in epileptic areas, although opposite trend has been found from the BOLD signal connectivities. This observation illustrates a negative correlation between the two modalities and suggests the tangible effect of epilepsy on coupling alteration in pathological and other regions without epileptic discharges. According to this study, the epileptogenic areas of the brain affect the nonepileptic regions during the interictal period due to the consistency of the indices of directionality from both brain modalities.

Determination of abnormal patterns in EEG signal oscillation in schizophrenia patients with epilepsy has been investigated in the study by Canuet et al. [63] in 2011. The functional connectivity of EEG signals in these patients has been compared with epileptic patients without schizophrenia deficit. Resting state EEG signals of 21 psychotic schizophrenia epileptic patients as well as EEG recordings of 21 focal epileptic patients without schizophrenia have been studied in this research.The functional connectivity and source current density have been analyzed with the use of a software based on eLORETA algorithm. Nonlinear measurement of connectivity named lagged phase synchronization has been used for analyzing the connectivity. The lateral and medial part of parietal cortex involved in the default mode network have represented increased oscillations for psychotic patients for theta frequency band. Positive symptoms of increased connectivity have been reported in tempro-prefrontal region for psychotic schizophrenia patients.

The prediction of seizure upcoming and localization of the seizure onset zone using the functional connectivity of intracranial EEG have been studied in the research by Van Mierlo et al. [64] in 2014. The assessment of the value of the functional connectivity information extraction that is not identifiable visually from EEG data has been the objective of this study. The classification of pediatric subjects with epilepsy and pediatric controls has been studied in the research by Sargolzaei et al. [65] in 2014. In classification procedure, three sets of topological features have been used and the general linear model has been employed for clustering these two groups.

In spite of the fact that discharges of interictal epileptiform (IED) are not observable, seizure onset and behavioral disorders can be seen in patients with epilepsy. The use of granger causality in directed functional connectivity networks has been investigated by Coito et al. [66] in 2016 to see the alterations in EEG epochs without IEDs of epileptic patients. The alterations of connectivity have been compared for patients with epilepsy sourced in right and left temporal lobe and the healthy control subjects. 20 number of left temporal lobe epilepsy, 20 patients with epilepsy sourced right temporal lobe and 20 number of healthy controls have been considered in this study. Source activity for 82 regions of interest has been obtained according to a distributed linear inverse solution and an individual head model. The connectivities in regions of default mode network has decreased in patients.

A tangible network difference can be seen between patients and healthy controls. The ipsilateral hippocampus is the region with strongest connections in patients and the connections in posterior cingulate cortex are the strongest in healthy controls. Longer duration for disease has been detected in right temporal lobe epilepsy (RTLE) patients with EEG signals driving from ipsilateral mediolimbic and contralateral regions. A lower outflow in patients with depression and learning losses from the anterior cingulate cortex have been detected compared to healthy controls and other patients without learning deficits. Reorganization of the resting-state connectivity network without interictal epileptiform discharges reinforces the changes of functional network in temporal lobe epilepsy. Prediction of the epilepsy disorder according to this study can be done using the aforementioned symptoms of changes and alterations that are the biomarkers of temporal lobe epilepsy without observable IEDs.

Benign epilepsy in children using the resting state EEG has been studied in research by Adebimpe et al. [67] in 2016. The exact Low Resolution Electromagnetic Tomography (eLORETA) has been performed for EEG source recognition. Functional connectivities of 84 Brodmann areas in four frequency bands (delta, theta, alpha, and beta) have been analyzed with the use of lagged phase synchronization. The network degree, efficiency and clustering coefficient have been computed. Higher lagged phase synchronization has been reported for patients in theta, alpha and lower beta frequency bands. Less well ordered brain networks with increased global degrees and efficiencies along with decreased clustering coefficients have been obtained for patients. Loss of local functional connections in disparate regions in beta band of patients is the cause of reduced functional segregation and integration. Furthermore, the altered functional reestablishment especially in alpha and beta frequency bands is the reason for functionally disruption of benign epileptic brain networks.

The interictal EEG-based functional connectivity effects on refractory focal epilepsies have been studied by Lagarde et al. [68] in 2018. Number of studies on the interictal or resting state focused on the functional connectivity extracted according to the functional MRI. A few number of studies have considered EEG signals to compute the functional connectivities. The EEG signals of 59 patients with cortical development of epilepsy have been the dataset studied in this research. The directionality of functional connectivity has been analyzed between three zones described with the epileptogenic, the propagation and a non-valid zones. The effects of functional connectivity measures on post-surgical prognosis have been measured and the alterations according to each zone have been considered. Modern network examination methods have revealed primitive aspects of normal brain network structure including small-worldness, modularity, scale-free patterns and hub presence. The reinforcement of connectivity within the zones have happened with a gradual organization. Larger alterations of functional connectivity have related with weak post-surgical prognosis. These connectivities have been needed for modeling the spatiotemporal specifications of seizure disease.

A number of 6 patients with childhood absence epilepsy have been studied in another research [69] in 2020. The patients are pediatrics and the network of functional connections has been constructed to infer and verify the alterations due to the epilepsy. The enhanced synchronicity during epileptic episodes have been indicated and specific spatial changes have been revealed in brain electrical activity. According to this study, clinicians have been provided with detailed insights into the activity of a pathologically damaged brain using functional connectivity measures. Hence, diagnosis and treatment of various neurologic diseases would have been realized.

The evaluation of resting EEG corresponding to the psychogenic nonepileptic seizures has been done by Varone et al. [70] in 2021. The power spectrum density (PSD), functional connectivity metrics including the phase lag index and graph driven measures have been utilized in order to assess and analyze the information distributed in different brain areas. 20 number of unhealthy individuals along with 19 healthy controls have been studied to evaluate the functional connectivity features with multi-layer perceptron (MLP), linear discriminant analysis (LDA) and SVM algorithms. The pathophysiological mechanisms in patients with psychogenic seizure disorder could be inferred from the fact that dysfunctional levels have been in relation with the intrinsic organization of functional brain networks. According the results achieved by this research, promising method to classify the resting state EEG data from PNES healthy subjects is the integration of functional connectivity features with MLP.

3.2.5. ADHD

A difficulty in hyperactivity and attentional maintenance is named attention deficit hyperactivity disorder and since 1980, ADHD has been analyzed using the EEG signals by considering the changes in either each of EEG channels or between different channels of recorded neural activity.

The spectral power and coherency techniques of brain functional connectivity have been studied for 42 ADHD patients and 21 healthy children with ages between 10 and 13 years old [71]. The coherence for ADHD group in lower alpha frequency band has increased and in upper alpha frequency band, a decrease in coherency has been observable. For control group, the coherence has increased in frequency range of 2 Hz–6 Hz independent of representing the stimulation. The EEG recordings in response to visual stimulation has been analyzed and elevation of coherency in frontal cortex has been deduced. Furthermore, the evoked potential power has decreased in this area for the ADHD group. A static state of deficient connectivity for ADHD patients can be seen according to the findings in this research. Also, the overconnectivity state in response to stimulus has been occurred within and between frontal hemispheres. An abnormal function of dorsal anterior cingulate cortex (dACC) would result in ADHD according to brain signal analysis.

The objective of another research in 2009 [72] has been to highlight the recent advances in characterization of ADHD appearing as the result of endophenotypic EEG characteristics. Addressing the complex heterogeneity of ADHD would be realizable considering endophenotypic fractionation of pathophysiology models focusing on intrinsic activity of the brain, induced variabilities of subject and reward response related brain fluctuations.

The nonlinear synchronization of EEG-based functional connectivity of children with ADHD has been the aim of another study in 2010 [73]. The EEG signals of 12 male gender with ADHD and 11 male individuals have been recorded. A nonlinear index of generalized synchronization between the amplitudes of signals has been assessed to analyze the interhemispheric cortical connectivities. The increased interhemispheric nonlinear synchronization has been dedicated to ADHD children. EEG-based diagnosis of ADHD children would be realized according to this research through nonlinear EEG interhemispheric synchronization measures.

A wavelet synchronization method for EEG-based functional connectivity has been introduced by Ahmadlou et al. [74] in 2010 for diagnosis of ADHD patients. Detection of synchronized regions and discriminative regions in patients with attention deficit have been focused in this research. The EEG data of 47 ADHD and 7 healthy individuals in closed-eye state has been recorded and analyzed with radial basis function-based neural network. ADHD detection has been realized in this research with this wavelet-based synchronization features and a good classification accuracy has been reported through the designed neural network.

The connection between the frontal cortex and visual cortex in ADHDs has been investigated in research by Mazaheri et al. [75] in 2010. The EEG recordings of 14 ADHD and 11 normal children aged between 8 and 12 years have been analyzed. A cross-modal attention task has been designed and represented to subjects whereas a cue signal has been illustrated to them which encompasses the information of modality in next target. The power spectra in theta and alpha bands have been calculated in 1 s after the representation of cue signal and also before the illustration of target to subjects. The aim of this calculation is to distinguish different targets of interest. The accuracy of targets with correct cues and the speed of response are more better than other targets with incorrect cue signals for example auditory related targets with preceding cues of visual related ones. Furthermore, the speed to response in typical subjects has been faster and independent of correctness in cue signals.

Overally, the advantage of the correct cues is definite about both the ADHD and typical group for the quality of the response. The activity in alpha frequency band has been affected by the attentional cues in typical subjects. Also, the activity in theta frequency band has a reverse relation/anticorrelation with the brain activity in midfrontal lobe. These correlations and affections by attentional cues have not been observed in these brain regions of ADHDs. This evidence confirms the top-down attention control deficiencies in ADHD children. According to the results of this study, the functional connectivity has been removed between the occipital cortex and the frontal cortex of ADHD children.

The study by Ahmadlou et al. [76] in 2012 presented a new methodology for investigating the organization of hemispheric network activity in ADHD patients with the use of a weighted graph to discover the topology of brain in them. The nonlinear fuzzy synchronization likelihood (FSL) has been used in this study to extract the brain topology. The small-world of network of normal cortex indicates a correspondence of the characteristics of global and local structures. This normal network could compromise between the integration and decomposition of information essential for fast message delivery in a complex synaptic network in brain. The existence of dense clustering connections and short path lengths among the network units in a network are the essentials of small-world networks. Analyzing dense clustering connections represents divergence of local functional left hemisphere network for ADHD and normal cases in delta frequency band. The short path length indicates difference between the global functional network in left hemisphere for patients and normal ones in delta frequency band. The network structures in left hemisphere are distinguishable for ADHD and normal subjects considering these two parameters.

The brain connectivities by analyzing the EEG recordings in different resting states of young ADHD subjects have been studied by Alba et al. [77]. The EEG signals have been recorded from 16 cortical regions at resting states with closed eyes and opened eyes from 10 male ADHD patients and 12 healthy subjects. The mean measure of global connectivity for each brain region and the temporal variability of connectivity have been calculated with EEG recordings in both open and closed eye states. The magnitude squared coherency in different frequency bands and nonlinear index of generalized synchronization have been extracted. Any difference between ADHD and healthy controls could not be deduced through the mean measure of global connectivity in every state. Temporal variability has shown differences corresponding to both states in two groups of patients and normal subjects. It is greater for ADHD patients than the other group in parieto-occipital and frontal regions. In order to discriminate ADHD from healthy ones, temporal variability of the nonlinear index of generalized synchronization seems to be the best measurement independent of eye state and temporal variability of coherency is a measure dependent to eye state. Temporal variability of the coherency increased from closed-eye to open eye state in ADHDs and this measure is greater in comparison to the healthy controls.

The markers of persistence and remission of ADHD in event related potential (ERP) signals have been focused by Michelini et al. [78] in 2019. This study considered 87 ADHD persisters and 23 remitters of ADHD among young adults as well as 169 typical individuals. The EEG signals have been recorded during an arrow-flanker task. The graph theory metrics of functional connectivity-based networks have been quantified before the target onset and during the processing of target. Also, these metrics have been computed in degree of change between these two phases of pre and post stages of the stimulus representation. ADHD outcome has been examined with symptoms reported from parents utilizing the dimensional and categorical approaches. The metrics represent an incremental connectivity in persisters of ADHD in pre-stimulus stage in theta, alpha and beta frequency ranges. Furthermore, the incremental connectivity trend has been observed in persisters after the stimulation. The change in connectivity of theta frequency band has reduced in both stages. The majority of connectivity metrics differed between the ADHD remitters and healthy controls but not with ADHD persisters. The connectivity measures have been unrelated to continuous measures of ADHD symptoms in participants with childhood ADHD. Abnormal hyper-connectivity has been reported in adolescents as well as young adults with persistent along with remitted ADHD. The capability of modulation in brain functional connectivity patterns in the case of task demands has reduced in comparison to healthy controls. According to the results of this research, task-based functional connectivity impairments according to childhood ADHD without considering the adulthood ADHD diagnosis would cause enduring deficiencies.

Topographic maps according to the scalp distribution of imaginary part of coherence (iCoh) in theta, alpha and beta frequency ranges are illustrated in Fig. 15. The EEG records before presenting the stimulation for trials with correct responses have been considered for topomap representation corresponding to three groups of ADHD persisters, remitters and controls.

An EEG-based construction method for brain network has been proposed in another research in 2019 [79] by convolutional neural network (CNN). A deep network approach of connectivity matrix formation has been proposed in order to adapt the process to the concept of convolution operation in CNNs along with applying the reorganization of the channel orders. The correlations have been calculated between the features derived from deep CNN layers and 13 manually extracted measures of the brain network. The EEG data of 50 children with ADHD and 51 healthy controls have been considered through this research. The mutual information (MI) has been utilized to quantify the connection and synchronization between channels. The proposed method has achieved a compelling performance considering the accuracy of 94.67% on test data to classify ADHD and healthy subjects.

The objective of research by Kiski et al. [80] in 2020 is about alterations of functional connectivity in adult ADHD and its relation to the heritable properties of ADHD. The EEG signals from 38 ADHD adults, 45 first-degree ADHD relatives of them and 51 normal people has been recorded to investigate the objectives of this research. The weighted lag index connectivity metric for all frequency bands has been computed and linear regression has been utilized to ADHD symptoms prediction. Also, the examination of EEG functional connections has been done for classification of the subjects into three different groups of ADHD, first-degree ADHD relatives and healthy group. The symptoms of hyperactivity have been predicted by EEG connectivity with open eye state in three bands of delta, beta and gamma bands. The symptoms of attention deficit has been predicted in open eye state in delta, alpha and gamma frequency bands and in closed eyes state in delta and gamma frequency bands. According to this study, the representation of neuromarkers for ADHD can be explained with the EEG functional connectivity.

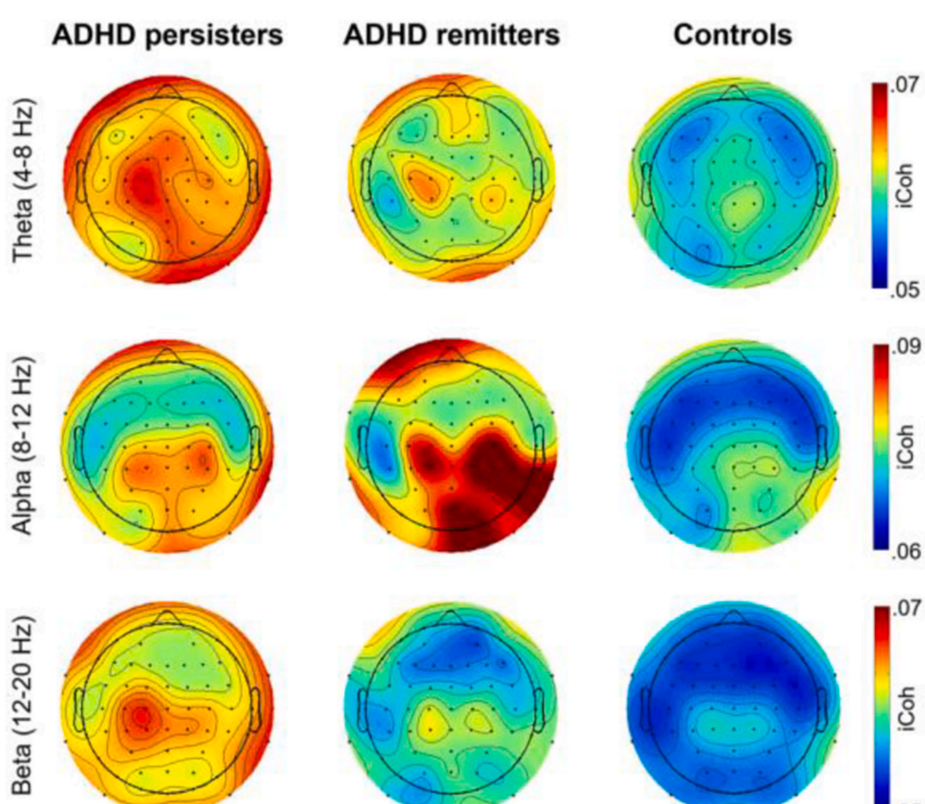

Fig. 15. Topomaps illustrating the imaginary part of coherence (iCoh) before the stimulation for different frequency bands according to trials with correct responses of persisters, remitters, and healthy subjects [78].

3.2.6. Autism

Recently, functional connectivity differences between sexes in infants have been considered by O'Reilly et al. [81] in order to analyze the relation between autism and EEG connectivity. The International Infant EEG Platform (EEG-IP) dataset studied in this research consists of EEG records from two independent siblings to identify neural developments in the early years of life. EEG records have been accumulated at ages of 6, 12 and 18 months for 97 number of infants and 98 number of infants with an older sibling with diagnosed autism and high risk of familial autism. The functional connectivity has been calculated using the imaginary part of phase-lock value corresponding to EEG signals in response to watching a video stimuli. Different regional specificity for male and female infants have been revealed among the results. Autism Diagnostic Observation Schedule (ADOS) scores have been considered and compared with functional connectivity measures. The results shows negative correlation between the scores and connectivity measures. This negative correlation has been deduced at 12 months males for some behaviors with repetition and restriction. The results insist on the effect of EEG signals of male and female infants with autism disorder on the brain functional connectivity of each sex. A symptom of later restrictions in behaviors and autism disorder has been studied by Haartsen et al. [82] in 2019. The EEG signals in 14 months after birth have been recorded and the incremental trend of EEG connectivity in alpha frequency band have been acquired as the symptom of autism disorder. The EEG records of 143 infants during displaying videos of singing women and spinner toys and the corresponding functional connectivity in alpha frequency band between 7 and 8 Hz have been computed based on phase lag index metric. Furthermore, the ASD symptoms have been investigated in EEG signals of 36-months-old infants as well as brain signals of 20 infants with low familial risk of ASD, 47 infants with high familial risk of ASD with typical development, 21 with atypical development. The important result of this study is the relation between functional connectivity in 14-months-old infants and intensity of restriction and repetitions in behaviours of 36-months-old infants with autism disorder. The higher intensity of disorder have been observed as the result of significant increase in functional connectivity. The proposed method in this research could be considered the first predictor of later autism disorder symptoms based on EEG functional connectivity in 14 months old infants.

Deficiencies in social communication, speaking and behavioral interests are symptoms of autism disorder. Transcranial direct current stimulation (tDCS) have shown valuable signs of therapy for autism. The effects of tDCS on brain activity have been studied by Zhou et al. [83] in 2020. EEG recordings of 5 min resting state before and after a single session of stimulation by tDCS. The specifications of temporal EEG networks during the stimulation have been considered and the alterations in flexibility have been compared. Also, non-negative matrix factorization (NMF) has been applied to identify frequency-related network changes. Analyzing the flexibility shows an increasing trend following the stimulation of tDCS. The connectivity in alpha band of interhemispheric regions have increased after tDCS. The dynamics of local and global networks of brain activity could be modified with tDCS and reconfiguration of networks could be highlighted following the stimulation for treatment of autism brain deficiency. The subnetworks obtained from NMF show frequency and region-specific interaction. The interactions in these subnetworks are illustrated in Fig. 16.

A number of 12 autism disorder children and 12 non-ASD children have been studied in a research by Alotaibi et al. [84] in 2021. The functional connectivity networks have been constructed with phase lock values. The cubic SVM classification algorithm has been applied to the features extracted from graphs and functional connectivity-based classification algorithm has been presented in this research for classifying ASD from typical children.

3.2.7. Alzheimer's disease

Automatic diagnosis of Alzheimer's disorder and schizophrenia

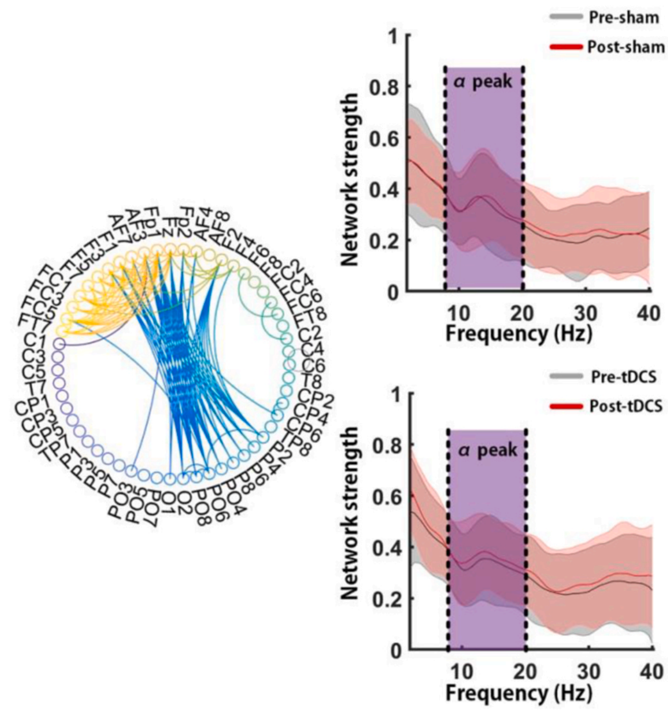

Fig. 16. Subnetwork obtained from non-negative matrix factorization (NMF) illustrates frequency and region-related interaction [83]. Left panel shows topological graph structure. The prestimulation is shown with gray spectrum. The post-stimulation in response to tDCS is shown with red spectrum. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

disease has been studied in a research by Alves et al. [85] in 2022. The proposed method in this research has been presented with a matrix of EEG functional connectivity and deep network. The connection matrices have been calculated based on the Pearson correlation coefficient for an individual with diagnosed Alzheimer's disease as well as a healthy control individual. The example of this connection metric is illustrated in Fig. 17. An example of matrices of connectivity calculated with Granger causality for a patient with diagnosed schizophrenia and healthy individual is illustrated in Fig. 18.

The EEG investigation of patients with early Alzheimer's disease have been studied in another study by Briels et al. [86] in 2020. The case studies have undergone a treatment of using a glutaminylcyclase inhibitor and other group have received a placebo. Number of inhibitor receivers is 47 and the number of placebo received patients is 56. A sensitive measure of EEG-based functional connectivity named amplitude envelope correlation with leakage correction and the phase lag index has been compared in multiple bands of frequency between two groups of treatment and placebo. An increase in the new defined correlation measure in alpha frequency band has been found in PQ912 treatment in comparison to receiving placebo. According to this research, amplitude envelope correlation would be a significant and efficient factor for Alzheimer treatment assessment.

In another research in 2020 [87], the reproducibility of EEG driven functional connectivity in Alzheimer's disorder has been studied. 21-channel EEG records of patients with Alzheimer and subjective cognitive decline (SCD) in closed eye state have been investigated in this study. The coherence, amplitude envelope correlation, PLV, PLI and imaginary coherence have been estimated for five frequency bands. These metrics have been calculated with respect to different phase and grades of Alzheimer disease including amyloid, tau and neurodegeneration. Reproducibility of amplitude envelope correlation has been observed in alpha and beta frequency bands. Also, reproducible effects of PLI have been confirmed for theta band. Only the effects of the

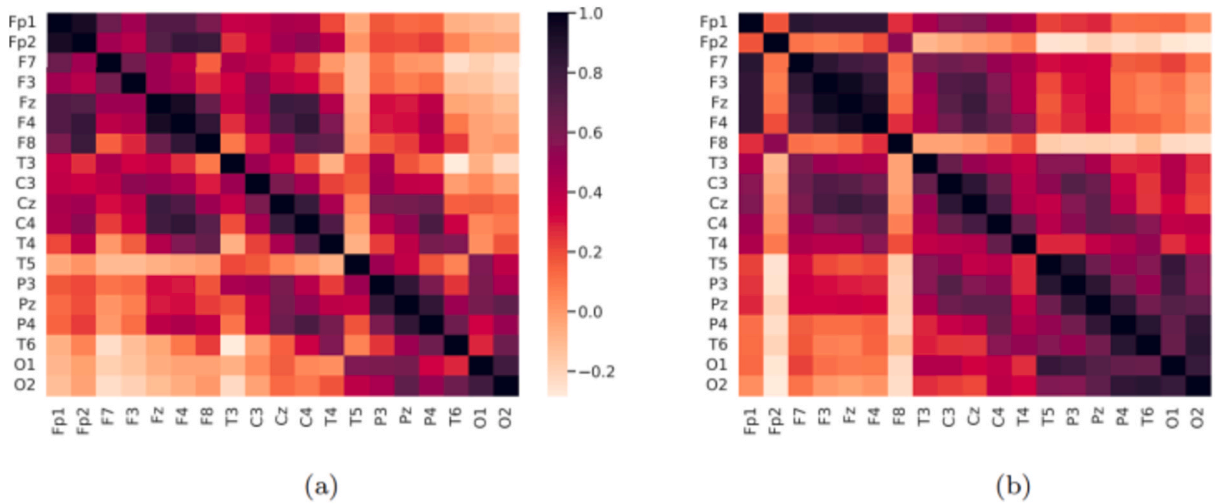

Fig. 17. Connection matrices computed with Pearson correlation for (a) a patient with diagnosed Alzheimer's Disorder and (b) a normal subject [85].

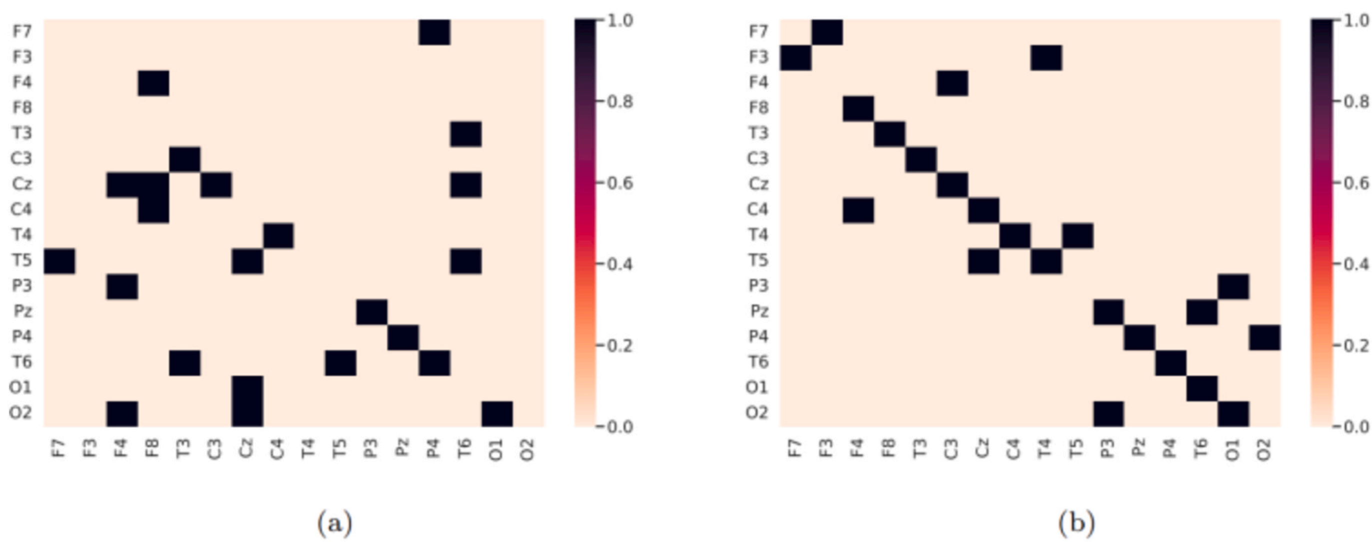

Fig. 18. Connection matrices computed with Granger causality for (a) a patient with diagnosed Schizophrenia and (b) a normal subject [85].

amplitude envelope correlation have remained noticeable for relative power of the determined frequency band. Furthermore, the aforementioned measure of connectivity in alpha frequency band have correlated with disease severity represented by mini-mental state exam score of subjects with Alzheimer disorder. This study have illustrated that the choice of frequency band and corresponding functional connectivity measure prominently affect the obtained results from EEG studies of Alzheimer disorder. According to this research, the amplitude envelope correlation as well as phase-related metrics are reproducible in beta band and theta frequency range, respectively.

The impact of cortical glucose metabolism on mild cognitive impairment and alzheimer disease diagnosed patients has been studied in a research by Smailovic et al. [88] in 2020. The EEG-based connectivity from cotical sources along with the standardized low-resolution electromagnetic tomography (sLORETA) analysis have been estimated. Hypometabolism of the glucose in temporal and parietal lobes has associated with the functional connectivity in MCI and patients with Alzheimer's disorder. The pattern of connection between the connectivity disruption in these lobes as detected by sLORETA algorithm comprised of different patterns in slow and fast frequencies. The instantaneous connectivity has decreased in fast frequencies and the lagged connectivity has increased in slow frequency oscillations. Regional function abruption has been detected by topographicaly measured EEG functional connectivity and has been associated with cortical glucose hypometabolism in AD and MCI patients.

Computational modeling of the effects corresponding to the EEG volume conduction on functional connectivity measurements related to AD patients has been analyzed in research by Roiz Gomez et al. [89] in 2019. The imaginary part of coherence, magnitude squared coherence, amplitude envelope correlation, phase locking value, lagged coherence, phase lag index and synchronization likelihood have been calculated with synthetic signals and a database of resting-state EEG signal recordings. Synthetic signals have been constructed from a Kuramoto-based model of interacted oscillators. The considered database consists of 51 healthy ones, 51 MCI subjects, 51 cases with mild AD, 50 moderate and 50 severe AD ones. The effect of simulated volume conduction model on the PLI measure was the least significant. The spontaneous brain activity in MCIs is affected by incremental trend of coupling in theta frequency range. As dementia develops in a patient, increasing of this coupling in theta frequency band has accelerated. Although, this coupling has decreased in the alpha frequency band. This study has insisted on the advantage of PLI against other metrics considering the most negligible impact of volume conduction and can detect the brain activity dynamics in different stages of dementia and

AD.

3.2.8. *Other brain abnormalities*

Table 5 describes the other abnormalities as in Fig. 19 analyzed with the use of EEG-based brain functional connectivity. According to this table, meditation, diabetes, obsessive-compulsive disorder (OCD), tinnitus, psychotic, West syndrome infants, hypnosis and hand somatosensory network have been studied to be assessed via EEG functional connectivity.

A reduction in coherence functional connectivity metric have been obtained during meditation in all frequency bands in comparison to the rest and none-task state [90]. The graph properties of the functional connectivity network extracted with synchronization likelihood metric for OCD patients have been studied [91] in 2019. The connectivity assessments in alpha and beta frequency bands have shown impaired small world features and a reduction have been observed for alpha rhythm in the bilateral posterior areas in patients with OCD abnormality compared to the healthy subjects. The functional connectivity in beta frequency band has increased by the opened eye state [91]. Lagged coherence has decreased in frontal brain areas for OCD cases in beta frequency band compared with healthy subjects. A decremental trend of connectivity in frontal phase synchronization of theta and beta frequency bands has been yielded for high vigilance stages [92]. There is no significant variations in phase lage index-related connectivity metric between OCD and the healthy ones. A reduction in functional connectivity of coherence metric have been obtained for OCD in comparison to normal controls in delta frequency band [93].

Fig. 19. Other brain abnormalities with EEG-based functional connectivity analysis.

Table 5
Studies related to other brain abnormalities analyzed via EEG-based functional connectivity.

Paper ref	disorder	year	subjects	objective	Method	signal
[90]	Meditation	2012	71 men	Connectivity patterns for 5 meditation groups	Lagged coherence	19-channel EEG
[63]	Psychotic disorder	2011	21 patients with focal epilepsy and SLPE and 21 clinically-matched non-psychotic epilepsy controls	determining the abnormal patterns of functional connectivity in patients with schizophrenia-like psychosis of epilepsy (SLPE)	Lagged phase synchronization	19-channel EEG
[94]	Psychotic disorder	2021	-	the effect of dopamine dysregulation on brain functional connectivity in psychotic disorders, specifically through the modulation of antipsychotic medication	-	-
[95]	Hand somatosensory network	2013	6 healthy volunteers	Investigating the functional connectivity network related to communication within the primary somatosensory.	Partial Directed Coherence (PDC)	32 -channel EEG
[92]	OCD	2013	30 OCD- 30 healthy controls	Altered neuronal communication within frontal brain areas during rest in OCD	Lagged coherence	40-channel
EEG						
[96]	Hypnosis	2014	12 low susceptible and 11 low susceptible participants	Alterations in the network organization in theta and beta frequency	Coherence and Imaginary part of coherence	28 -channel EEG
[91]	OCD	2019	28 OCD- 28 healthy controls	Alteres functional connectivity of Alpha rhythm	Synchronization likelihood and graph theory	64-channel EEG
[97]	Tinnitus	2019	8 subjects with tinnitus- 8 healthy subjects	distinguish tinnitus individuals from healthy controls	Weighted Phase Lag Index (WPLI)	64-channel EEG
[98]	Diabetes mellitus	2022	30 MCI and 30 healthy	Identification of Mild cognitive impairment	Phased Lag index	64-cgannel EEG
[99]	West syndrome infants	2022	15 children	Scalp EEG functional brain network in pre-seizure, seizure, and post-seizure states	Correlation, Time Frequency Cross Mutual Information, Coherence, Phase Lag Index, Phase-Locking Value, Weighted Phase Lag Index	19 -channel EEG
[93]	OCD	2023	25 OCD- 27 healthy controls	Delta and that oscillatory patterns	Coherence, Weighted phase lag index (WPLI)	64-channel EEG

4. Discussion

In order to have a comparison between the preprocessing stage of network constuction and the network patterns according to brain abnormalities, we discuss around the results in the above-mentioned studies. The preprocessing stage in these studies includes rereferencing the EEG recordings, artifact removal and noise reduction. As illustrated in Fig. 20, graph properties would be discussed corrsponding to different brain abnormalities. Furthermore, we present a brief overview on EEG-based functional connectivity analysis in clinical treatment of the abnormalities.

4.1. Comparison of connectivity metrics and network properties in brain abnormalities

The EEG-based functional connectivity network of stroke abnormality has been constructed using the spectral coherence metric in [28]. The network analysis of ankel movement in pre-exam stage and during the exam intervals have been accomplished using the degree value of each vertice. The global and local efficiencies have been calculated using the obtained networks and the comparison plots for healthy and abnormals are illustrated in Fig. 21.

The left ones are for global efficiency parameter and the right ones are for local efficiency. The red bars indicate the efficiencies for the stroke patients and the blue ones are for healthy controls. These parameters are smaller for stroke patients as illustrated in this figure. The obtained Z-scores of the degree distributions for the stroke and control subjects in the frequency bands of Beta and Gamma bands in the patient's network indicate many nodes with a lower degree and few nodes with a higher degree than control subjects. The number of disconnected nodes is higher in comparison to the healthy ones.

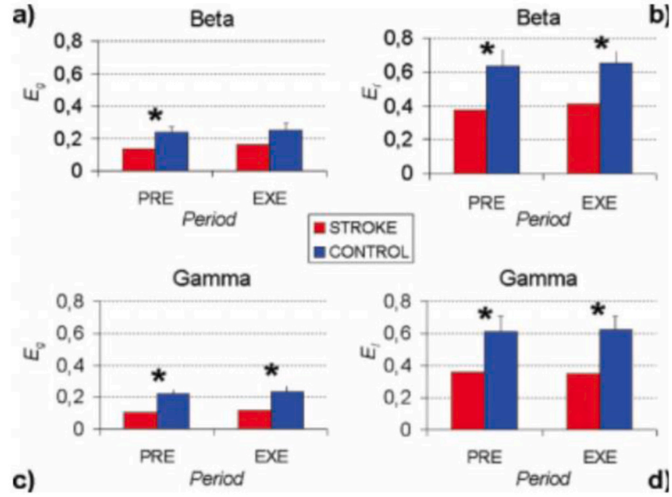

Fig. 21. Global and local efficiencies in pre ankle movement and during the process are shown to compare the healthy subjects with stroke patients [28].

The connection patterns in the aspect of partial directed coherence for stroke abnormality analysis in [31] can be seen in Fig. 22. All channels in [31] were rereferenced to bilateral mastoid, and band pass filtered at 1–45 Hz. The left one in Fig. 22 is the figure for causal interactions with significant causality for healthy controls and the right

Fig. 20. The graph properties discussed for different abnormalities.

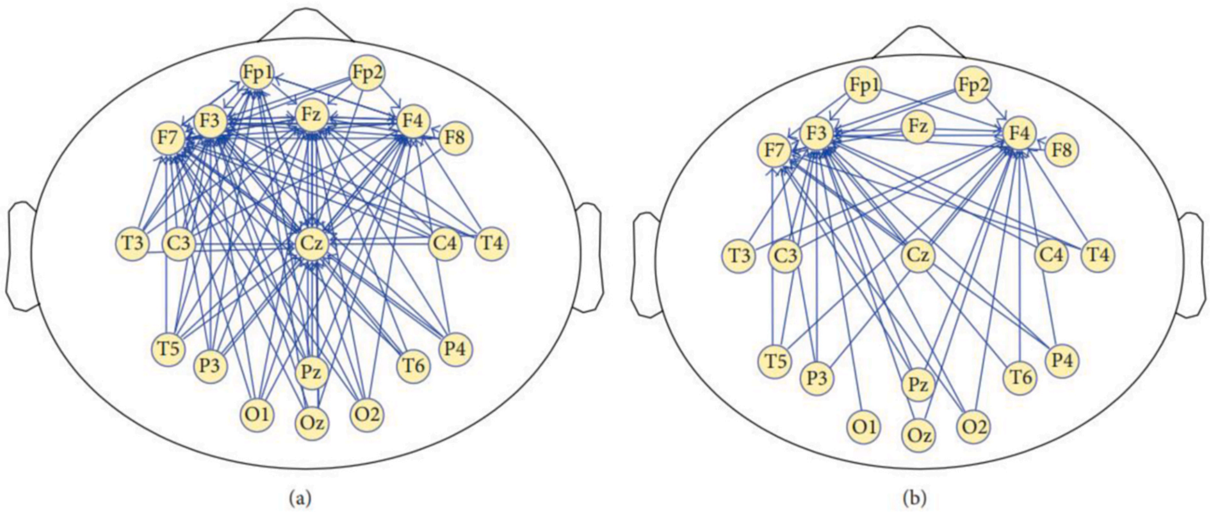

Fig. 22. The connection patterns for healthy subjects and stroke patients [31].

one is the connections and interactions for stroke patients. The difference is tangible and a decrease can be seen for stroke patients in number of connections between frontal and temporal, frontal and occipital, frontal and central, and also between the right and left hemisphere regions.

The connectivities for depression abnormality in the aspect of time-based amplitude envelope correlation have been analyzed in [33]. The reference electrode in this study has been considered a linked earlobe electrode. The eye blinks and heartbeat-related artifacts were removed respectively by visual identification and electrocardiogram signals. The Fugl-Myer Assessment of the lower limb section scores have been investigated to extract the correlation with the functional connectivity (AEC) metric and the obtained results are illustrated in Figs. 7 and 8. The regression coefficients between AEC and the FMAL have been assessed in different frequency bands of alpha, beta, low beta and high beta. The positive regression coefficient have been obtained for AEC calculated in four weeks after the stroke recovery and the FMAL calculated in 8th week of recovery stage. In the resting state, connection between the contralateral lesion with ipsilateral frontocentral regions in alpha band is negatively correlated with the ankle movement score and this also happens in high beta band. A positive correlation have been observed for the connection between the FC and the ipsilateral (iC) region in eight weeks after stroke recovery and the functional connectivity in 4th weeks after the recovery. These two sets of connections can be a predictive sign of stroke recovery. This study used EEG-based functional connectivity to predict the lower limb function in patients after stroke recovery and is one of the applications of assessing the functional connectivity.

The structural synchrony index (ISS) has been evaluated for depressed patients and the healthy controls for each of the nine categories of connections in each hemisphere in another study [37]. The international 10/20 extended system has been used in recording procedure and the reference electrode has been considered the nose

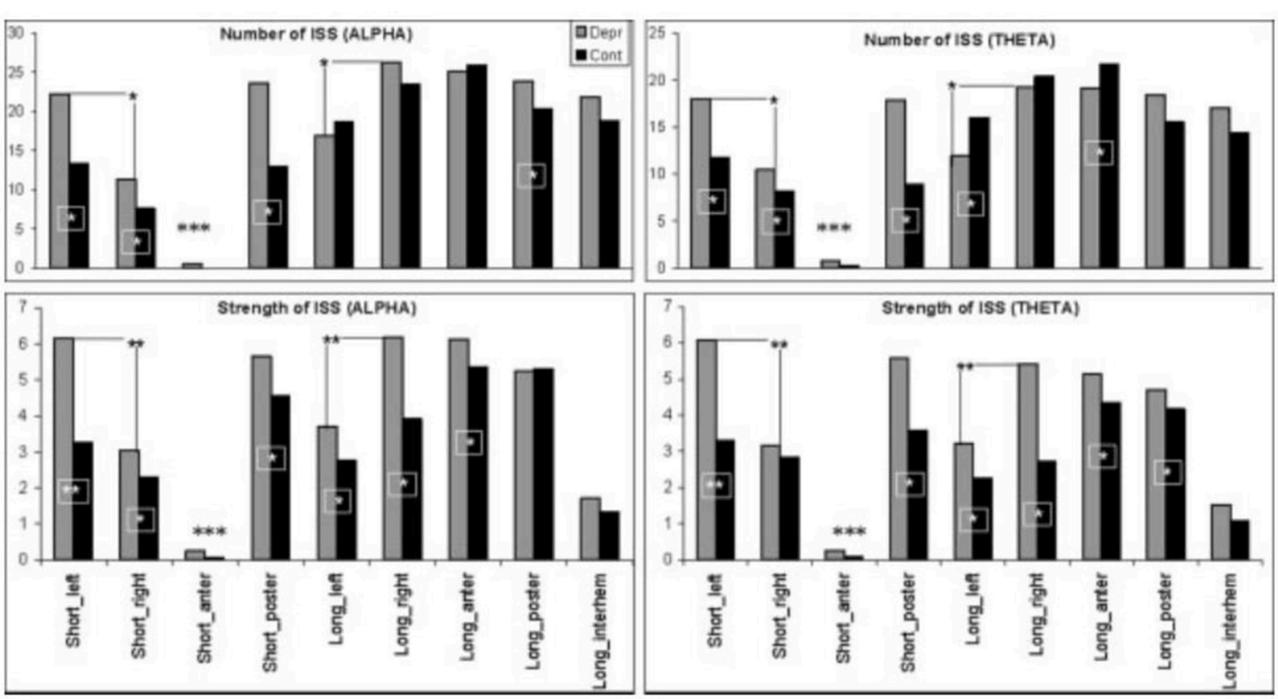

Fig. 23. The structural synchronization index difference in number and strength between depressed and healthy ones [37].

electrode. Epochs containing artifacts of eye movements and muscle movements on EEG channels were automatically rejected and rewritten. The ISS parameter has been considered as the functional connectivity metric and the obtained indexes of number and strength of ISS in each of the EEG pairs as illustrated in Fig. 23 are overally larger for depressed ones in comparison to the healthy subjects in alpha band. A discriminant factor can be extracted according to this figure for connection categories with large difference between the depressed and the healthy ones. The strength and number of short cortex functional connectivities in depressive subjects are greater for the left than for the right hemisphere, while the strength and number of long functional connectivities are greater for the right than the left hemisphere.

The topology of the most discriminative connectivities among all depressive patients demonstrates that the connections between the right anterior and left posterior brain parts are key factors to discriminate the patients with depression abnormality from healthy subjects [37] as illustrated in Fig. 24. This happens in both frequency bands of alpha and theta.

The between-channel coherence and its relation to the clinical treatment response (TR) at week 8 in major depressive disorder (MDD) have been studied in [38]. A modified version of Hjorth's method of surface Laplacian filtering has been adopted to re-reference the EEG data [100–102]. The connectivities between frontal and temporal lobes in addition to the connectivities of temporal and parietal lobes have been the main focus in the study. The right hemispheric (F8-T6) connection at the delta band has been the only interaction in order to differentiate responders and nonresponders at week 8 of treatment. The stronger the between-region connections would result in poorer treatment response (TR). The ROC curve analysis of classification with the use of F8-T6 connectivity strengths at the delta confirms that the stronger right hemisphere interaction associates with poorer treatment response [38] as indicated in Fig. 25.

Deep brain stimulation for MDD patients has been studied in [39] as

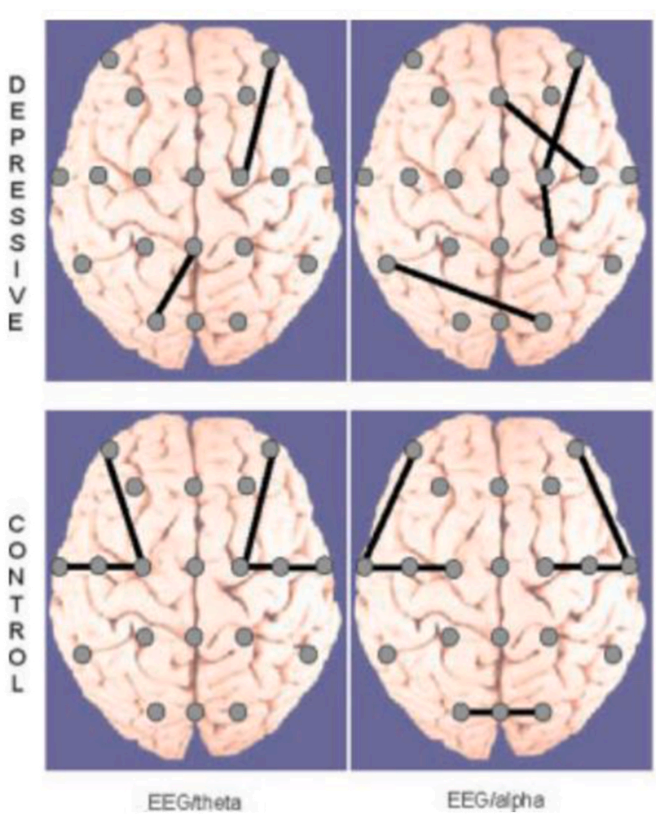

Fig. 24. The connections between right anterior and the left posterior brain regions in depression abnormality vs. healthy controls [37].

a therapy method for treatment-resistant patients. 12 patients with DBS surgery have been investigated to be classified into responders and nonresponders to DBS. The average of all channels in the preprocessing stage has been considered to re-reference all the channels and to avoid systematic effects that may arise from referencing to a particular channel. A DC offset was subtracted based on the entire time range, and bad channels were removed then interpolated from neighboring channels. The classification has been done according to the improvement of 50% or more in the 17 items of Hamilton Rating Scale for Depression (HAMD-17). Frontal and parietal synchronization have been studied in this paper. A significant difference in hemispheric mean synchronization asymmetry have been derived with an asymmetry similar ro responders in healthy controls but opposite to non-responders.

An increamental trend in the right frontal lobe synchronization in comparison to the left in non-responders to the treatment compared with responders. Also, the synchronization in parietal lobe would increase in the left hemisphere to the right. As illustrated in Fig. 26, stronger cross-hemispheric connectivity has happened in treatment responders, remarkably between right frontal to central and left parietal channels. The connectivity patterns differ in non-responders to treatment in such a way that higher connections would be seen from the right parietal to frontal electrodes. Furthermore, higher connections between hemispheres in the parietal and parietooccipital regions would be observable that are largely left–right symmetric. A higher overall number of edges can be observed in the ON than the OFF condition [39].

We see that the number of functional connections in stroke would decrease and the strength of the connections according to the functional connectivity metrics would be lower than the healthy ones. After the recovery stage, the ipsilesional and contralesional connections would be different and the incremental trend in connectivity of the ipsilesional regions with frontal regions of the brain would be a prediction of recovery score. On the other hand, the connections in depression patients would be different in right and left hemispheres. In short connections, an increase in functional connectivity metrics would be observed.

The connectivities between parietal and frontal would increase in non-responder patients to DBS treatment, while the connections would be stronger in responders to DBS like healthy controls but are lower than non-responders. Furthermore, the connections between right hemispheric frontal to central and left hemispheric parietal channels in responders are higher than non-responders. The coherence functional connectivity metrics have been compared for 16 depression patients and 14 healthy controls during emotional face recognition task [40]. Data recording in [40] was referenced to the tip of the nose. Artifacts from eye movements and blinks were removed off-line using a Brain Vision Analyzer by an ocular correction algorithm. The artifact-free data were band-pass-filtered between 0.05 and 100 Hz. In negative conditions as illustrated in Fig. 27, the connectivities are higher than the positive emotional stimuli. Also, the connectivities in depressed groups are more than healthy group in response to the emotional stimulation.

The global coherence of the low gamma and high gamma band in the positive condition for the depressed group in response to emotional stimulation are greater than healthy controls as illustrated in Fig. 28. Also, this connectivity metric in low gamma and high gamma frequency band for negative condition are higher than positive condition for normal controls [40].

The synchronization likelihood in Ref. [41] have been used to extract the EEG data matrix and the feature extraction and classification have been done according to this data matrix. The 19-channel EEG recording according to the 10–20 electrode placement standard has been done with linked ear (LE) as reference in [41]. The EEG data were re-referenced to infinity reference (IR) using the reference electrode standardization technique (REST) as suggested by Refs. [103–106]. The noise from the EEG data reduced multiple source modeling technique [107], implemented in the standard brain electric source analysis (BESA) software [108]. The construction of artifact-related topographies including muscular, eye blinks, and heart activities was based on the

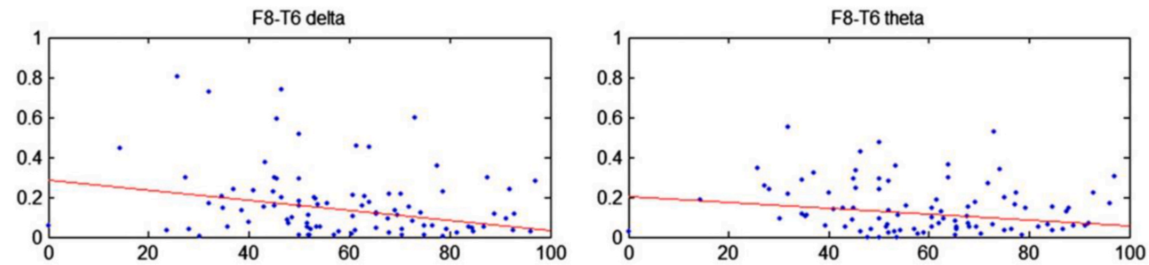

Fig. 25. The correlation between the functional connectivity strengths (x-coordinate) and the treatment response (y-coordinate) of the depressive patients with major depressive disorder [38].

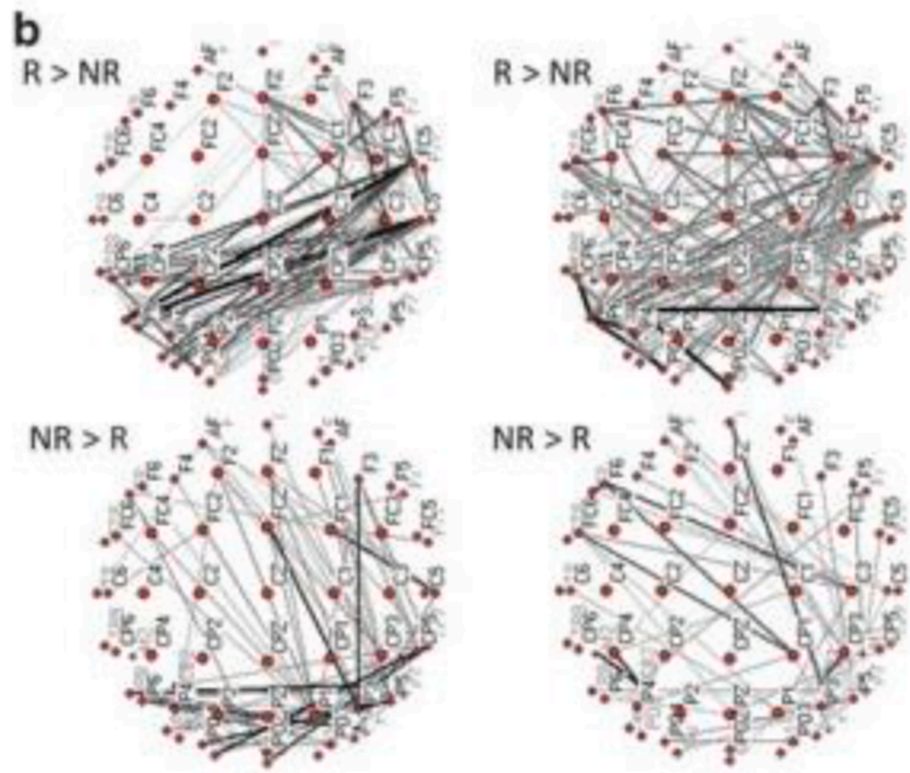

Fig. 26. The connectivity networks in for comparing the DBS responders and non-responders in OFF (left) and ON (right) conditions [39].

recorded EEG data and then can be applied to whole recording. The result and evaluation of the classification between the connectivities in depressed patients and the healthy controls can be seen in Fig. 29.

As can be inferred through a comparison between strokes and depressions, the local efficiencies have decreased in stroke and these connections would increase in the post-stroke recovery stage. In spite of the fact that the connections have increased in depression patients, medication intake would decrease these connections to match to the healthy controls connections.

Increased right amygdala directed functional connectivity in depression patients have been observed in another study about functional connectivity analysis of depression abnormality [44]. Cz is used as the EEG acquisition reference and re-referenced to the average reference. Infomax-based independent component analysis has been applied in order to remove physiological artifacts. The components related to ballistocardiogram, eye blinking saccadic, and eye movements have been removed based on the waveform, topography and time course of the component. Futhermore, increased right caudate directed functional connectivity in depression and increased theta and alpha powers in depression have been observable as illustrated in Fig. 30.

The intake of antidepressants, antipsychotics, mood stabilizers (AD/AP/MS) for depression recovery and its relationship with global efficiency (GE) have been illustrated in Fig. 31. Higher intake of medications is linked with lower GE. The predicted value for each patient using GE is illustrated with the orange dashed line [44]. As expected to have lower global efficiency in comparison to the healthy subjects, the global efficiency would decrease after medication intake by depressed patients.

The clustering coefficient and the characteristic path length for music perception of depressive patients have been derived according to the phase lag index measure of delta and beta frequency bands in Ref. [43] as illustrated in Fig. 9. Electrodes placed at the left and right earlobes were used as the references to remove obvious artifacts from head movements. The 50-Hz artifacts were removed by short time Fourier transform (STFT) and the eye movements artifacts were rejected by independent component analysis (ICA). In Figs. 9 and 13 crucial connectivities in the delta frequency band are between the left parietal and the right temporal regions. 43 important connectivities are between the frontal regions and parietal and occipital areas of the brain. These substructures have been considered to be important discriminative indicators of the connectivities in two groups and these connections under

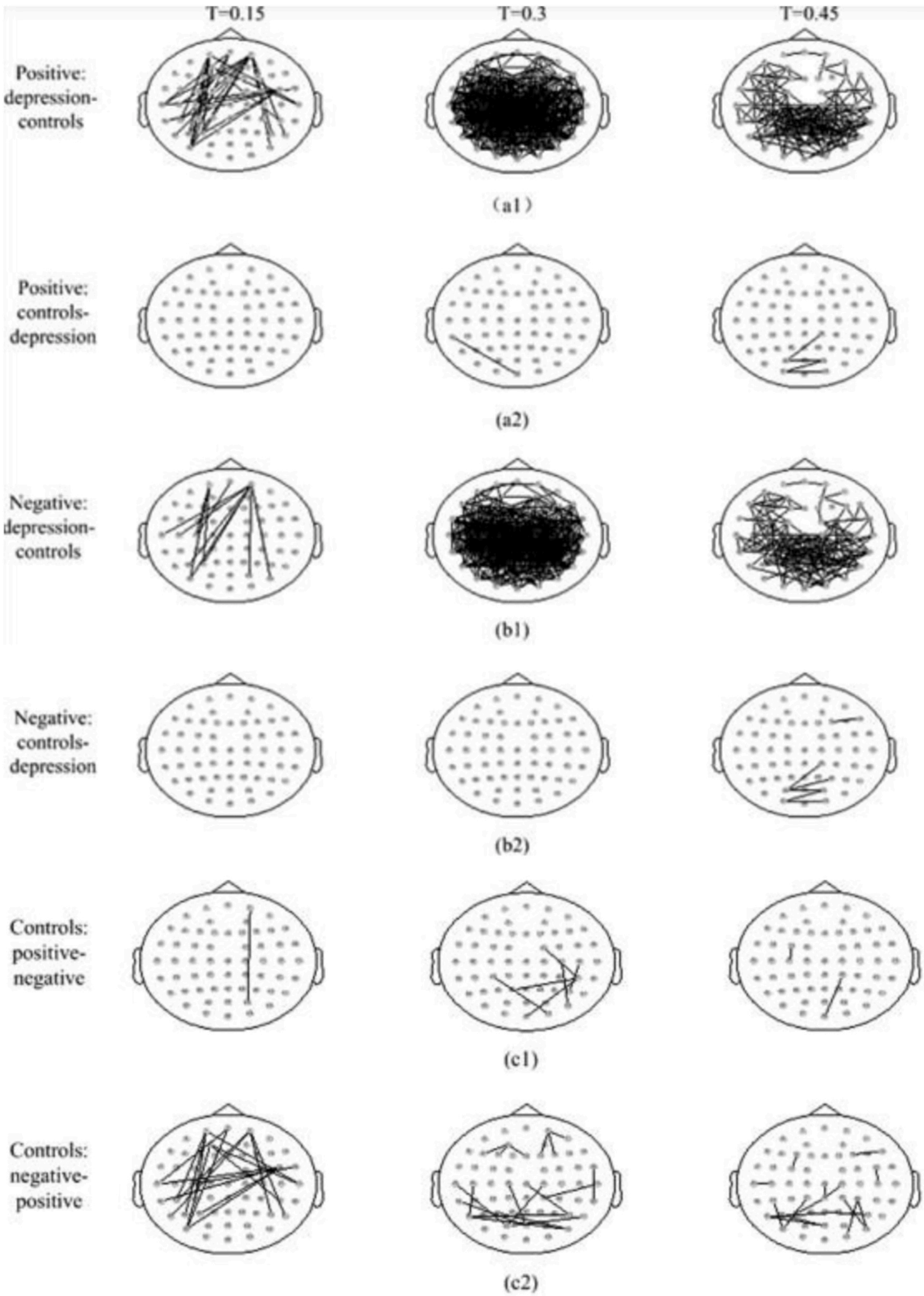

Fig. 27. The higher connectivity in negative and positive emotional stimulation for depressive patients. Also, higher connections in negative conditions in comparison to the positive states for healthy subjects [40].

conditions of music perception can be promising biomarkers for mild depressive disorder.

PLI index has been evaluated for 60 number of depressed patients with different severities of depression [45]. Independent component analysis (ICA) as an accepted tool in artifacts rejection was used to eliminate nonbrain sources like eye blinks, muscle artifacts, and electrocardiogram (ECG). PLI matrix has been analyzed for delta, theta, alpha and beta frequency bands and the this synchronization metric has decreased according to the severity stages of depression. The average functional connectivity matrices (phase lag index [PLI] values) of

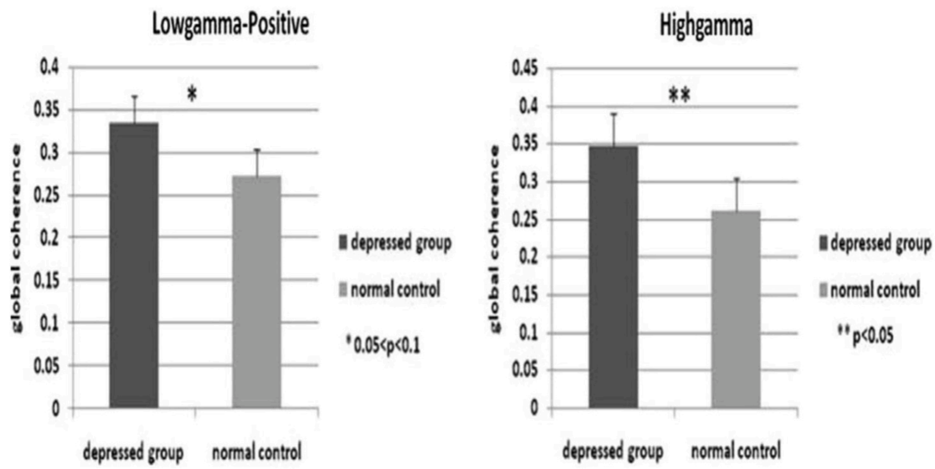

Fig. 28. The global coherence in the low gamma and high gamma band for depressed and healthy controls [40].

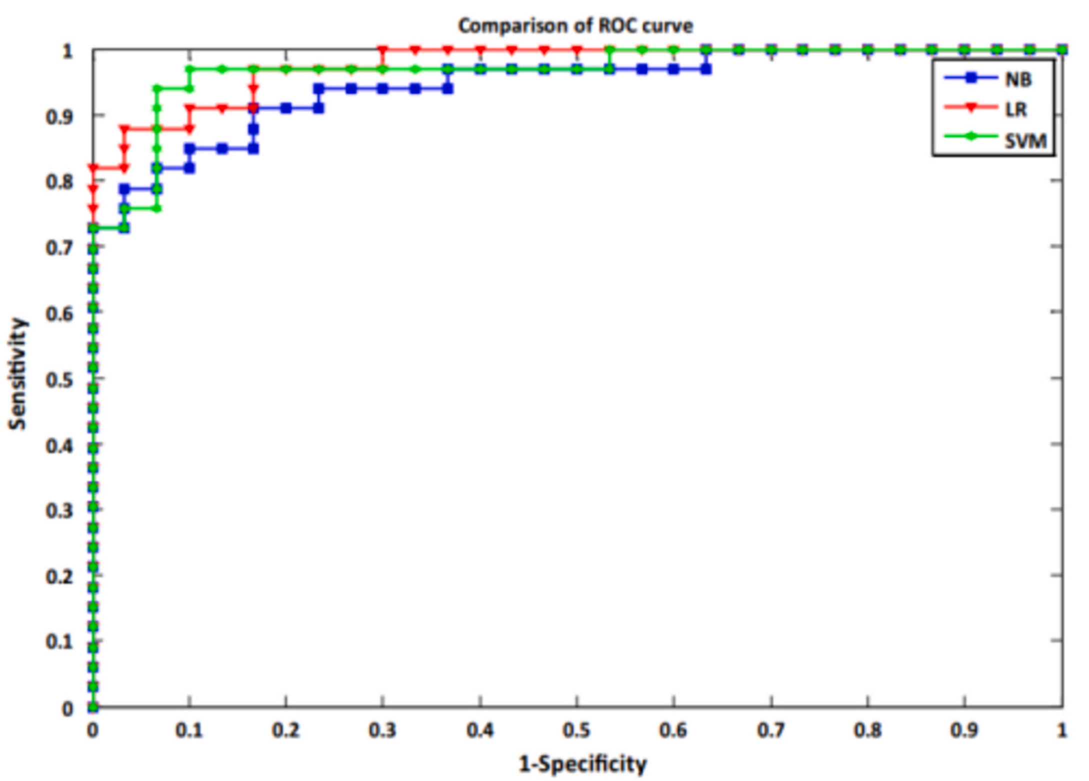

Fig. 29. The ROC curve for classification using the functional connectivity-based features [41].

depression groups (minimal, mild, moderate, and severe) are illustrated in Fig. 32. It can be observed that the mean PLI connectivity strength in the alpha band decreases along with increamental trend of depression severity.

A linear regression model is defined in this study to be a predictive biomarker of the severity of depression on the alpha frequency band. Different parameters according to the extracted networks including the degree, LempelZiv complexity (LZC) and fuzzy entropy are extracted for regression analysis. The phase lag index –based networks have been studied. The degree metric has a negative relationship in alpha frequency band. The LZC reveals a strong positive relationship with the depression score as the complexity has increased with the severity. It seems that the complexity and brain connectivity illustrate a different trend in depression patients.

Coherence and mutual information have been used successfully for classification of positive, negative and neutral valence in emotion recognition [49]. Furthermore, these two metrics of functional connectivity have been used successfully for arousal detection. These are good evidence for emotional recognition using functional connectivity metrics.

Patterns of functional connectivity in patients with Parkinson disease and healthy controls in response to emotional stimuli have been investigated in [51]. The reference electrodes in recording procedure have been considereds the linked ear electrodes. The EEG signals with artifacts due to blinking have been removed by discarding the amplitudes more than 80 μV in [51]. Coherence, correlation and synchronization index confirm that the functionally connected regions would change in patients and it would have a negative impact on classifying the

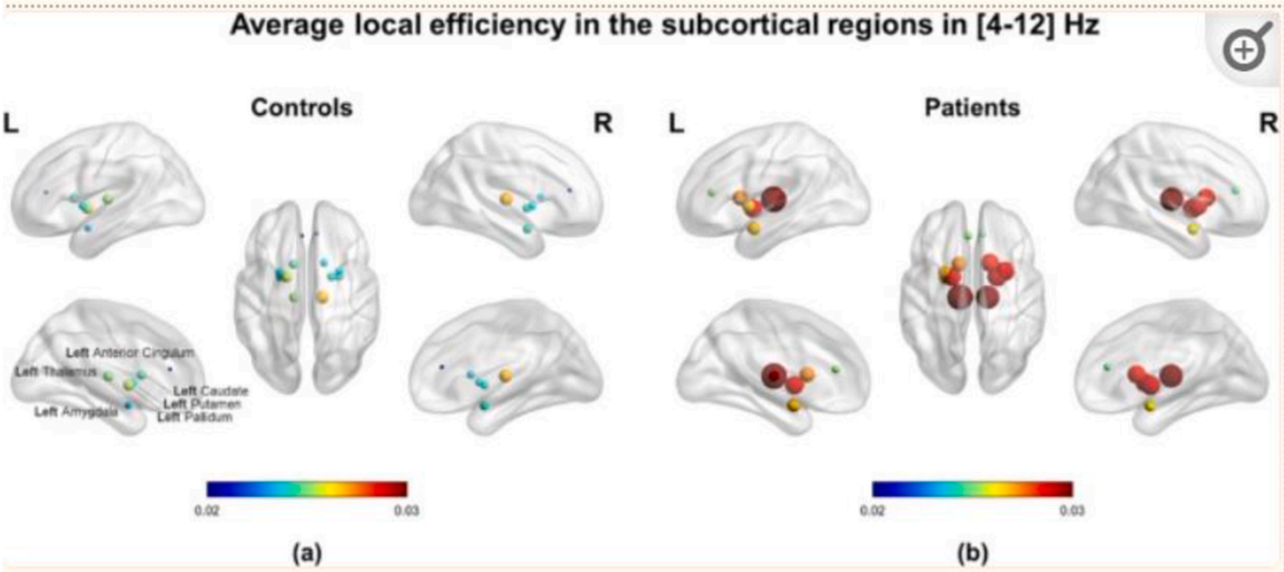

Fig. 30. Averaged local efficiencies in the subcortical regions for depressive patients in comparison to the healthy controls [44].

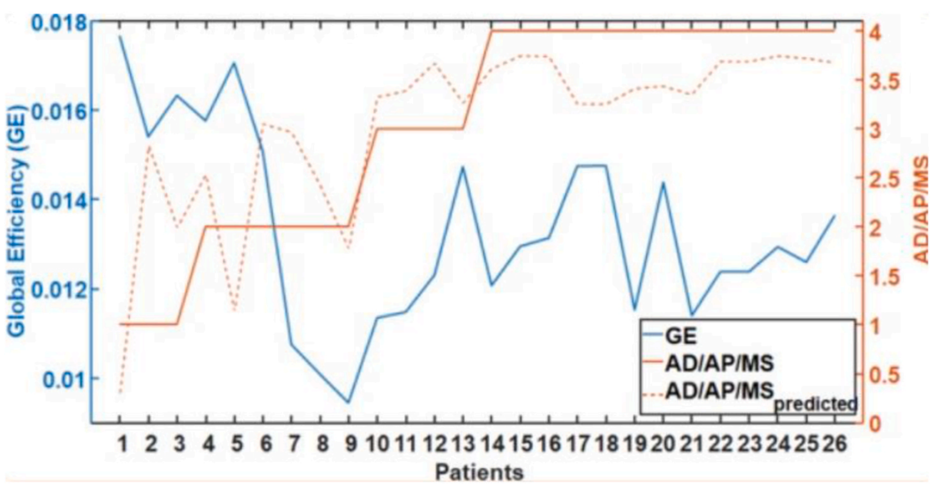

Fig. 31. Global efficiency comparison for medication intake of depressive patients [44].

emotional states of patients. But the functional connectivity related classification of healthy controls has been successful. The functional connections in theta frequency band are shown in Fig. 33 and the parietal lobe connections are shown for Parkinsons and the red lines for healthy subjects can be seen in this figure.

Patients with anxiety disorder have been analyzed in reponse to emotion regulation tasks in 2016 [52]. Phase lag index has been considered to construct the network. Graph theory measures of characteristic path length (CPL) and clustering coefficient (CC) have been computed and integration measured via CPL have increased in the theta band network along with the increamental trend of cognitive load during the emotion regulation task as indicated in Fig. 34. A reverse trend in the CC have been observed such that low CPL and high integration have been obtained in response to emotional task with higher cognitive load.

Coherence, phase lag index and phase locking value have been most used in emotion recognition related EEG signal processing. About emotion recognition related studies, Parkinson's disease patients' reaction and the subjects with anxiety disorder have been considered to analyze the abnormal emotional response in comparison to the healthy subjects. About EEG-based functional connectivity analysis of the epilepsy disorder, mesial temporal lobe epilepsy is an important point to be studied in comparison to the healthy subjects. The correlations of MTLE patients are higher in comparison to other abnormalities. Another important point in connectivity analysis in epilepsy abnormality is the schizophrenia-like psychosis of epilepsy versus those with nonpsychtic epilepsy. A higher and stronger connections have been observed in epileptogenic zones and the functional connectivity metrics related with epilepsy are greater for epileptic patients. Another important point in epileptic related networks is the network for psychogenic non-epileptic seizures (PNES). In which the connectivities decrease in comparison to the healthy subjects.

The mean synchronization likelihood (SL) have been illustrated in Fig. 35 for 5 epochs of interest including the first interictal, second before rapid discharges (BRD), third during rapid discharges (DRD), fourth after rapid discharges (ARD) and fifth postictal through the seizure in separate frequency bands. As can be seen in this figure, the mean synchronization likelihood have increased in all frequency bands during the seizure [60]. The midline parietal (Pz) has been considered as the original reference electrode. A scalp reference has been selected as reference because the intracerebral signal is largely of higher amplitude than the surface one.

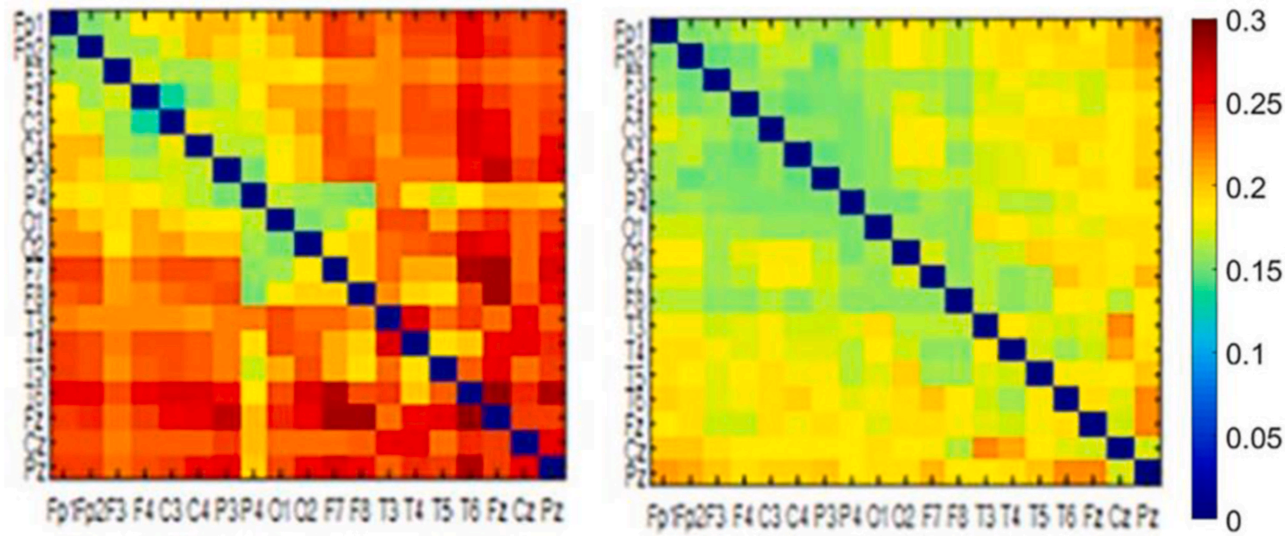

Fig. 32. The connection matrices for mild (left) and severe (right) depression abnormality [45].

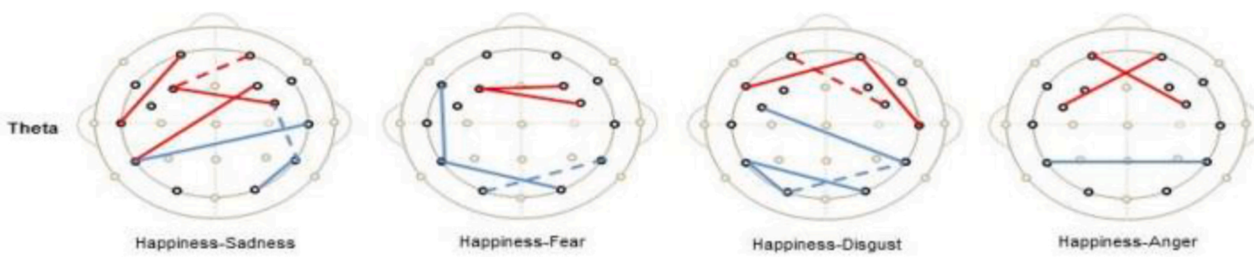

Fig. 33. Coherence connectivities with red lines for healthy controls and blue lines for patients with Parkinson disease. Significant increases indicated with solid lines and decreases indicated with dashed lines for the theta, alpha, beta, and gamma frequency bands (from left to right), in response to emotional stimuli [51]. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

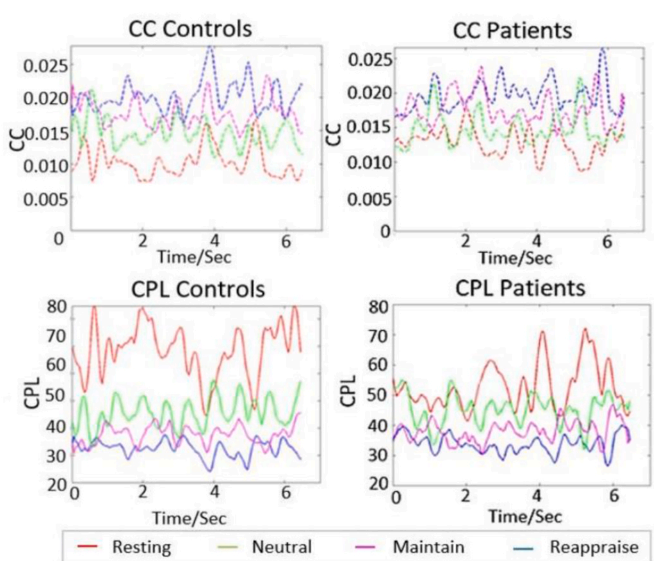

Fig. 34. The connectivity metrics of clustering coefficient (CC) and characteristic path length (CPL) in response to emotion regulation task with phase lag index for patients with anxiety disorder [52].

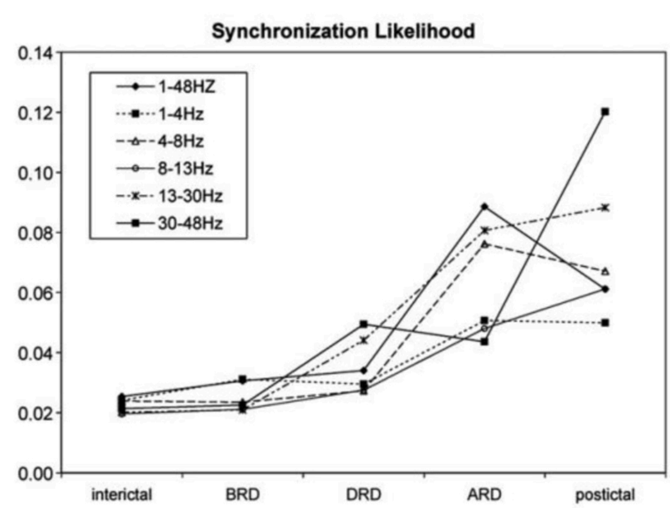

Fig. 35. Mean synchronization likelihood (SL) curves for all filtered frequency bands (delta 1–4 Hz, theta 4–8 Hz, alpha 8–13 Hz, beta 13–30 Hz and gamma 30–48 Hz) and the broad filtered signal (1–48 Hz). Each curve shows the changes in the different EEG epochs through seizure activity [60].

Interictal EEG activity in mesial temporal lobe (MTL) including amygdala, entorhinal cortex and hippocampus has been obtained from intracerebral recordings performed in 21 patients with mesial temporal lobe epilepsy (MTLE group) and resistant to drug medication [61]. This group has been compared with a control group of patients (non-MTLE group) in which seizures did not start from the MTL as indicated in Fig. 36. Comparison criteria were based on spectral properties and

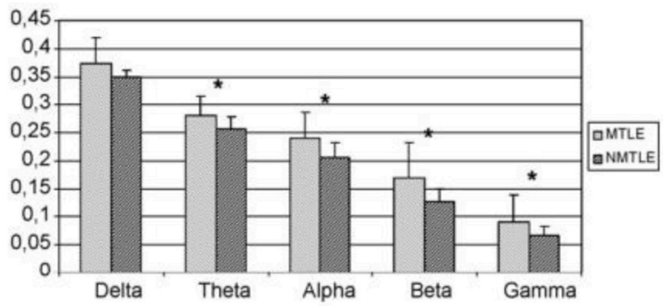

Fig. 36. Correlation of MTLE vs NMLTE [61].

statistical coupling (nonlinear correlation coefficient h2) of MTL signals.

The mean value of correlation metric within zones for iEEG sub-bands [62] have been calculated in non irritative zone (NIZ), primary irritative epileptogenic zone (EZ/IZ1) and secondary irritative epileptic zone (IZ2) and illustrated in Fig. 37. The correlation value in within zones assessment is higher for epileptogenic zone in comparison to the non-epileptogenic areas. H^2 mean values according to the correlation value of between zones illustrated in Fig. 38 which are lower for epileptogenic zone.

The eLORETA wire diagram has been analyzed for patients with schizophrenia-like psychosis epilepsy versus the patients with nonpsychotic epilepsy [63]. The reference electrode in this study has been the linked ears electrode in Ref. [63]. It has been illustrated in Fig. 39 which shows increased lagged phase synchronization in the beta frequency band for right temporal to frontal connections. Fig. 40 illustrates the eLORETA wire diagram and scatterplots of important correlations of lagged phase synchronization in beta frequency band between 21 and

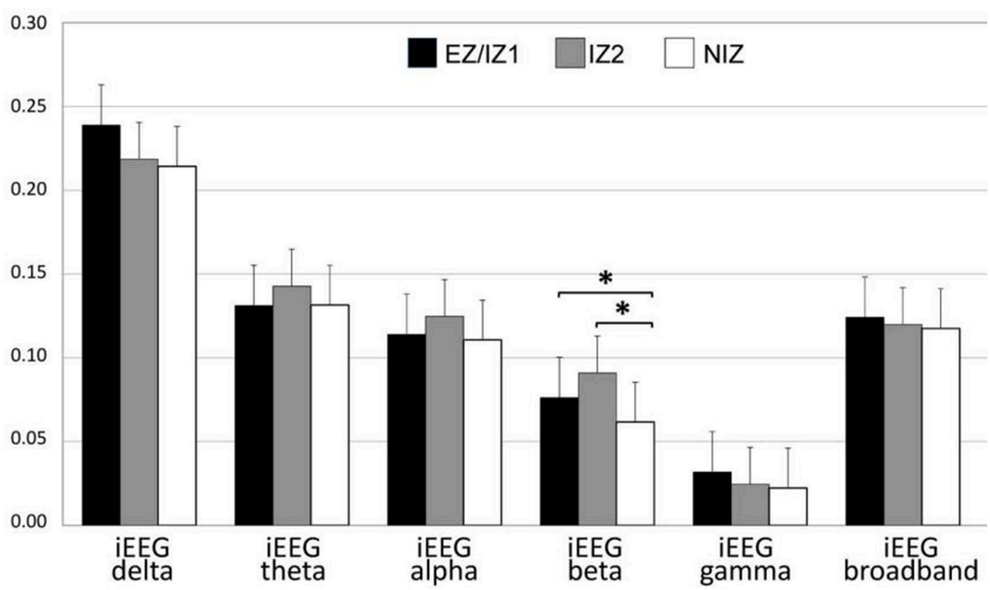

Fig. 37. The correlation metric in different frequency bands of non irritative zone (NIZ), primary irritative epileptogenic zone (EZ/IZ1) and secondary irritative epileptic zone (IZ2) [62].

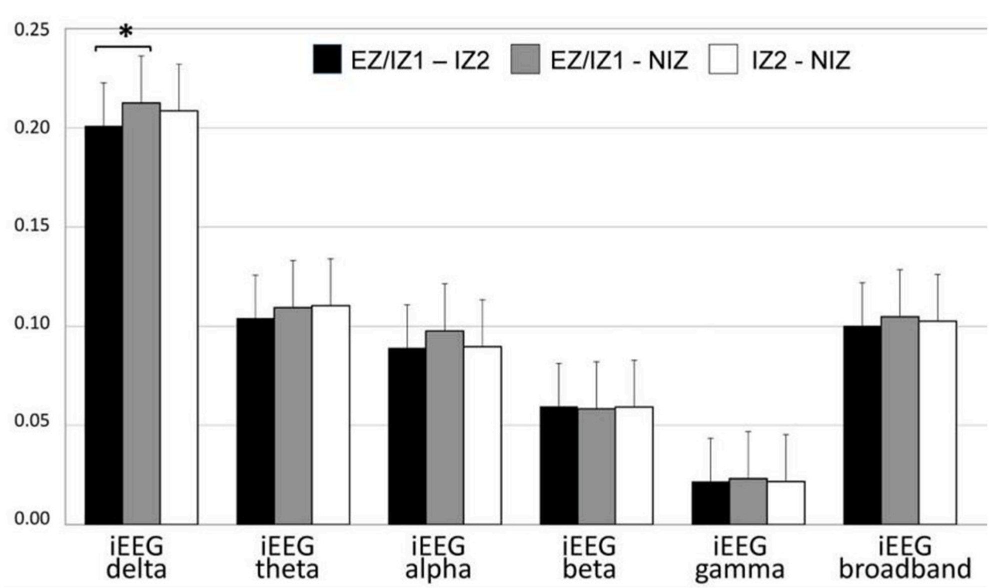

Fig. 38. The correlation metric in different frequency bands between zones of NIZ, EZ/IZ1, IZ2 [62].

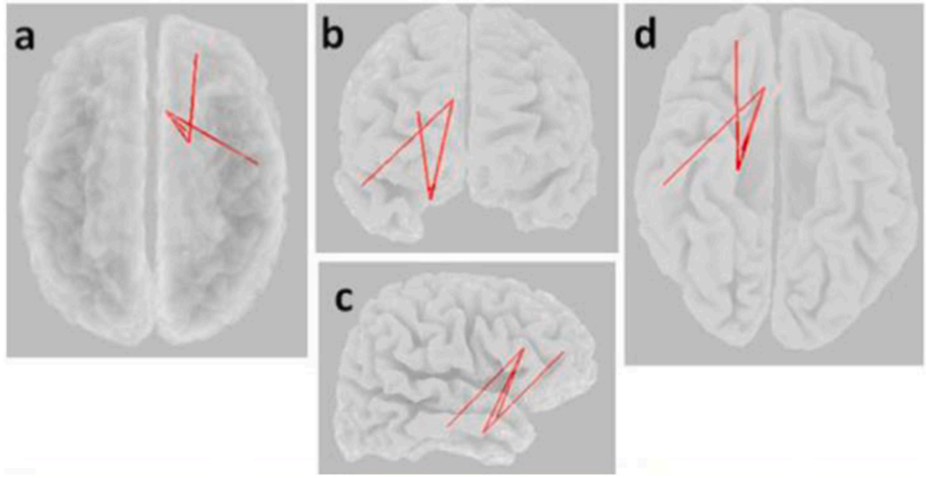

Fig. 39. The connectivity pattern for patients with schizophrenia-like psychosis epilepsy [63].

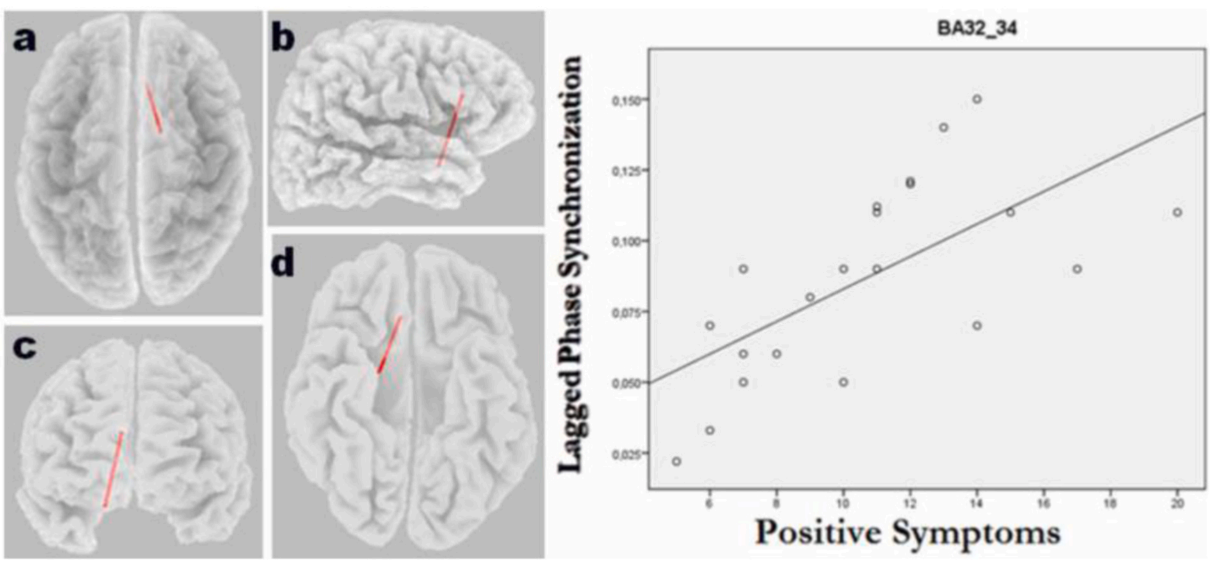

Fig. 40. The scatterplots of important correlations of lagged phase synchronization in beta frequency band between 21 and 30 Hz with psychpathology scores for schizophrenia-like psychosis of epilepsy [63].

30 Hz with psychopathology scores for schizophrenia-like psychosis of epilepsy at important regions [63].

The studies for epilepsy abnormality is mostly based on the deep EEG or eLoreta analysis of EEG recordings. The functional connectivity map illustrated in Fig. 41 are for patients with epilepsy [65]. The reference in recording stage has been located in the midline of the scalp based on the 10/20 system. The electrode recordings were then referenced to the average of all referential recordings. Artifact removal in this study has been based on blind source separation using independent component analysis. According to Fig. 41, the maps in (a) are for subject diagnosed with left frontal region epilepsy and the maps in (b) are for subject diagnosed with generalized epilepsy.

High density EEG and stereotactic EEG (SEEG) have been used for EEG-based functional connectivity in epilepsy abnormality [68]. Summary of changes in functional connectivity with lines between small circles represent the functional connectivity within structures of a zone in Fig. 42. The lines between large-circles represent the functional connectivity between zones. The greater functional connectivity has been illustrated with solid lines and the dashed lines represent lower functional connectivity. Concerning within-zone functional connectivity, the epileptogenic zone (EZ) and propagation zone (PZ) have significantly higher functional connectivity than the non-involved zone (NIZ). Concerning between-zone functional connectivity, the EZ and PZ have significantly greater functional connectivity between them than with the NIZ. The absence of arrows in the lines shows the lack of significant directionality in the functional connectivity between zones [68].

EEG-based brain networks for healthy subjects and the epileptic subjects are illustrated in Fig. 43 [69]. The maps of B and C in Fig. 43 indicate the interlayer correlation for the control (B) and epileptic (C) epochs. The colours denote the degree of similarity between layers, as indicated by the color bar at the top. The maps of D and E in Fig. 43 indicate the average interlayer correlations for node degrees (D) and clustering coefficients (E) for the normal (orange) and epileptic (green) epoch series [69].

The connectivity network for psychogenic non-epileptic seizures (PNES) shows that the connections of PLI in healthy subjects are higher and stronger than patients with PNES in different frequency bands [70]. In spite of the fact that in epileptic patients, the connectivity network becomes complex and the connectivities become more than healthy subjects, for the PNES subjects the complexity of the connectivity network decreases (see Fig. 44).

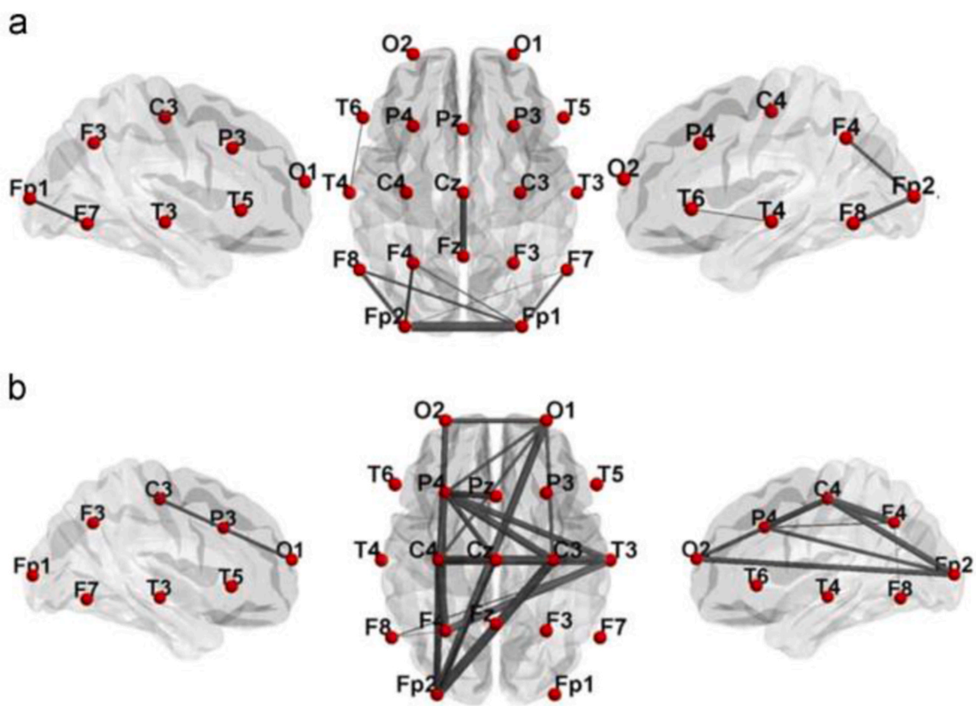

Fig. 41. The connectivityy maps in (a) is for subject diagnosed with left frontal region epilepsy and (b) is for subject diagnosed with generalized epilepsy [65].

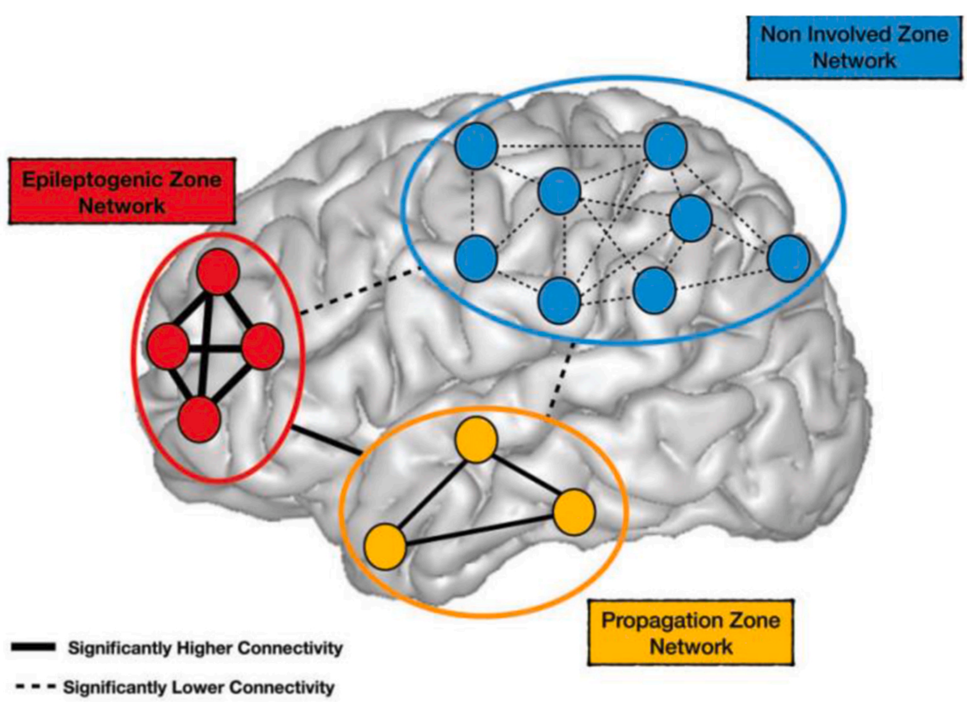

Fig. 42. The functional connectivity within structures of NIZ, EZ and PZ [68].

The temporal variability of connectivity (CV) with the use of the synchronication likelihood ranges in ADHD and control groups extracted for theta band of channel O2, theta band of channel P4 and delta band of channel T5 are illustrated in Fig. 45 for closed eye state and for the open eye state [77]. Monopolar derivations has been used and referenced to the average of the mastoid electrodes. The visual selection of EEG segments have been done with the recording of the electrooculogram, the abdominal breathing movements and the ECG to be used in the artifact removal stage. The synchronization likelihod analysis in subjects with ADHD in three regions of T4, P4 and O4 in Ref. [77] indicates lower quantities for patients in comparison to heathy controls. The graph metrics of clustering coefficient and efficiency are greater in ADHD in comparison to the healthy subjects.

One important point about ADHD is the analysis of the connectivities in persisters to adulthood and the remitters in which the symptoms only remain in the childhood. Also, the connectivity difference between the first order relatives of ADHD patients and healthy control subjects is another important point. Topographic maps as illustrated in Fig. 13

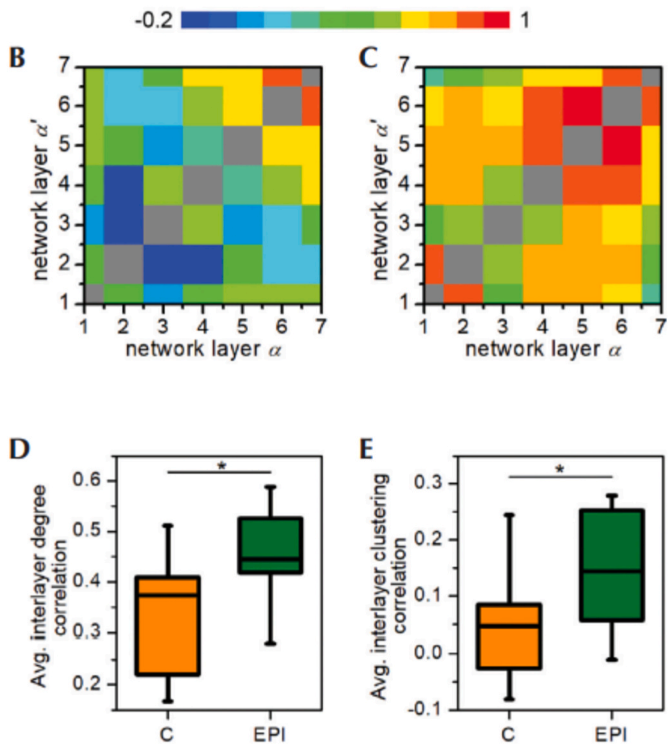

Fig. 43. EEG-based brain networks for healthy subjects and the epileptic subjects [69].

show the scalp distribution of the imaginary part of coherence (iCoh) in pre-stimulus theta, alpha, and beta frequencies for correctly-responded trials, for groups of healthy controls, ADHD persisters and remitters [78]. The average of all electrodes has been considered in re-referencing procedure in [78]. The global brain network measures of ADHD children and the control group are shown in Fig. 46 using the mutual information for calculating the functional connections between the electrodes [79]. All the 32 channels in Ref. [79] have been re-referenced to an ear-linked reference (M1/M2). The EEG signals were cut into 4-s non-overlapping epochs and an automatic algorithm [109] was applied to remove the epochs with artifacts such as breathing, outlier values, electrode-pops, power supply fluxes (50 Hz), muscular electrical activities or eye movements.

The connectivity plots for eyes-closed condition predicting hyperactivity and inattention symptoms are illustrated in Fig. 47. Blue lines indicate a negative association between the ADHD symptoms and the connectivity. Red lines indicate a positive association between the ADHD symptoms and the connectivity. The left connection plots in this figure indicate hyperactivity and restlessness symptoms and the right plots in this figure illustrate the inattention symptoms [80]. EEG data were average referenced across all scalp electrodes. EEG data pre-processing employed the EEGLAB toolbox [110] in conjunction with the FASTER plug-in [111]. EEG data were bandpass filtered between 1 and 95 Hz, notch frequencies were set to 48–52 Hz. FASTER automatically identified artefactual independent components and removed them from the EEG data.

The red lines in topographical plots in Fig. 48 in the ADHD versus first degree relative classification models for eyes open condition indicate a positive weight assigned to the connectivity as well as a higher weight towards the group ADHD. Blue lines in connectivity plots in this figure indicate a negative weight associated with the connectivity which means a higher weight towards the group 1st degree relative. This figure compares the connections for ADHD and the 1st degree relatives for eyes-open condition in the left and for the eyes-closed in the right of the figure [80].

The connection plots for EEG data collected from 14-month-old infants with and without older siblings with ASD are illustrated in Fig. 49 for high risk (HR) infants, low risk (LR) ones and typical development (TD) infants [82]. As it can be seen in this figure, the phase lag index metric has a decremental trend with the increase of the severity.

PLI results for each classical EEG-frequency band of Alzheimer's disease are illustrated in Fig. 50. Signals in Ref. [89] have been recorded at a sampling frequency of 500 Hz using the Nihon Kohden Neurofax

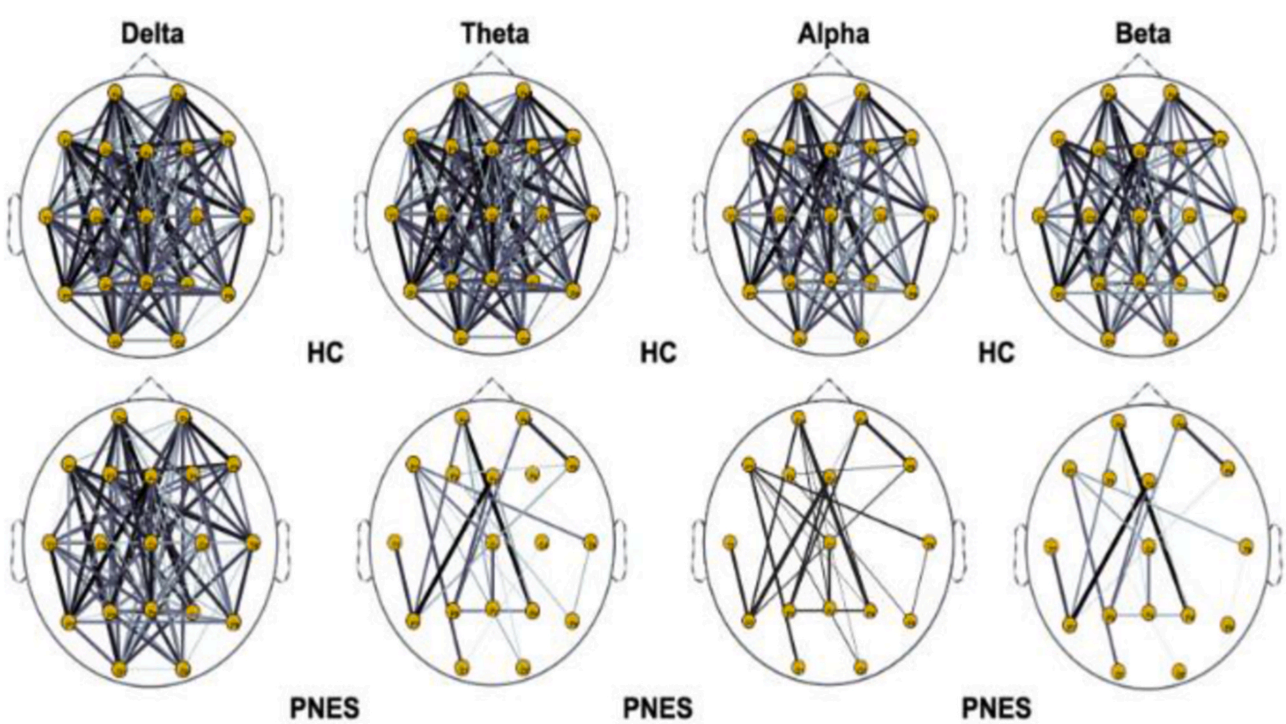

Fig. 44. The connectivity network for psychogenic non-epileptic seizures (PNES) in comparison to the healthy controls [70].

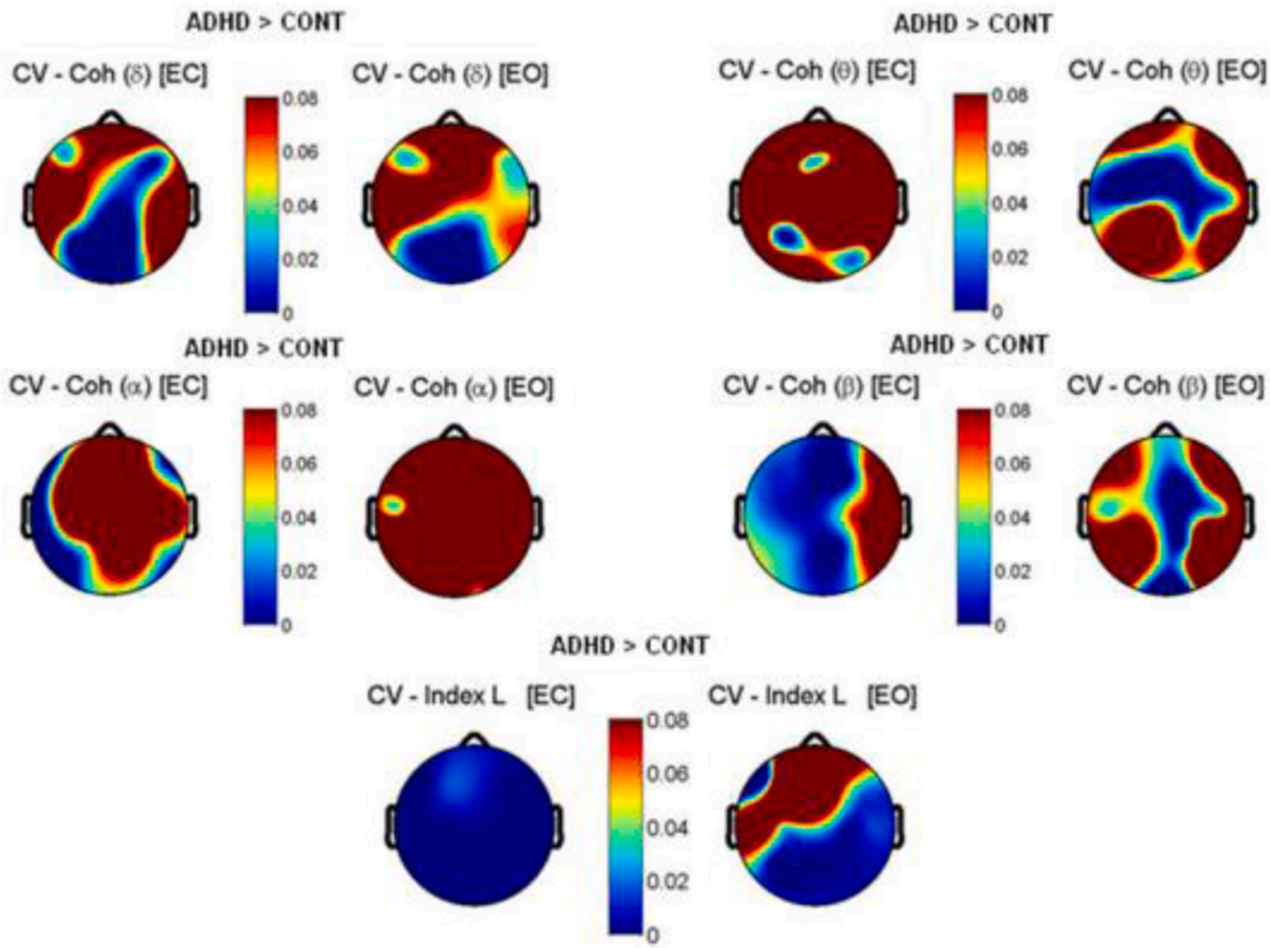

Fig. 45. The temporal variability of connectivity (CV) with the use of the synchronication likelihood ranges in ADHD and control groups [77].

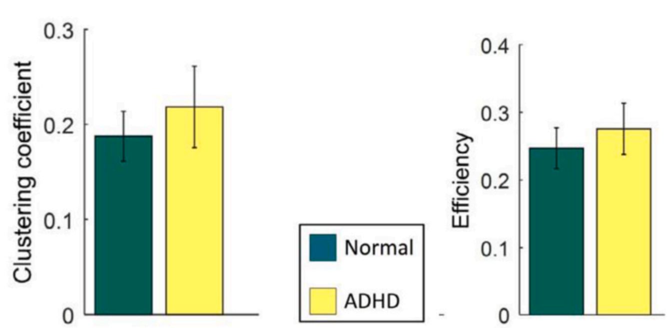

Fig. 46. The global brain network measures of ADHD children and the control group using mutual information [79].

JE-921 A system with common average reference. For each recording, the preprocessing procedure steps have been applied. These steps are as follows: (i) digital filtering using a notch filter to remove the power line frequency interference (50 Hz) and a Hamming window bandpass FIR filter in the band of interest (1–70 Hz); (ii) independent component analysis (ICA) to minimize the presence of cardiographic, oculographic, and myographic artifacts; and (iii) visual inspection for selecting the 5s artifact-free epochs. The connections between electrodes were only displayed when statistically significant within group differences have been obtained. The red color tones in Fig. 50 define significant increases of the functional connectivity in Alzheimer's disease patients compared to controls, whereas blue color tones denote significant decreases [89]. The theta frequency band can be a representative predictor of Alzheimer's disease. This figure illustrates that in this frequency band, the connectivities of electrode channels have increased with the severity of the abnormality from mild cognitive impairment to severe Alzheimer's disorder.

4.2. EEG-based functional connectivity analysis in clinical treatment

A brief overview of the functional connectivity variations in response to treatment and medical intake have been provided in this section about each abnormal conditions of the brain.

The assessment of recovery stage with analysis of the lower limb section in stroke patients have shown that the connection between frontocentral regions in contralateral and ipsilateral lesion is correlated negatively with the FMAL score. Although, the correlation is positive for the connection between the frontocentral and ipsilateral lesion. Furthermore, the correlation-based connectivity analysis have shown positive regression coefficient with the FMAL score. This connectivity metric is a predictor of the stroke recovery.

The global efficiency in depressive patients with higher medication intake such as antidepressants has shown decremental trend. A sign of depression patients responded to DBS is the similarity of the hemispheric mean phase coherence asymmetry trend to that of the healthy ones. This analysis shows phase coherence of the electrodes in left hemisphere are smaller than the right hemisphere for depressive patients and the subjects who not responded to treatment. This sign can be used as a predictor of treatment response. The hemispheric connectivity would be negative for the non-responders and the positive one would happen for

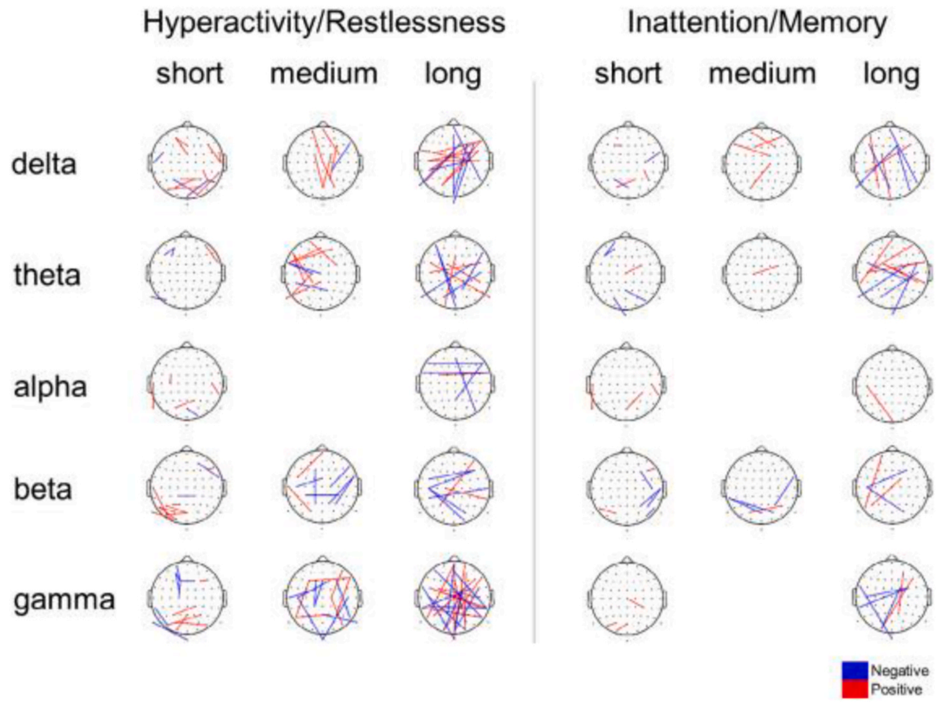

Fig. 47. The connectivity plots for eyes-closed condition predicting hyperactivity and inattention symptoms [80].

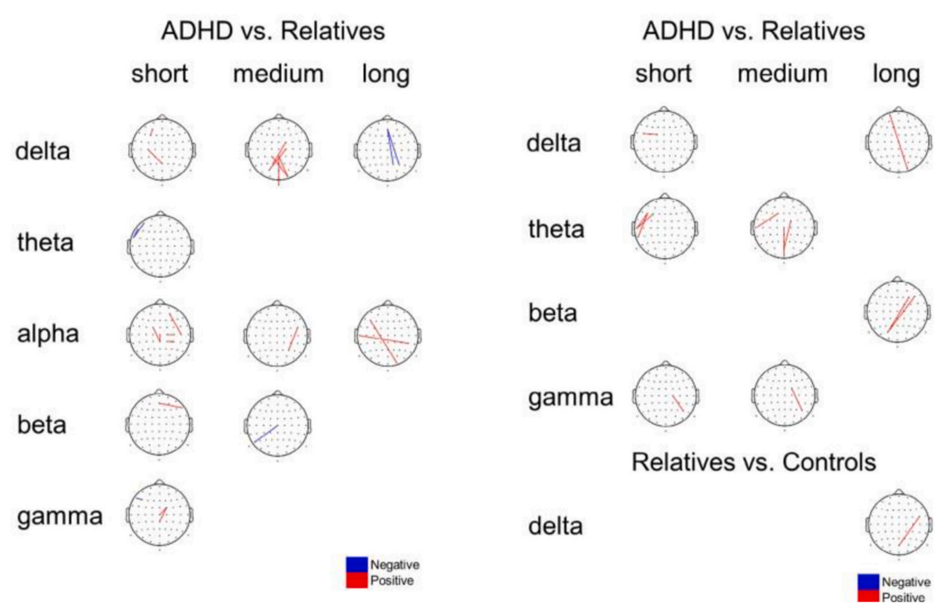

Fig. 48. The connections for ADHD and the 1st degree relatives for eyes-open condition (left) and for the eyes-closed (right) [80].

the responders and the healthy controls. The long phase coherence connections from right frontal lobe channels are stronger than the left ones in patients. The cross-hemispheric connections are stronger in responders in comparison to the patients specifically about the connections between the right frontal and left parietal. The number of connections from the right parietal to frontal electrodes in the phase-coherence network are higher for non-responders.

A significant increase in global correlation-based connectivity metric in the alpha frequency band was found in Alzheimer's disease with PQ912 treatment compared to placebo [86].

The between-channel coherence and its relation to the clinical treatment response (TR) at week 8 in major depressive disorder (MDD) have been studied in Ref. [38]. The connectivities between frontal and temporal lobes in addition to the connectivities of temporal and parietal lobes have been the main focus in the study. The right hemispheric (F8-T6) connection at the delta band has been the only interaction in order to differentiate responders and nonresponders at week 8 of treatment. The stronger between-region connections would result in poorer treatment response (TR). The ROC curve analysis of classification with the use of F8-T6 connectivity strengths at the delta confirms that the stronger right hemisphere interaction associates with poorer treatment response [38] as indicated in Fig. 25.

The global and regional connectivity have reduced in response to epileptic medication and antiepileptic drug (AED) for patients without seizure after receiving the drug [112]. The disruption induced in the epileptogenic zone have resulted in the temporal epileptic pulse failure

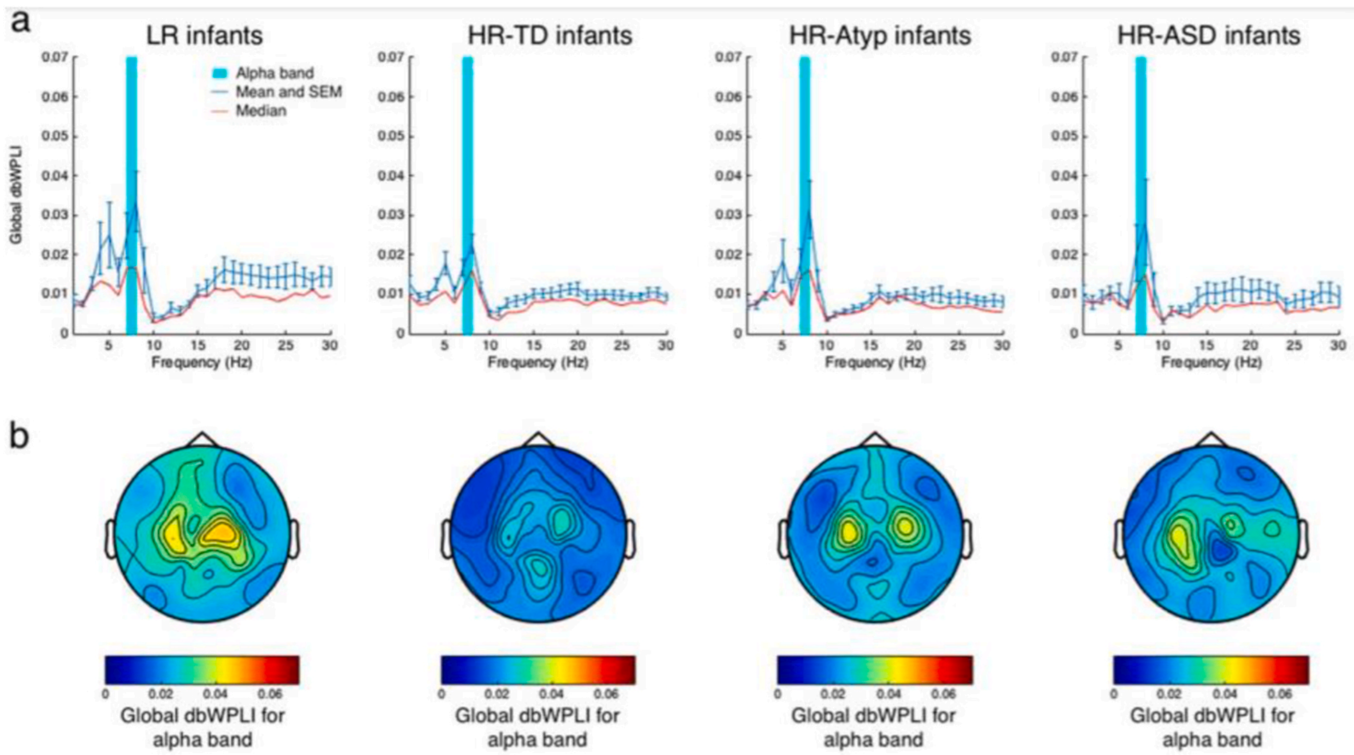

Fig. 49. The connection plots for infants with low risk (LR), high risk (HR), typical development (TD) and typical development (TD) of autism spectrum disorder [82].

during seizures. An increased failure of connections have happened in the epileptic zone using the antiepileptic drug in seizure free patients, with unequivocal response of therapy. The imperfect regulation of the reinforced abnormal epileptic network have been resulted by regional connectivity and global connectivity after Levetiracetum (LEV) therapy, also involved the connectivity of long global connections [113].

In the analysis of AED poor responders with the functional connectivity using coherence as a connectivity measure, the global efficiency and local efficiency have decreased, whereas the small-worldness index have increased. In the analysis of functional connectivity using phase locking value as a connectivity measure, the global efficiency and local efficiency in the AED poor responders decreased. However, the network measures in the AED good responders have been same to those in healthy controls [114].

The neurofeedback therapy for ADHD patients have been accomplished in 2012 [115]. The fuzzy synchronization likelihood have been calculated for functional connectivity analysis of the ADHD patient's network in response to the treatment. Computation of the mean path length of the graphs, before and after neurofeedback training have been done to obtain the efficiency of the functional connected networks in synchronizability and high speed information transmission. In the beta range of the ADHD subjects with positive response, the synchronizability of the neocortex activity network has been less than the ADHD resistants.

Virtual reality therapy for patients with autism spectrum disorder have been accomplished in 2021 [116]. A reshape of frontopaietal connectivity has been observed in the theta and alpha frequency bands for ASD patients. A significant improvement related with visual and spatial recognition, attention and anxiety have been reported among all subjects. The obtained changes in frontoparietal network connectivity following VRT would result in these improvements.

The study by Aiyer et al., in 2016 confirms that the EEG-based brain functional connectivity have been influenced by the heterogeneity of medication dose and duration of treatment for brain psychotic abnormality. The EEG measurements are affected by psychotropic drugs and it is notable that different drugs affect in different ways [117].

A dopamine-agonist dexamphetamine intervention compared to placebo in the study by Albrecht et al., in 2016 of healthy controls has assessed the use of the power envelope correlation and weighted phase lag index functional connectivity analysis. Connectivities have decreased in the theta, alpha and low beta bands and connectivity have increased in the gamma band in bilateral frontal, central, parietal and occipital areas for the intervention timepoint compared to placebo [118]. On the other hand, connectivities have increased in the theta and alpha frequency band in occipital, parietal, central, bilateral frontal areas with the use of weighted phase lag index for the intervention timepoint in comparison to placebo.

In medicated psychosis patients studied by Krukow et al., in 2019 compared to healthy controls, theta frequency band connectivities have increased between occipital, parietal, central and fontal areas using the EEG phase-lag index [119].

In the study by Zaytseva et al., in 2018, connectivity decreases according to the EEG phase-lag index have been reported in medicated psychosis patients for the alpha frequency band compared to healthy controls between fontal, central, parietal and occipital areas. Furthermore, decreases of EEG interhemispheric and intrahemispheric coherence in anterior regions have been reported [120]. Also, in the study by Umesh et al., in 2018 [121] for the assessment of the effects of dopaminergic medication on EEG functional connectivity, the EEG cross-spectral coherence of gamma frequency band have decreased in right fronto-occipital and right temporal regions. Another study for the medication of patients with psychotic abnormality assessed the EEG intra- and inter-hemispheric coherence and reported connectivity increases as well as connectivity decreases in anterior, central and parietal regions [120].

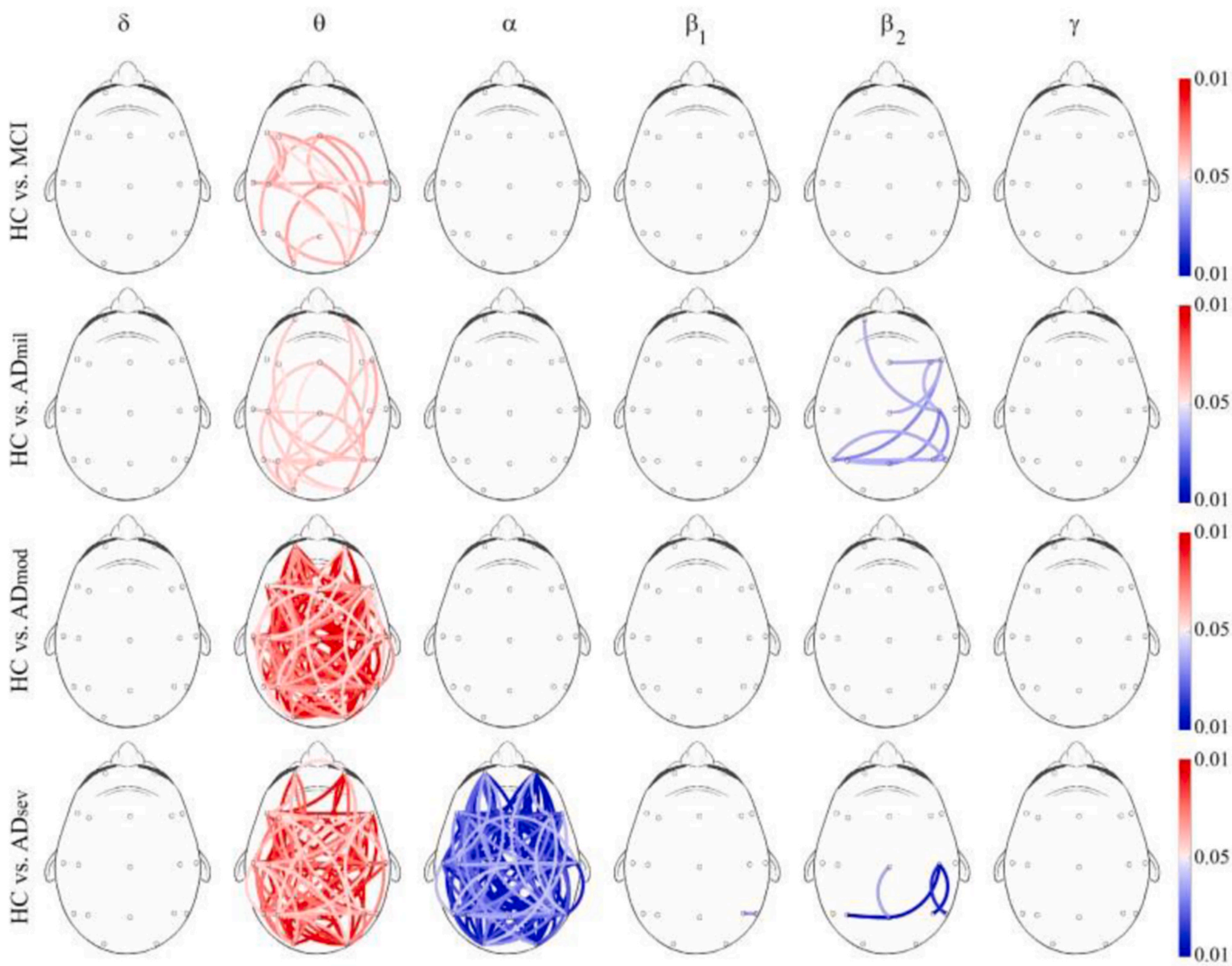

Fig. 50. The functional connectivity in Alzheimer's disease patients compared to controls considering the severity of the abnormality from mild to severe [89].

5. Conclusions

Considering question 1 in Section 2, it is revealed that different functional connectivity metrics have been proposed to investigate the functional connections of EEG signals. The details of each method are explained in Section 3.1. Each metric prioritize some aspects of the oscillations between brain recordings. The coherency, correlation and phase lag index metrics are the most used methods through the studies. The differences of connectivity networks corresponding to different metrics have been presented in some studies and the patterns according to different frequency bands have been represented.

In accordance with the statements in previous sections, the second question about the abnormalities analyzed by brain functional connectivity is answered in this review. According to this review, it is revealed that many brain abnormalities have been studied to survey the corresponding effects on brain functional connectivity. A comprehensive systematic review of these studies is presented in Sections 3 and 4. The functional connectivity alterations in disorders of epilepsy, autism, ADHD, stroke and depression are reviewed and compared with healthy controls in this paper. A large percentage of these studies are dedicated to epilepsy and depression.

For stroke abnormality, the global and local efficiency extracted from spectral coherence-based connection network in pre-ankle and during the movement are good indicators of the abnormality. During the movement, the incremental trend of these two parameters is observed and both in pre and during the execution, the efficiency parameters are lower than that of the healthy controls. Furthermore, the coherence-based network of this abnormality shows decrease in number of connections between frontal and other lobes including occipital, central and temporal. Also, the number of connections between the right and left hemisphere have decreased.

The recovery stage assessment in stroke patients with analysing the lower limb section have shown negative correlation of the FMAL score with the connection between frontocentral regions in contralateral and ipsilateral lesion. This correlation for stroke patients is positive for the connection between the frontocentral and ipsilateral lesion. Furthermore, the correlation-based connectivity analysis have shown positive regression coefficient with the FMAL score. This connectivity metric have been assigned as a predictor of the stroke recovery in number of studies.

The frequency domain coherence and time domain correlation are the mostly used metrics in the studies related with stroke and stroke recovery. About the studies related with depression, the coherence related functional connectivity network parameters and phase lag index of functional connectivity have been investigated. According to the analysis in studies related with the stroke abnormality, decreased number of functional connections in stroke and lower strength of the connections corresponding to the functional connectivity metrics in comparison to the healthy ones have been reported. The functional connectivity analysis after the recovery stage in stroke patients have illustrated the difference in ipsilesional and contralesional connections and the incremental trend in connectivity of the ipsilesional regions with frontal regions of the brain. These signs could be used as predictors of recovery score in patients with the stroke abnormality.

It has been shown that the functional connectivity analysis with the structural synchrony index metric for patients with depressive abnormality reports higher strength and number in short connections in left hemisphere and it is greater in right hemisphere for longer connections. Overally, the strength and the number of connections are greater than the normal ones. The discriminative connectivity pattern happens with connections in the right anterior and left posterior brain parts in alpha and theta frequency bands for depressed patients. Furthermore, another discriminative connection for patients with major depressive disorder is between the frontal and temporal lobes. A predictive factor of treatment would be the weaker connection trend of these two lobes in delta and theta frequency bands.

The PLI connectivity analysis of depressive patients in response to music perception shows different results in different frequency bands. The crucial connections in delta frequency band is between the left parietal and the right temporal regions. For the beta band, the crucial connections are between the frontal and parietal and occipital areas. The resulted network, degree, clustering coefficient and the characteristic path length for depressive patients in response to music perception in delta frequency band shows higher degrees for patients but it is lower for beta frequency band in comparison to the healthy ones in terms of PLI.

The PLI analysis for severity scores of depressive patients shows decremental trend of PLI with severity of depression in alpha frequency band. Partial directed coherence network of the EEG sources has shown increased right amygdala and right caudate functional connections in depression patients. The global efficiency in depressive patients with higher medication intake such as antidepressants has shown decremental trend of connections in functional connectivity network.

Therapy of deep brain stimulation has been used for patients with depression abnormality and similarity of the hemispheric mean phase coherence asymmetry trend to that of the healthy ones have illustrated as a sign of patients responded to DBS. Smaller phase coherence of the electrodes has been obtained in left hemisphere compared with the right hemisphere for depressive patients and the subjects who not responded to treatment. These observations could be used as predictor signs of treatment response. The negative hemispheric connectivity would be for the non-responders and the positive hemispheric connectivity for the responders and the healthy controls are reported. The long phase coherence connections from right frontal lobe channels are stronger than the left ones in patients. The stronger cross-hemispheric connections in responders have been observed in comparison to the patients specifically about the connections between the right frontal and left parietal. The higher number of connections from the right parietal to frontal electrodes in the phase-coherence network have been observable for non-responders.

The connections in depression patients would be different in right and left hemispheres. In short connections, increased number and strength of functional connectivity metrics would be recognized. For non-responder depressive patients to DBS treatment, increased connectivities between parietal and frontal have been reported. While the stronger connections in responders to DBS like healthy controls have been observed but lower number of connections would exist in comparison to non-responders. Furthermore, higher number of connections between right hemispheric frontal to central and left hemispheric parietal channels have been obtained in responders compared to non-responders.

The local efficiencies have decreased in stroke and these connections would increase as the post-stroke recovery stage. In spite of the fact that the connections have increased in depression patients, medication intake would decrease these connections to match to the healthy controls connections.

The analysis of coherence-based functional connectivity for depressed patients in response to emotional stimulation could be another indicator of this abnormality. The connectivities for patients are higher than the healthy controls remarkably in negative emotional state for gamma frequency band. Emotional stimuli also have been used to analyze the response of Parkinson disease connectivity patterns in comparison to the healthy subjects. Among the coherence, correlation and phase synchronization index, the coherence metric index illustrates discriminative patterns of increase or decrease of connectivities for theta frequency band in frontal region of the brain for healthy controls in response to sadness, fear, disgust and anger compared to the happiness. And these connections are in posterior regions of the brain for Parkinson patients. The emotion response analysis of anxiety disorder patients via the PLI-based connection network has been done. The characteristic path length have illustrated reverse correlation and clustering coefficient have a positive correlation during the incremental trend of cognitive load. These observations are for the anxiety disorder connectivity analysis in theta frequency band.

Coherence, phase lag index and phase locking value have been most used in emotion recognition related EEG signal processing. About emotion recognition related studies, Parkinson's disease patients' reaction and the subjects with anxiety disorder have been considered to analyze the abnormal emotional response in comparison to the healthy subjects.

The mean synchronization likelihood plot for seizure abnormality have shown an incremental trend during the interictal, before rapid discharges, during rapid discharges, after rapid discharges and postictal seizure. This is true for all frequency bands during the seizure. Correlation analysis of interictal EEG in mesial temporal lobe (MTL) including amygdala, entorhinal cortex and hippocampus in comparison to the N-MTLE have illustrated higher connectivities for MTL patients. The correlation metric is higher in epileptogenic zone in comparison to the non-epileptic zone. The correlation have a decremental trend with increasing the frequency band in epilepsy abnormality. The mean synchronization likelihood shows decremental trend with increasing the frequency. For schizophrenia-like psychosis epilepsy patients, the eLORETA wire diagram shows increased lagged phase synchronization in the beta frequency band for right temporal to frontal region connections. The degree and clustering correlation of subsequent epochs of healthy subjects have been compared with epileptic subjects. Higher degree and clustering correlation have been obtained for patients. There is an evidence for the psychogenic non-epileptic seizures which have shown lower PLI-based connectivities than the healthy controls in all frequency bands.

An important point about EEG-based functional connectivity analysis to be compared with the healthy subjects of the epilepsy disorder is the patients with mesial temporal lobe epilepsy. Higher number of correlations of MTLE patients have been reported in comparison to other abnormalities. Another important point in connectivity analysis in epilepsy abnormality is the schizophrenia-like psychosis of epilepsy versus those with nonpsychotic epilepsy. A higher and stronger connections have been observed in epileptogenic zones and the functional connectivity metrics related with epilepsy are greater for epileptic patients. Another important point in epileptic related networks is the decreased number of connectivities for Psychogenic Non-Epileptic Seizures (PNES) in comparison to the healthy subjects.

For ADHD abnormality, the efficiency and clustering coefficient obtained for patients using the imaginary part of coherence (iCoh) have greater values than the normal ones. The connectivity pattern of eyes-closed conditions could be a predictor of hyperactivity and inattention states in which the connections in hyperactivity in eyes-closed condition are greater than the inattention state. Also, in comparison to the first degree relatives, the ADHDs in eyes-open condition show stronger connectivities. One important point about ADHD is the analysis of the connectivities in persisters to adulthood and the remitters in which the symptoms only remain in the childhood. And the connectivity difference between the first order relatives of ADHD patients and with healthy control subjects. Furthermore, the synchronization likelihod in three regions of T4, P4 and O4 are lower than heathy controls.The graph metrics of clustering coefficient and efficiency are greater in ADHD in comparison to the healthy subjects.

The frontoparietal cortex is a vital region to be examined in depression disorder. The connection between temporal and anterior lobes along with the connection between occipital and parietal lobes in emotion recognition have been prioritized. Also, the mesial temporal lobe, focal, temporal and prefrontal connections have a significant importance in the case of epilepsy. Furthermore, the function and connectives of dorsal anterior cingulate cortex has been focused in ADHD patients.

The PLI metric analysis for infants with autism spectrum abnormality shows a decrease with incremental trend of the severity. It decreases in high risk infants in comparison to the low-risk ones. PLI connectivity plots for Alzheimer's disease in different frequency bands illustrates that the theta frequency band connectivities could be a predictor of Alzheimer's disease. The connectivities in this frequency band have increased with the severity increment from mild cognitive impairment to severe Alzheimer's disease.

The effects of treatment and medical intake on functional connectivity alterations in accordance with brain abnormalities have been studied in this review. About the stroke disorder, the post stroke recovery stage has been studied with the usage of functional connectivity patterns. The focus of studies about stroke patients is around the connection between the motor cortex with other brain regions. The connectivity patterns analyzed after medical intake and antiepileptic drugs in patients with depressive abnormality and epilepsy have illustrated alterations in functional connections before and after the medical intake. The neurofeedback therapy for treatment stage of ADHD abnormality have shown remarkable difference in connectivity patterns before and after the therapy. The connectivities in autism spectrum disorder experiencing virtual reality therapy confirms the impact of the treatment on the functional connections in order to change to the same of the healthy controls. Also, different dopaminergic agents have shown distinctive effects on EEG-based functional connections in patients with psychotic disorder. Furthermore, PQ912 intake affected the network in patients with Alzheimer's disease.

Finally, to answer the third question about the suggestions for future research on EEG-based functional connectivity of brain abnormalities, it has been illustrated that the issue of EEG brain connectivity of epilepsy and depression has very much attracted the attention of the researchers. The coherency and correlation-based algorithm has been used more than other connectivity metrics, while novel brain functional connectivity methods could be used instead to verify the performance and reliability of the algorithms. A valuable research could be done around detection of different brain disorders via assessing the connectivity patterns of brain areas because there is not enough research concentrating on this issue in recent years. Applying an effective treatment order depending on each abnormality would increase the speed of patient recovery. The effects of drugs for curing patients on brain functional connectivity has been less studied and it would be important to dedicate new projects to this topic and assess the alterations of brain functional connectivity in response to different treatment and corresponding drugs. The connectivities could be compared with healthy states to adjust or change the treatment process of patients according to each abnormality.

The discussed results of this review article show that significant achievements have been obtained in the field of brain abnormality analysis through EEG-based functional connectivity and the studies would be continued. It is necessary to study and research about the recommendations addressed the limitations of the past EEG-based functional connectivity brain abnormality analysis to improve the applications.

Funding

This research received no external funding.

Institutional review board statement

In this research, experimental data was not recorded.

Ethics approval statement

No human or animal data has been used in this research.

CRediT authorship contribution statement

Nastaran Khaleghi: Writing – original draft, Visualization, Supervision, Software. **Shaghayegh Hashemi:** Writing – original draft, Visualization. **Mohammad Peivandi:** Writing – original draft, Software. **Sevda Zafarmandi Ardabili:** Visualization, Validation. **Mohammadreza Behjati:** Data curation. **Sobhan Sheykhivand:** Software, Investigation. **Sebelan Danishvar:** Supervision, Project administration, Data curation, Conceptualization.

Declaration of competing interest

The author is a Guest Editor for [Bioengineering journal] and was not involved in the editorial review or the decision to publish this article.

Data availability

The article is in review form and no data is used for processing in it.

Acknowledgements

This study does not include appreciation and thanks to any particular institution/organization or person.

Nomenclature

AD	Alzheimer's Disease
ADHD	Attention Deficit Hyperactivity Disorder
AEC	Amplitude Envelope Correlation
ARAT	Action Research Arm Test
ASD	Autism Spectrum Disorder
BCI	Brain-Computer Interface
BOLD	Blood Oxygen Level Dependent
CNN	Convolutional Neural Network
CPL	Characteristic Path Length
DBS	Deep Brain Stimulation
DTF	Directed Transfer Function
EEG	Electroencephalogram
EMG	Electromyogram
EOG	Electrooculogram
eLORETA	exact Low Resolution Electromagnetic Tomography
FMAL	Fugl-Myer Assessment of the Lower Limb Section
fMRI	functional Magnetic Resonance Imaging
HCI	Human-Computer Interaction
iCoh	imaginary part of Coherence
ITD	Intrinsic Time-scale Decomposition
KNN	K-Nearest Neighbour
LZC	Lempel-Ziv Complexity
MDD	Mild Depressive Disorder
MEG	Magnetoencephalogram
MI	Mutual Information
MST	Minimum Spanning Tree Algorithm
MTLE	Mesial Temporal Lobe Epilepsy
NIHSS	National Institutes of Health Stroke Scale
NMF	Non-negative Matrix Factorization
OCD	Obsessive-Compulsive Disorder
PDC	Partial Directed Coherence
PET	Positron Emission Tomography

PLI	Phase Lag Index
PLV	Phase Locking Value
PNES	Psychogenic Non-Epileptic Seizures
PPC	Pairwise Phase Consistency
PRISMA	Preferred Reported Items for Systematic Reviews and Meta-Analyses
PSD	Power Spectrum Density
PSI	Phase-Slope Index
SL	Synchronization Likelihood
sLORETA	standardized Low-Resolution Electromagnetic Tomography Algorithm
SCD	Subjective Cognitive Decline
SPECT	Single-Photon Emission Computerized Tomograph
SVM	Support Vector Machine
tDCS	transcranial Direct Current Stimulation
WPLI	Weighted Phase Lag Index

References

[1] Ardabili SZ, Bahmani S, Lahijan LZ, Khaleghi N, Sheykhivand S, Danishvar S. A novel approach for automatic detection of driver fatigue using EEG signals based on graph convolutional networks. Sensors 2024;24(2):364.
[2] Zhang D, Yao L, Chen K, Wang S, Haghighi PD, Sullivan C. A graph-based hierarchical attention model for movement intention detection from EEG signals. IEEE Trans Neural Syst Rehabil Eng 2019;27(11):2247–53.
[3] Ak A, Topuz V, Midi I. Motor imagery EEG signal classification using image processing technique over GoogLeNet deep learning algorithm for controlling the robot manipulator. Biomed Signal Process Control 2022;72:103295.
[4] Jia Z, et al. GraphSleepNet: adaptive spatial-temporal graph convolutional networks for sleep stage classification. In: Ijcai; 2020. p. 1324–30.
[5] Khaleghi N, Rezaii TY, Beheshti S, Meshgini S, Sheykhivand S, Danishvar S. Visual saliency and image reconstruction from EEG signals via an effective geometric deep network-based generative adversarial network. Electronics 2022;11(21):3637.
[6] Khaleghi N, Hashemi S, Ardabili SZ, Sheykhivand S, Danishvar S. Salient arithmetic data extraction from brain activity via an improved deep network. Sensors 2023;23(23):9351.
[7] Wu X, Zheng W-L, Li Z, Lu B-L. Investigating EEG-based functional connectivity patterns for multimodal emotion recognition. J Neural Eng 2022;19(1):016012.
[8] Cao J, et al. Brain functional and effective connectivity based on electroencephalography recordings: a review. Hum Brain Mapp 2022;43(2):860–79.
[9] Khaleghi N, Rezaii TY, Beheshti S, Meshgini S. Developing an efficient functional connectivity-based geometric deep network for automatic EEG-based visual decoding. Biomed Signal Process Control 2023;80:104221.
[10] Rivera MJ, Teruel MA, Mate A, Trujillo J. Diagnosis and prognosis of mental disorders by means of EEG and deep learning: a systematic mapping study. Artif Intell Rev 2022:1–43.
[11] Moher D, Liberati A, Tetzlaff J, Altman DG, Group P. Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. Ann Intern Med 2009;151(4):264–9.
[12] Schoppenhorst M, Brauer F, Freund G, Kubicki S. The significance of coherence estimates in determining central alpha and mu activities. Electroencephalogr Clin Neurophysiol 1980;48(1):25–33.
[13] Rappelsberger P, Petsche H. Probability mapping: power and coherence analyses of cognitive processes. Brain Topogr 1988;1:46–54.
[14] Andrew C, Pfurtscheller G. Event-related coherence as a tool for studying dynamic interaction of brain regions. Electroencephalogr Clin Neurophysiol 1996;98(2):144–8.
[15] Gerloff C, Richard J, Hadley J, Schulman AE, Honda M, Hallett M. Functional coupling and regional activation of human cortical motor areas during simple, internally paced and externally paced finger movements. Brain: J Neurol 1998;121(8):1513–31.
[16] Nolte G, et al. Robustly estimating the flow direction of information in complex physical systems. Phys Rev Lett 2008;100(23):234101.
[17] Rana P, Lipor J, Lee H, Van Drongelen W, Kohrman MH, Van Veen B. Seizure detection using the phase-slope index and multichannel ECoG. IEEE (Inst Electr Electron Eng) Trans Biomed Eng 2012;59(4):1125–34.
[18] Nolte G, Bai O, Wheaton L, Mari Z, Vorbach S, Hallett M. Identifying true brain interaction from EEG data using the imaginary part of coherency. Clin Neurophysiol 2004;115(10):2292–307.
[19] Blinowska KJ. Review of the methods of determination of directed connectivity from multichannel data. Med Biol Eng Comput 2011;49:521–9.
[20] Lachaux JP, Rodriguez E, Martinerie J, Varela FJ. Measuring phase synchrony in brain signals. Hum Brain Mapp 1999;8(4):194–208.
[21] Stam CJ, Nolte G, Daffertshofer A. Phase lag index: assessment of functional connectivity from multi channel EEG and MEG with diminished bias from common sources. Hum Brain Mapp 2007;28(11):1178–93.
[22] Vinck M, van Wingerden M, Womelsdorf T, Fries P, Pennartz CM. The pairwise phase consistency: a bias-free measure of rhythmic neuronal synchronization. Neuroimage 2010;51(1):112–22.
[23] Granger CW. Investigating causal relations by econometric models and cross-spectral methods. Econometrica: J Econom Soc 1969:424–38.
[24] Geweke J. Measurement of linear dependence and feedback between multiple time series. J Am Stat Assoc 1982;77(378):304–13.
[25] Kaminski MJ, Blinowska KJ. A new method of the description of the information flow in the brain structures. Biol Cybern 1991;65(3):203–10.
[26] Ding M, Chen Y, Bressler SL. Granger causality: basic theory and application to neuroscience. In: Handbook of time series analysis: recent theoretical developments and applications; 2006. p. 437–60.
[27] Li P, et al. Robust Granger analysis in Lp norm space for directed EEG network analysis. IEEE Trans Neural Syst Rehabil Eng 2017;25(11):1959–69.
[28] De Vico Fallani F, et al. Evaluation of the brain network organization from EEG signals: a preliminary evidence in stroke patient. Anat Rec: Advances in Integrative Anatomy and Evolutionary Biology: Advances in Integrative Anatomy and Evolutionary Biology 2009;292(12):2023–31.
[29] Jiang L, Xu H, Yu C. Brain connectivity plasticity in the motor network after ischemic stroke. Neural Plast 2013;2013.
[30] Wu J, et al. Connectivity measures are robust biomarkers of cortical function and plasticity after stroke. Brain 2015;138(8):2359–69.
[31] Liu S, et al. Abnormal EEG complexity and functional connectivity of brain in patients with acute thalamic ischemic stroke. Comput Math Methods Med 2016;2016.
[32] Philips GR, Daly JJ, Príncipe JC. Topographical measures of functional connectivity as biomarkers for post-stroke motor recovery. J NeuroEng Rehabil 2017;14(1):1–16.
[33] Hoshino T, Oguchi K, Inoue K, Hoshino A, Hoshiyama M. Relationship between lower limb function and functional connectivity assessed by EEG among motor-related areas after stroke. Top Stroke Rehabil 2021;28(8):614–23.
[34] Vecchio F, et al. Cortical connectivity from EEG data in acute stroke: a study via graph theory as a potential biomarker for functional recovery. Int J Psychophysiol 2019;146:133–8.
[35] Knott V, Mahoney C, Kennedy S, Evans K. EEG power, frequency, asymmetry and coherence in male depression. Psychiatr Res Neuroimaging 2001;106(2):123–40.
[36] Fingelkurts AA, Fingelkurts AA, Rytsälä H, Suominen K, Isometsä E, Kähkönen S. Composition of brain oscillations in ongoing EEG during major depression disorder. Neurosci Res 2006;56(2):133–44.
[37] Fingelkurts AA, Fingelkurts AA, Rytsälä H, Suominen K, Isometsä E, Kähkönen S. Impaired functional connectivity at EEG alpha and theta frequency bands in major depression. Hum Brain Mapp 2007;28(3):247–61.
[38] Lee T-W, Wu Y-T, Yu YW-Y, Chen M-C, Chen T-J. The implication of functional connectivity strength in predicting treatment response of major depressive disorder: a resting EEG study. Psychiatr Res Neuroimaging 2011;194(3):372–7.
[39] Quraan MA, et al. EEG power asymmetry and functional connectivity as a marker of treatment effectiveness in DBS surgery for depression. Neuropsychopharmacology 2014;39(5):1270–81.
[40] Li Y, Cao D, Wei L, Tang Y, Wang J. Abnormal functional connectivity of EEG gamma band in patients with depression during emotional face processing. Clin Neurophysiol 2015;126(11):2078–89.
[41] Mumtaz W, Ali SSA, Yasin MAM, Malik AS. A machine learning framework involving EEG-based functional connectivity to diagnose major depressive disorder (MDD). Med Biol Eng Comput 2018;56:233–46.
[42] Peng H, et al. Multivariate pattern analysis of EEG-based functional connectivity: a study on the identification of depression. IEEE Access 2019;7:92630–41.
[43] Liu W, et al. Functional connectivity of major depression disorder using ongoing EEG during music perception. Clin Neurophysiol 2020;131(10):2413–22.
[44] Damborská A, et al. Altered directed functional connectivity of the right amygdala in depression: high-density EEG study. Sci Rep 2020;10(1):4398.
[45] Mohammadi Y, Moradi MH. Prediction of depression severity scores based on functional connectivity and complexity of the EEG signal. Clin EEG Neurosci 2021;52(1):52–60.
[46] Movahed RA, Jahromi GP, Shahyad S, Meftahi GH. A major depressive disorder classification framework based on EEG signals using statistical, spectral, wavelet, functional connectivity, and nonlinear analysis. J Neurosci Methods 2021;358:109209.
[47] Movahed RA, Jahromi GP, Shahyad S, Meftahi GH. A major depressive disorder diagnosis approach based on EEG signals using dictionary learning and functional connectivity features. Physical and Engineering Sciences in Medicine 2022;45(3):705–19.
[48] Yang L, Wei X, Liu F, Zhu X, Zhou F. Automatic feature learning model combining functional connectivity network and graph regularization for depression detection. Biomed Signal Process Control 2023;82:104520.
[49] Khosrowabadi R, Heijnen M, Wahab A, Quek HC. The dynamic emotion recognition system based on functional connectivity of brain regions. In: 2010 IEEE intelligent vehicles symposium. IEEE; 2010. p. 377–81.
[50] Lee Y-Y, Hsieh S. Classifying different emotional states by means of EEG-based functional connectivity patterns. PLoS One 2014;9(4):e95415.
[51] Yuvaraj R, Murugappan M, Acharya UR, Adeli H, Ibrahim NM, Mesquita E. Brain functional connectivity patterns for emotional state classification in Parkinson's disease patients without dementia. Behav Brain Res 2016;298:248–60.
[52] Xing M, et al. EEG based functional connectivity reflects cognitive load during emotion regulation. In: 2016 IEEE 13th international symposium on biomedical imaging (ISBI). IEEE; 2016. p. 771–4.

[53] Al-Shargie F, Tariq U, Alex M, Mir H, Al-Nashash H. Emotion recognition based on fusion of local cortical activations and dynamic functional networks connectivity: an EEG study. IEEE Access 2019;7:143550–62.
[54] Wu X, Zheng W-L, Lu B-L. Identifying functional brain connectivity patterns for EEG-based emotion recognition. In: 2019 9th international IEEE/EMBS conference on neural engineering (NER). IEEE; 2019. p. 235–8.
[55] Li P, et al. EEG based emotion recognition by combining functional connectivity network and local activations. IEEE (Inst Electr Electron Eng) Trans Biomed Eng 2019;66(10):2869–81.
[56] Klados MA, Konstantinidi P, Dacosta-Aguayo R, Kostaridou V-D, Vinciarelli A, Zervakis M. Automatic recognition of personality profiles using EEG functional connectivity during emotional processing. Brain Sci 2020;10(5):278.
[57] Cao R, et al. EEG functional connectivity underlying emotional valance and arousal using minimum spanning trees. Front Neurosci 2020;14:355.
[58] Zhang Y, Yan G, Chang W, Huang W, Yuan Y. EEG-based multi-frequency band functional connectivity analysis and the application of spatio-temporal features in emotion recognition. Biomed Signal Process Control 2023;79:104157.
[59] Supriya S, Siuly S, Wang H, Zhang Y. Epilepsy detection from EEG using complex network techniques: a review. IEEE Reviews in Biomedical Engineering 2021;16: 292–306.
[60] Ponten S, Bartolomei F, Stam C. Small-world networks and epilepsy: graph theoretical analysis of intracerebrally recorded mesial temporal lobe seizures. Clin Neurophysiol 2007;118(4):918–27.
[61] Bettus G, et al. Enhanced EEG functional connectivity in mesial temporal lobe epilepsy. Epilepsy Res 2008;81(1):58–68.
[62] Bettus G, et al. Interictal functional connectivity of human epileptic networks assessed by intracerebral EEG and BOLD signal fluctuations. PLoS One 2011;6(5): e20071.
[63] Canuet L, et al. Resting-state EEG source localization and functional connectivity in schizophrenia-like psychosis of epilepsy. PLoS One 2011;6(11):e27863.
[64] Van Mierlo P, et al. Functional brain connectivity from EEG in epilepsy: seizure prediction and epileptogenic focus localization. Prog Neurobiol 2014;121:19–35.
[65] Sargolzaei S, Cabrerizo M, Goryawala M, Eddin AS, Adjouadi M. Scalp EEG brain functional connectivity networks in pediatric epilepsy. Comput Biol Med 2015; 56:158–66.
[66] Coito A, et al. Altered directed functional connectivity in temporal lobe epilepsy in the absence of interictal spikes: a high density EEG study. Epilepsia 2016;57 (3):402–11.
[67] Adebimpe A, Aarabi A, Bourel-Ponchel E, Mahmoudzadeh M, Wallois F. EEG resting state functional connectivity analysis in children with benign epilepsy with centrotemporal spikes. Front Neurosci 2016;10:143.
[68] Lagarde S, et al. Interictal stereotactic-EEG functional connectivity in refractory focal epilepsies. Brain 2018;141(10):2966–80.
[69] Leitgeb EP, Šterk M, Petrijan T, Gradišnik P, Gosak M. The brain as a complex network: assessment of EEG-based functional connectivity patterns in patients with childhood absence epilepsy. Epileptic Disord 2020;22(5):519–30.
[70] Varone G, et al. A machine learning approach involving functional connectivity features to classify rest-EEG psychogenic non-epileptic seizures from healthy controls. Sensors 2021;22(1):129.
[71] Murias M, Swanson JM, Srinivasan R. Functional connectivity of frontal cortex in healthy and ADHD children reflected in EEG coherence. Cerebr Cortex 2007;17 (8):1788–99.
[72] Castellanos FX, Kelly C, Milham MP. The restless brain: attention-deficit hyperactivity disorder, resting—state functional connectivity, and intrasubject variability. Can J Psychiatr 2009;54(10):665–72.
[73] Méndez L, et al. 582 inter and intrahemispheric eeg nonlinear synchronization in children with attention deficit hyperactivity disorder. Pediatr Res 2010;68(1): 298–9.
[74] Ahmadlou M, Adeli H. Wavelet-synchronization methodology: a new approach for EEG-based diagnosis of ADHD. Clin EEG Neurosci 2010;41(1):1–10.
[75] Mazaheri A, Coffey-Corina S, Mangun GR, Bekker EM, Berry AS, Corbett BA. Functional disconnection of frontal cortex and visual cortex in attention-deficit/ hyperactivity disorder. Biol Psychiatr 2010;67(7):617–23.
[76] Ahmadlou M, Adeli H, Adeli A. Graph theoretical analysis of organization of functional brain networks in ADHD. Clin EEG Neurosci 2012;43(1):5–13.
[77] Alba G, et al. The variability of EEG functional connectivity of young ADHD subjects in different resting states. Clin Neurophysiol 2016;127(2):1321–30.
[78] Michelini G, et al. Atypical functional connectivity in adolescents and adults with persistent and remitted ADHD during a cognitive control task. Transl Psychiatry 2019;9(1):137.
[79] Chen H, Song Y, Li X. A deep learning framework for identifying children with ADHD using an EEG-based brain network. Neurocomputing 2019;356:83–96.
[80] Kiiski H, et al. Functional EEG connectivity is a neuromarker for adult attention deficit hyperactivity disorder symptoms. Clin Neurophysiol 2020;131(1):330–42.
[81] O'Reilly C, et al. EEG functional connectivity in infants at elevated familial risk for autism spectrum disorder. 2023.
[82] Haartsen R, Jones EJ, Orekhova EV, Charman T, Johnson MH. Functional EEG connectivity in infants associates with later restricted and repetitive behaviours in autism; a replication study. Transl Psychiatry 2019;9(1):66.
[83] Zhou T, Kang J, Li Z, Chen H, Li X. Transcranial direct current stimulation modulates brain functional connectivity in autism. Neuroimage: Clinica 2020;28: 102500.
[84] Alotaibi N, Maharatna K. Classification of autism spectrum disorder from EEG-based functional brain connectivity analysis. Neural Comput 2021;33(7): 1914–41.
[85] Alves CL, Pineda AM, Roster K, Thielemann C, Rodrigues FA. EEG functional connectivity and deep learning for automatic diagnosis of brain disorders: alzheimer's disease and schizophrenia. J Phys: Complexity 2022;3(2):025001.
[86] Briels CT, Stam CJ, Scheltens P, Bruins S, Lues I, Gouw AA. In pursuit of a sensitive EEG functional connectivity outcome measure for clinical trials in Alzheimer's disease. Clin Neurophysiol 2020;131(1):88–95.
[87] Briels CT, Schoonhoven DN, Stam CJ, de Waal H, Scheltens P, Gouw AA. Reproducibility of EEG functional connectivity in Alzheimer's disease. Alzheimer's Res Ther 2020;12:1–14.
[88] Smailovic U, et al. Regional disconnection in Alzheimer dementia and amyloid-positive mild cognitive impairment: association between EEG functional connectivity and brain glucose metabolism. Brain Connect 2020;10(10):555–65.
[89] Ruiz-Gómez SJ, Hornero R, Poza J, Maturana-Candelas A, Pinto N, Gómez C. Computational modeling of the effects of EEG volume conduction on functional connectivity metrics. Application to Alzheimer's disease continuum. J Neural Eng 2019;16(6):066019.
[90] Lehmann D, Faber PL, Tei S, Pascual-Marqui RD, Milz P, Kochi K. Reduced functional connectivity between cortical sources in five meditation traditions detected with lagged coherence using EEG tomography. Neuroimage 2012;60(2): 1574–86.
[91] Tan B, Liu Q, Wan C, Jin Z, Yang Y, Li L. Altered functional connectivity of alpha rhythm in obsessive-compulsive disorder during rest. Clin EEG Neurosci 2019;50 (2):88–99.
[92] Olbrich S, Olbrich H, Adamaszek M, Jahn I, Hegerl U, Stengler K. Altered EEG lagged coherence during rest in obsessive–compulsive disorder. Clin Neurophysiol 2013;124(12):2421–30.
[93] Perera MPN, Mallawaarachchi S, Bailey NW, Murphy OW, Fitzgerald PB. Obsessive-compulsive disorder (OCD) is associated with increased electroencephalographic (EEG) delta and theta oscillatory power but reduced delta connectivity. J Psychiatr Res 2023;163:310–7.
[94] Mackintosh AJ, et al. Psychotic disorders, dopaminergic agents and EEG/MEG resting-state functional connectivity: a systematic review. Neurosci Biobehav Rev 2021;120:354–71.
[95] Porcaro C, et al. Multiple frequency functional connectivity in the hand somatosensory network: an EEG study. Clin Neurophysiol 2013;124(6):1216–24.
[96] Jamieson GA, Burgess AP. Hypnotic induction is followed by state-like changes in the organization of EEG functional connectivity in the theta and beta frequency bands in high-hypnotically susceptible individuals. Front Hum Neurosci 2014;8: 528.
[97] Mohagheghian F, et al. Computer-aided tinnitus detection based on brain network analysis of EEG functional connectivity. Journal of biomedical physics & engineering 2019;9(6):687.
[98] Kuang Y, et al. Phase lag index of resting-state EEG for identification of mild cognitive impairment patients with type 2 diabetes. Brain Sci 2022;12(10):1399.
[99] Zheng R, et al. Scalp EEG functional connection and brain network in infants with west syndrome. Neural Network 2022;153:76–86.
[100] Hjorth B. An on-line transformation of EEG scalp potentials into orthogonal source derivations. Electroencephalogr Clin Neurophysiol 1975;39(5):526–30.
[101] Pfurtscheller G, Andrew C. Event-related changes of band power and coherence: methodology and interpretation. J Clin Neurophysiol 1999;16(6):512.
[102] Phothisonothai M, Nakagawa M. EEG-based classification of new imagery tasks using three-layer feedforward neural network classifier for brain–computer Interface. J Phys Soc Jpn 2006;75(10):104801.
[103] Chella F, Pizzella V, Zappasodi F, Marzetti L. Impact of the reference choice on scalp EEG connectivity estimation. J Neural Eng 2016;13(3):036016.
[104] Qin Y, Xu P, Yao D. A comparative study of different references for EEG default mode network: the use of the infinity reference. Clin Neurophysiol 2010;121(12): 1981–91.
[105] Marzetti L, Nolte G, Perrucci MG, Romani GL, Del Gratta C. The use of standardized infinity reference in EEG coherency studies. Neuroimage 2007;36 (1):48–63.
[106] Yao D. A method to standardize a reference of scalp EEG recordings to a point at infinity. Physiol Meas 2001;22(4):693.
[107] Berg P, Scherg M. A multiple source approach to the correction of eye artifacts. Electroencephalogr Clin Neurophysiol 1994;90(3):229–41.
[108] Hoechstetter K, Berg P, Scherg M. BESA research tutorial 4: distributed source imaging. BESA Research Tutorial; 2010. p. 1–29.
[109] Durka PJ, Klekowicz H, Blinowska KJ, Szelenberger W, Niemcewicz S. A simple system for detection of EEG artifacts in polysomnographic recordings. IEEE Trans Biomed Eng 2003;50(4):526–8.
[110] Delorme A, Makeig S. EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. J Neurosci Methods 2004;134(1):9–21.
[111] Nolan H, Whelan R, Reilly RB. FASTER: fully automated statistical thresholding for EEG artifact rejection. J Neurosci Methods 2010;192(1):152–62.
[112] Ricci L, et al. Measuring the effects of first antiepileptic medication in Temporal Lobe Epilepsy: predictive value of quantitative-EEG analysis. Clin Neurophysiol 2021;132(1):25–35.
[113] Wendling F, Badier J, Chauvel P, Coatrieux J. A method to quantify invariant information in depth-recorded epileptic seizures. Electroencephalogr Clin Neurophysiol 1997;102(6):472–85.
[114] Kim J, Lee WG, Park S, Park KM. Can we predict drug response by functional connectivity in patients with juvenile myoclonic epilepsy? Clin Neurol Neurosurg 2020;198:106119.
[115] Ahmadlou M, Rostami R, Sadeghi V. Which attention-deficit/hyperactivity disorder children will be improved through neurofeedback therapy? A graph

theoretical approach to neocortex neuronal network of ADHD. Neurosci Lett 2012;516(1):156–60.
[116] De Luca R, et al. Improvement of brain functional connectivity in autism spectrum disorder: an exploratory study on the potential use of virtual reality. J Neural Transm 2021;128:371–80.
[117] Aiyer R, Novakovic V, Barkin RL. A systematic review on the impact of psychotropic drugs on electroencephalogram waveforms in psychiatry. PGM (Postgrad Med) 2016;128(7):656–64.
[118] Albrecht MA, Roberts G, Price G, Lee J, Iyyalol R, Martin-Iverson MT. The effects of dexamphetamine on the resting-state electroencephalogram and functional connectivity. Hum Brain Mapp 2016;37(2):570–88.
[119] Krukow P, Jonak K, Karpiński R, Karakuła-Juchnowicz H. Abnormalities in hubs location and nodes centrality predict cognitive slowing and increased performance variability in first-episode schizophrenia patients. Sci Rep 2019;9(1):9594.
[120] Zaytseva Y, et al. EEG coherence in a mental arithmetic task performance in first episode schizophrenia and schizoaffective disorder. Clin Neurophysiol 2018;129(11):2315–24.
[121] Umesh S, Nizamie SH, Goyal N, Tikka S, Bose S. Social anhedonia and gamma band abnormalities as a composite/multivariate endophenotype for schizophrenia: a dense array EEG study. Early intervention in psychiatry 2018;12(3):362–71.